

**ADDRESSING THE RISKS OF INVASIVE
PLANTS THROUGH SPATIAL PREDICTIVE
MODELLING**

by

Cory John Lindgren

A Thesis submitted to the Faculty of Graduate Studies of

The University of Manitoba

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Department of Environment and Geography

University of Manitoba

Winnipeg

Copyright © 2013 by Cory Lindgren

ABSTRACT

The objective of this dissertation is to extend the use of spatial predictive modelling for use by biosecurity agencies to help prevent the introductions of new and emerging invasive plants (i.e., pests). A critical review of international and national policy instruments found that they did not effectively articulate how spatial predictive modelling could be incorporated into the biosecurity toolbox. To determine how spatial predictive modelling could be extended I modelled the potential distribution of *Tamarix* and *Lythrum salicaria* in Prairie Canada using a genetic algorithm. New seasonal growth data was used to interpolate a growing degree-day's risk surface for *L. salicaria*. Models were developed using suites of predictive variables as well as different data partitioning methods and evaluated using different performance measures. Expert evaluation was found to be important in final model selection. The results indicated that both invasive plants have yet to reach their potential distribution in Prairie Canada. The spatial models can be used to direct risk-based surveillance efforts and to support biosecurity policy decisions. The results of this dissertation conclude that spatial predictive modelling is an informative tool that needs to be incorporated into the biosecurity toolbox. A phytosanitary standard is proposed to guide toolbox development.

ACKNOWLEDGEMENTS

I would like to thank the members of my examining committee Dr. David Walker (Advisor), Department of Environment and Geography at the University of Manitoba; Dr. Doreen Watler (Internal Examiner), Canadian Food Inspection Agency, National Manager of the Plant Health Risk Assessment Unit in Ottawa; Dr. Rene Van Acker (Internal Examiner), University of Guelph, Department of Plant Agriculture in Ontario; and Dr. Jeanne Jones (External Examiner), Mississippi State University. Special thanks to Brandy Usick for her support and guidance as well as Dr. Rick Baydack, University of Manitoba, Department of Environment and Geography. I also thank the journal reviewers and editors whose comments improved upon the published portions of this dissertation. I would like to further extend my thanks to the Canadian Food Inspection Agency for its support.

And to those friends and family who helped along the way.....Thanks!



TABLE OF CONTENTS

ABSTRACT	I
ACKNOWLEDGEMENTS	II
LIST OF TABLES	V
LIST OF FIGURES	VII
CHAPTER 1 – STATEMENT OF PROBLEM AND OBJECTIVES	1
1.1 PROBLEM AND OBJECTIVES	1
1.2 THESIS STRUCTURE	2
1.3 REFERENCES	4
CHAPTER 2 – WHY INVASIVE PLANTS ARE A PROBLEM	6
2.1 WHAT IS AN INVASIVE ALIEN PLANT?	6
2.2 WHY ARE INVASIVE PLANTS A PROBLEM?	7
2.3 ENVIRONMENTAL COSTS OF INVASIVE PLANTS	10
2.4 ECONOMIC COSTS OF INVASIVE PLANTS	13
2.5 IMPACTS ON HUMAN HEALTH	19
2.6 CONCLUSIONS	21
2.7 REFERENCES	21
CHAPTER 3 - BIOSECURITY POLICY AND THE USE OF SPATIAL PREDICTIVE TOOLS TO ADDRESS INVASIVE PLANTS: THE NEED TO UPDATE THE RISK ANALYSIS TOOL BOX 31	
3.1 INTRODUCTION	31
3.2 INTERNATIONAL PLANT BIOSECURITY	33
3.3 INTERNATIONAL PLANT PROTECTION CONVENTION	34
3.4 UNITED NATIONS CONVENTION ON BIODIVERSITY	38
3.5 UPDATING THE BIOSECURITY RISK ANALYSIS TOOL BOX	40
3.6 CONCLUSIONS	43
3.7 REFERENCES	44
CHAPTER 4 – SPATIAL PREDICTIVE MODELLING LITERACY	50
4.1 SPATIAL PREDICTIVE MODELLING AND NICHE SPACE	50
4.2 WHY ARE SPECIES WHERE THEY ARE?	50
4.3 TYPES OF SPATIAL MODELS	55
4.4 SPATIAL PREDICTIVE MODELLING APPROACHES	58
4.4.1 <i>BIOCLIM</i>	59
4.4.2 <i>CLIMEX</i>	62
4.4.3 <i>GARP</i>	65
4.4.4 <i>Why use GARP?</i>	69
4.5 CHALLENGES IN SPATIAL PREDICTIVE MODELLING	72
4.5.1 <i>Choosing the Appropriate Model - All Things are Not Equal</i>	73
4.5.2 <i>Estimating Prediction Error (Omission and Commission)</i>	74
4.5.3 <i>Measuring Model Accuracy and Performance</i>	76
4.5.4 <i>Data Quality</i>	78
4.5.5 <i>Can Models Account for Biotic Interactions?</i>	79
4.5.6 <i>Spatial Autocorrelation</i>	80
4.5.7 <i>Dispersal</i>	81
4.5.8 <i>Modelling Fundamental vs. Realized Niche Space</i>	82
4.6 CONCLUSION	83
4.7 REFERENCES	83

CHAPTER 5 –ASSESSING THE SPATIAL RISK OF PURPLE LOOSESTRIFE (<i>LYTHRUM SALICARIA</i>) TO PRAIRIE CANADA USING GROWING-DEGREE DAYS AND FIELD COLLECTED DATA	99
5.1 INTRODUCTION	100
5.2 MATERIALS AND METHODS	104
5.3 RESULTS AND DISCUSSION	109
5.4 CONCLUSIONS	123
5.5 LITERATURE CITED	123
CHAPTER 6 - PREDICTING THE SPATIAL RISK OF PURPLE LOOSESTRIFE (<i>LYTHRUM SALICARIA</i>) TO PRAIRIE CANADA; EXTENDING THE APPLICATION OF ECOLOGICAL NICHE MODELLING TO BIOSECURITY RISK ANALYSIS	133
6.1 INTRODUCTION	134
6.2 MATERIALS AND METHODS	142
6.3 RESULTS AND DISCUSSION	154
6.3.1 <i>Geographic partitioning of data</i>	155
6.3.2 <i>Expert evaluation</i>	157
6.3.4 <i>Areas at risk - wetlands</i>	171
6.3.5 <i>Implications for Biosecurity Risk Analyses and Policy</i>	171
6.3.6 <i>Practical applications of the model</i>	173
6.3.7 <i>Future research</i>	175
6.4 CONCLUSIONS	176
6.5 REFERENCES.....	178
CHAPTER 7 – <i>TAMARIX RAMOSISSIMA</i> LEDEB., <i>T. CHINENSIS</i> LOUR. AND HYBRIDS A NEW INVASIVE PLANT TO CANADA; EXTENDING THE APPLICATION OF ECOLOGICAL NICHE MODELLING TO BIOSECURITY RISK ANALYSIS	191
7.1 INTRODUCTION	192
7.2 DESCRIPTION AND ACCOUNT OF VARIATION	193
7.3 ECONOMIC IMPORTANCE AND ENVIRONMENTAL IMPACT.....	197
7.4 GEOGRAPHICAL DISTRIBUTION	200
7.5 HABITAT	202
7.6 HISTORY	204
7.7 GROWTH AND DEVELOPMENT	206
7.8 REPRODUCTION	208
7.9 HYBRIDS.....	210
7.10 POPULATION DYNAMICS	211
7.11 RESPONSE TO HERBICIDES AND OTHER CHEMICALS	211
7.12 RESPONSE TO OTHER HUMAN MANIPULATIONS.....	213
7.13 RESPONSE TO HERBIVORY, DISEASE AND HIGHER PLANT PARASITES	216
7.14 SPATIAL PREDICTIVE MODELLING OF SALT CEDAR IN PRAIRIE CANADA	217
7.14.1 <i>Study Area</i>	217
7.14.2 <i>Modelling Methods</i>	218
7.14.3 <i>Results and Discussion</i>	226
7.15 CONCLUSIONS	235
7.16 REFERENCES.....	236
CHAPTER 8 – CONCLUSIONS AND CONTRIBUTION TO NEW KNOWLEDGE	254
8.1 SUMMARY	254
8.2 APPLICATIONS OF NEW KNOWLEDGE	254
8.2.1 <i>Biosecurity Decision-Making</i>	254
8.2.2 <i>An RSPM on Spatial Predictive Modelling</i>	255
8.2.3 <i>Risk-based Early Detection and Rapid Response (EDRR) Programs</i>	261
8.3 CONTRIBUTIONS TO NEW KNOWLEDGE.....	263
8.4 REFERENCES.....	265

LIST OF TABLES

Table 4.1 Comparative summary of common spatial predictive modeling approaches.....	59
Table 5.1 Monthly mean temperature and total precipitation followed by 30-year average (1971-2000) in brackets. Cumulative growing degree-days (GDD's) for each month of the study period.....	110
Table 5.2 Annual stem growth data for the Libau fixed monitoring stations (FMS). For each FMS, growing degree-days (GDD's), mean stem height, standard error (SE) and change in centimeters of growth between data collection dates (in brackets) is provided.....	111
Table 5.3 Phenology as a function of cumulative growing degree days. Cumulative growing degree-days followed by calendar date data in brackets, followed by the mean stem height.....	113
Table 5.4 Purple loosestrife seed production. Mean number of seed pods per stem and mean number of seeds per pod, followed by the standard error in brackets, and range.....	116
Table 5.5 Comparative studies on purple loosestrife seed production.....	118
Table 6.1 Summary of predictor variables used to develop ecological niche models. Predictor variables were obtained from the Intergovernmental Panel on Climate Change (IPCC, 2001).....	147
Table 6.2 Confusion matrix used to measure the accuracy of GARP models.....	149
Table 6.3 Measures used to evaluate performance and accuracy of best subset composite models.....	152
Table 6.4 Measuring model performance using quintile approach with N=22 training points. Measures represent mean value for the best subset composite model.....	166
Table 6.5 Measuring model performance using stratified random sampling (i.e., provincial approach) with N=441 training points. Measures represent mean value for the best subset composite model.....	167
Table 6.6 Predictive accuracy of composite models based using independently with held test occurrence points. In the provincial approach N=188 occurrence points were withheld, and in the quintile approach N=609 occurrence points were withheld. The number of known occurrence points found outside the risk model is followed by the model accuracy.....	168

Table 6.7 The number of models and pixels predicted by each predictor variables final best subset top 10 composite risk model. The “0” column represents the number of pixels predicted as not suitable for purple loosestrife in prairie Canada.....168

Table 7.1 The interpolated predictive variables (i.e., independent variables) used in modeling the potential distribution of saltcedar in Prairie Canada. Climate variables represent annual average calculated from 1961 to 1990. Datasets are available from the Intergovernmental Panel on Climate Change world-wide Climate Data Distribution Centre (IPCC).....219

Table 7.2 Hierarchical partitioning of predictive variables using an *N - 1* jackknife procedure. Slope and aspect were excluded while elevation and all three climate variables were retained in final model building. Predictive accuracy (PA) $((a+b)/n)$, extrinsic omission error (EOE) $((c/n) \times 100)$ and the odds-ratio (OR) (ad/cb) was used to select predictive variables.229

Table 7.3 Measuring the predictive accuracy of the saltcedar ecological niche models. Each model was created using a suite of three climate variables and elevation as predictive variables. Specificity (Sp), sensitivity (Sn), correct classification rate (CCR), predictive accuracy (PA), extrinsic omission error (ExOm), extrinsic commission error (ExCom), and the odds-ratio (OR) were used as performance measures.....231

LIST OF FIGURES

- Figure 2.1** Invasive plants cost the Canadian economy billions of dollars annually. Examples include leafy spurge in Manitoba, knapweeds in British Columbia, and Canada thistle in wheat and canola.17
- Figure 2.2** A leafy spurge infestation along a rail line in West St Paul, Manitoba. Leafy spurge costs Manitoba as much as \$19 million dollars annually 18
- Figure 3.1** Spatial predictive modelling and geographic information systems (grey shaded triangles) can be incorporated into the risk analysis toolbox. The flowchart was adapted from Figure 2 in ISPM No. 2 (FAO 2006).....43
- Figure 4.1** The 2 x 2 confusion matrix. Elements of a confusion matrix are used to measure the performance of spatial predictive models. Measures include sensitivity, specificity, kappa, the odds ratio, omission and commission error.....75
- Figure 5.1** The Netley-Libau Marsh field study area. The locations of the three fixed monitoring stations (FMS) are identified by numbers 3, 4 and 5 in the map on the right. Season long field data on growth and was collected between 1995 and 1997 from each FMS.106
- Figure 5.2** Modelling the growth of purple loosestrife using growing degree-days (GDD's). Purple loosestrife emergence and growth in the Netley-Libau Marsh characterized by cumulative GDD's using a T_{base} of 8° C where $GDD_{daily} = (T_{max} + T_{min})/2 - T_{base}$. Circles are field data fitted to a logistic three-parameter nonlinear regression.119
- Figure 5.3** Spatial interpolation of cumulative mean growing degree-day's for Prairie Canada calculated using a T_{base} of 8°C. White circles indicate purple loosestrife occurrences with major city centres and provincial boundaries provided for context...121
- Figure 6.1** A study area project mask was used to develop the ecological niche models. It prevented the algorithm from selecting pseudoabsence data from areas from which the purple loosestrife is absent for biotic or dispersal reasons.148
- Figure 6.2** Illustration of geographic partitioning used to evaluate model predictivity. The quintile approach is illustrated where inside middle quintiles were used to train models using N=22 (dark circles) occurrence points, and the western, middle, and eastern quintiles were used to test the model N=609 (grey circles).....154
- Figure 6.3** Comparing risk maps created using the quintile (above) and provincial (below) approach. Topography and growing degree days were used as the predictive variables. Green circles are occurrence data used to test the model while yellow

circles were used to train the model. Major lakes are provided for context in blue.....159

Figure 6.4 Comparing risk maps created using the quintile (above) and provincial (below) approach. Topography was used as the predictive variable. Green circles are occurrence data used to test the model while yellow circles were used to train the model. Major lakes are provided for context in blue.160

Figure 6.5 Comparing risk maps created using the quintile (above) and provincial (below) approach. Topography and climate were used as the predictive variables. Green circles are occurrence data used to test the model while yellow circles were used to train the model. Major lakes are provided for context in blue.161

Figure 6.6 Comparing risk maps created using the quintile (above) and provincial (below) approach. Topography, climate and growing degree-day's were used as the predictive variables. Green circles are occurrence data used to test the model while yellow circles were used to train the model. Major lakes are provided for context in blue.162

Figure 6.7 Comparing risk maps created using the quintile (above) and provincial (below) approach. Climate was used as the predictive variable. Green circles are occurrence data used to test the model while yellow circles were used to train the model. Major lakes are provided for context in blue.....163

Figure 6.8 Comparing risk maps created using the quintile (above) and provincial (below) approach. Climate and growing degree-day's were used as the predictive variables. Green circles are occurrence data used to test the model while yellow circles were used to train the model. Major lakes are provided for context in blue.164

Figure 6.9 Comparing risk maps created using the quintile (above) and provincial (below) approach. Growing degree-day's was used as the predictive variable. Green circles are occurrence data used to test the model while yellow circles were used to train the model. Major lakes are provided for context in blue.165

Figure 6.10 Cloud of all 100 climate and GDD's risk models developed using the provincial approach. Plot of the top 10 best model subset inserted. Plot indicates that models reduce omission error while still predicting a reasonable proportion of the study area.....169

Figure 6.11 The model predicted a geographically disjunct area in north-western Alberta near Grande Prairie (as indicated by yellow circle), as having suitable habitat for invasion. This area was also predicted as suitable area by models using topography and climate, all layers, and climate alone as predictive variables, and in many of these models all 10 models agreed.....170

Figure 6.12 Illustration of spatial predictive modelling architecture used in this study.....	177
Figure 7.1 A <i>Tamarix</i> seedling. Photo taken in 2005 at Lake Sakakawea, North Dakota. Lake Sakakawea is on the Missouri River where unvegetated sand bars are becoming colonized by saltcedar.....	196
Figure 7.2 A chemically treated <i>Tamarix</i> plant at Lake Sakakawea, a reservoir in the Missouri River in central North Dakota, photo taken in 2005. Once saltcedar has established it is almost impossible to eradicate.....	213
Figure 7.3 Data was partitioned into testing and training subsets using quadrants. In building ecological niche models, the northwest and southeast (NWSE) quadrants were used to train the model while the northeast and southwest (NESW) quadrants were used to test the model.	226
Figure 7.4 Predictive potential distribution of saltcedar in Prairie Canada using all three climate variables and elevation as predictive variables using the NWSE (top) and NESW (bottom) data subset to train the model. Major lakes in the study area are outlined in black and shaded grey for reference.	228
Figure 7.5 Comparing the current and potential distribution of saltcedar. Current distribution of saltcedar is represented by black dots. The grey dots represent the predicted potential distribution as predicted by using the NWSE data subset for training.....	232

CHAPTER 1 – STATEMENT OF PROBLEM AND OBJECTIVES

“Nowadays we live in a very explosive world, and while we may not know where or when the next outburst will be, we might hope to find ways of stopping it or at any rate damping down its force. Its not just nuclear bombs and wars that threaten us, though these rank very high on the list at the moment: there are other sorts of explosions....ecological explosions....like potato disease, a green plant like prickly pear, or an animal like the grey squirrel...make no mistake we are seeing one of the great historical convulsions in the world’s fauna and flora” (Charles Elton 1958).

1.1 Problem and Objectives

The biosecurity risk analysis process is typically initiated in retrospect after a pest incursion has caused significant environmental, economic and/or human impact. Therefore, biosecurity agencies and land managers are continually seeking ways to predict and prevent the next new emerging pest. Prevention is widely recognized as the most effective and cost efficient strategy against invasive pests. However, the development of spatial predictive modelling tools has trailed behind the development of other risk analysis applications (Crossman and Bass 2007). This dissertation addresses the need to develop new spatial risk analysis tools that may predict areas that are susceptible to an emerging pest. There is a need for biosecurity tools that will help prevent introductions and guide biosecurity policy decision-making (Pheloung et al. 1999, Welk et al. 2002).

The overall objective of this dissertation is to explore how spatial predictive modelling can be used to address the biosecurity risks associated with invasive plants. To achieve this I will (1) explain why invasive plants are problem, (2) provide a critical

examination of how biosecurity agencies currently address invasive plants and make recommendations as to how spatial predictive modelling should be incorporated into the risk analysis processes, (3) critically review the most commonly used spatial modelling approaches and suggest a spatial predictive tool for use by biosecurity agencies (i.e., GARP), (4) explore how to use GARP as a spatial predictive modelling tool using an invasive plant that has not established in Prairie Canada (i.e., *Tamarix spp.*) and an invasive plant that has established in Prairie Canada (i.e., *Lythrum salicaria*) as examples, and (5) develop a new draft Regional Standard for Phytosanitary Measures that provides guidelines on how to incorporate spatial predictive modelling into the biosecurity toolbox.

1.2 Thesis Structure

This dissertation is written using a common sandwich style approach. Hence individual chapters follow the prescribed style and format of specific peer-reviewed scientific journals in which they were published. Chapter 1 provides the problem statement and objectives, Chapter 2 provides context as to why invasive plants are a problem, and Chapter 8 is the concluding chapter. The remaining chapters are the core chapters and are summarized below.

Chapter 3, entitled *Biosecurity Policy and the Use of Geospatial Tools to address Invasive Plants: Updating the Risk Analysis Tool Box*, provides a critical perspective on how invasive plants are addressed by international and national policy instruments, and makes novel recommendations on how the risk analysis toolbox needs to be updated to support biosecurity policy. The Chapter concludes that biosecurity agencies need to incorporate spatial predictive modelling, specifically GARP, into their risk analysis

frameworks. This chapter has been published in the journal *Risk Analyses* (Lindgren 2012).

In Chapter 4, I review ecological niche theory and introduce important spatial modelling principles and challenges. The chapter provides a critical examination of three different spatial modelling approaches and the advantages and disadvantages associated with each approach. The chapter concludes by discussing why GARP should be used by biosecurity agencies as a spatial decision making tool. Chapter 4 also critically evaluates the challenges associated with spatial predictive modelling.

Chapter 5 provides new spatial and biological data characterizing the growth and seed reproduction of purple loosestrife using original field data collected from three fixed monitoring stations (FMS) located in the Netley-Libau Marsh located in southern Manitoba. This chapter provides new biological data found to be lacking in the scientific literature. The new data was used to develop a new growing degree-day (GDD's) model for purple loosestrife using a T_{base} of 8°C , concluding that GDD's should be used as a variable in spatial predictive modelling. This chapter has been published in the journal *Wetlands* (Lindgren and Walker 2012).

In Chapter 6, I expand on the work presented in Chapters 4 and 5 by extending the use of spatial predictive modelling for use in the biosecurity risk analysis and in policy decision making. The chapter utilizes the new data presented in Chapter 5, and incorporates the GDD's predictive layer with climatic and topographic variables to model the potential distribution of purple loosestrife. The chapter study further evaluates how different methods of data partitioning and how different predictive variables affect GARP modelling results. A new model of the potential distribution of purple loosestrife

in Prairie Canada is presented. This chapter has been published in the journal *Canadian Field Naturalist* (Lindgren and Walker 2012).

Chapter 7 entitled *Tamarix ramosissima* Ledeb., *T. chinensis* Lour. And hybrids: a new invasive plant to Canada, provides a comprehensive review of a new invasive plant to Canada which was found to be lacking. The chapter also presents the first spatial predictive model for the *Tamarix spp.* in Prairie Canada using spatial predictive modelling. This chapter has been published in The Biology of Invasive Alien Plants in Canada series of the *Canadian Journal of Plant Science* (Lindgren et al. 2011). Portions of this chapter have also been published in the proceedings of the 2008 Weeds Across Borders conference (Lindgren 2008).

Chapter 8 is the concluding chapter. Extending upon the critical perspective provided in Chapter 3 and results of this dissertation, this chapter presents a draft Regional Standard for Phytosanitary Measures (RSPM) for consideration for use by biosecurity agencies. The chapter also discusses the applications of the results of the modelling studies in early detection rapid response (EDRR) systems.

1.3 References

- Lindgren, C.J. 2008. Addressing the Threats of Invasive Plants Through Spatial Predictive Modeling and Early Detection and Rapid Response. Proceedings of the Weeds Across Borders 2008 Conference. S. Darbyshire and R. Prasad (eds.). pp. 98-107.
- Lindgren, C.J., C. Pearce and K. Allison. 2010. The biology of invasive alien plants in Canada. 11. *Tamarix ramosissima* Ledeb., *T. chinensis* Lour. and hybrids. Canadian

Journal of Plant Science 90:111-124.

Lindgren, C.J. 2012. Biosecurity policy and the use of geospatial predictive tools to address invasive plants: updating the risk analysis toolbox. Risk Analysis 32:9-15.

Lindgren, C.J. and D. Walker. 2012. Growth rate, seed production, and assessing the spatial risk of *Lythrum salicaria* using growing degree-days. Wetlands 32:885-893.

Lindgren, C.J. and D. Walker. 2012. Predicting the spread of purple loosestrife (*Lythrum salicaria*) in the Prairies. Canadian Field Naturalist 126:xxx-xxx.

CHAPTER 2 – WHY INVASIVE PLANTS ARE A PROBLEM

2.1 What is an Invasive Alien Plant?

Widely-ranging species, abounding in individuals, which have already triumphed over many competitors in their own widely-extended homes, will have the best chance of seizing on new places, when they spread into new countries. In their new homes they will be exposed to new conditions, and will frequently undergo further modification and improvement; and thus they will become still further victorious (The Origin of Species – Charles Darwin)

A thing is right when it tends to preserve the integrity, stability, and beauty of the biotic community. It is wrong when it tends otherwise (Aldo Leopold 1949).

In order to understand why invasive plants are a problem, one needs to know what an invasive plant is. There are many definitions of what is considered an invasive plant however I will consider only a few as a comprehensive review is not within the objectives of this thesis. White et al. (1993) defined invasive plants as those that have moved into a habitat and reproduced so aggressively that they displaced some of the original components of the vegetative community. Richardson et al. (2000) provided recommended terminology suggesting that an alien plant is plant taxa in a given area whose presence there is due to intentional or accidental introduction as a result of human activity. They further suggested that an invasive plant is one that produces reproductive offspring, often in very large numbers, at considerable distances from parent plants. Richardson et al. (2000) also stressed that the introduction has to be a result of human activity, and Carroll (2011) referred to these as anthropogenic invasions. These definitions do not consider that invasive plants can also be introduced through natural

dispersal events such as seeds travelling along riparian areas or blowing in the wind. Koul et al. (2004) defined an invasive plant as a plant that has the potential to pose undesirable or deleterious impacts on humans, animals or ecosystems, often arriving from other areas and their spread and establishment is not suppressed by the natural forces present in their home environment.

For the purpose of this thesis, an invasive plant will be defined as a harmful plant whose introduction or spread threatens the environment, the economy, or society including human health. I have not included the term alien, as it traditionally leads one to think only about introductions between continents or countries, and not introductions between ecosystems within a country. This definition is an extension of the definition as provided by the Invasive Alien Species Strategy for Canada (2004), and is based upon impact (i.e., threatens the environment, economy or society).

2.2 Why are Invasive Plants a Problem?

A mine that modified the landscape on a similar scale (to invasive plants) would be subjected to intense scrutiny by the environmental impact assessment process and would probably not be approved (Lonsdale 1994).

In providing context to my overall thesis objectives, it is important to understand why invasive plants are considered a problem. In his landmark 1958 book, *The Ecology of Invasions by Animals and Plants*, Charles Elton discussed how the mingling of thousands of kinds of organisms from different parts of the world had changed the natural balance of the world (Elton 1958). Elton observed that over hundreds of millions

of year's plant and animal communities had become distinct from one another, however, human trade and travel obliterated these geographic distinctions by introducing new invasive species that brought deleterious implications. Elton described how faster, and bigger, air and vessel transport had resulted in foreign species being introduced into new locations. As an example of how species were being introduced into new areas, Elton described a survey conducted by an entomologist traveling on a rice ship from Trinidad to Manila in 1929. The entomologist found forty-one species on board the ship, mostly insects that walked out of his suitcase when he unpacked in his new destination. The hitch hikers included the invasive red flour beetle (*Tribolium castaneum*) a known pest of stored flour and grain. Fifty years after Elton's book, globalization continues to accelerate with annual advances in the speed and size of travel and transport, for example, since the 1970's international air freight alone has increased eightfold (Hulme 2009).

Elton's observations have been carried forward temporally, for example, Mullin et al. (2000) reported that the number of new invasive plant incursions and their impacts have increased rapidly over the past 30 years due to (1) exponential increases in air travel, (2) increased speeds at which commodities and people traverse the globe, (3) increased numbers of ports of entry, (4) expanded exports and imports into new international markets, (5) increased interest in the use of exotic plants in gardening and water gardening, and (6) increased access to foreign ecosystems. Subsequent studies also found that the number of new invasive species being introduced into new areas of the world is accelerating as the world's population multiplies, as trade increases, and as goods are transported more rapidly around the globe (Pimentel 2002, Work et al. 2005,

Hulme 2009, Bradley et al. 2012). Imports of live plants for example (i.e., recognized as the most common pathway for invasive forest insects) has increased 33% per decade over the past 43 years in the United States (Liebhold et al. 2012) and some of these plants themselves have become invasive such as kudzu (*Pueraria montana* var. *lobata*), purple loosestrife (*Lythrum salicaria*), and saltcedar (*Tamarix* spp.). It is clear that the deleterious impacts and threats posed by existing and emerging invasive plants are significant and continue to grow at an alarming rate. We are experiencing unprecedented increases in the global trade of commodities which also is bringing a proportional increase in the number of new invasive plants being introduced.

Biosecurity agencies which develop international standards (i.e., that provide guidelines that aim to prevent introductions of new pests) need to consider the correlates between increasing trade and invasive species introductions. Invasive species are introduced as contaminants in international trade, in many cases moving by ocean going ships. For example, in 2006, 90% of the global trade was conveyed by sea on cargo-carrying ships that have increased in size and speed, resulting in a fourfold increase in global imports (Hulme 2009). In exploring the correlates between international trade and the introductions of invasive species, it has been found that the amount of trade a country participates in proportionally determines the number of invasive species introduced into that country (Levine and D'Antonio 2003, Westphal et al. 2008). For example, Ding et al. (2008) reported that in China, imports and exports grew from US \$20.6 billion to US \$1422.1 billion from 1978-2005, and the number of invasive pests intercepted at the Chinese borders also ballooned a staggering 10-fold from 1990 to 2005. Considering that international trade has increased 25-fold from US \$192 billion in 1965 to \$4.8 trillion in

1995 (McNeely 2001), there is little doubt biosecurity agencies will need new tools to prevent the introductions of invasive plants globally that can also be expected. The conflicting challenge is that most governments focus on gross domestic product growth and invasive species are largely ignored (Ding et al. 2008).

Invasive plants impact our environment, economy, and society. Hence, to help provide context to this thesis, I will critically review the literature associated with these three areas of impact.

2.3 Environmental Costs of Invasive Plants

The environmental costs of deleterious invasive plants are wide and in many cases irreversible. Invasive plants compete with native flora, hybridize with genetically close species, alter physical and chemical characteristics of the soil, modify natural environments and propagate pests and diseases (Shine 2007). One government report suggested invasive plants are a leading factor in the extinction of native aquatic species second only to habitat destruction (Office of the Auditor General of Canada 2002), while a second government report suggested they are the second leading cause of the loss of biological diversity (U.S. Congress, Office of Technology Assessment 1993). In New Zealand, biological invasions are recognized as the primary factor attributed to the overall loss of native biological diversity, not traditional impacts such as habitat loss or the direct effects of people (Clout 2001). Similarly in South Africa, invasive plants are considered the single biggest threat to biological diversity (Heywood and Brunel 2009). Critics will argue however, that in some cases invasive species actually have increased species richness and diversity (Sagoff 2005). There are those that have also contested

that the above conclusions are not based on studies supported by field data but on literature reviews and field observations (Davis 2003, Gurevitch and Padilla 2004, Sagoff 2005) and other sources that were not published in peer-reviewed journals (Anderson 1995, Lavoie 2010). Others have argued that these statements are overgeneralized and exaggerated (Davis 2011) or are uncritically accepted untested hypotheses (Hager and McCoy 1998). What is interesting is that the above authors seem to be guilty of the same approach, that is, a review of the literature while providing no data (see Schlaepfer et al. 2010). However, there are studies that have indeed provided empirical data supporting the conclusion that species richness and biodiversity are reduced by invasive plants (see Hulme and Bremner 2006, Hejda et al. 2009), including purple loosestrife (see Hovick et al. 2011).

Invasive plants have been suggested to be a threat to endangered species or species at risk. Pimentel et al. (2005) estimated that 400 of the 958 species listed as threatened or endangered under the United States (US) Endangered Species Act are at risk by invasive species. They have been implicated in the decline of 42% of threatened or endangered species in the US (Stein and Flack 1997). In a widely cited paper, Wilcove et al. (1998) reported that nearly half of the imperilled species in the US are threatened by alien species. Critically, the conclusions of Wilcove et al. (1998) were based on a review of data from various grey sources which included the United States *Federal Register*, a survey of biologists and interviews with specialists. Hence it may be argued that empirical data to support their conclusions are lacking.

In reviewing how invasive species threaten freshwater fauna in Canada (i.e. using Committee on the Status of Endangered Wildlife in Canada (COSEWIC) status reports),

Dextrase and Mandrak (2006) found that invasive species were the second most prevalent threat (i.e., after habitat loss and degradation) to listed fishes in Canada and they were recognized as a primary threat to imperilled freshwater molluscs in the Great Lakes region. They also found that invasive species were a primary factor in four of five extinctions of Canadian freshwater fishes. Stronen (2002) also reported that 24% of Species at Risk listed by COSEWIC are further threatened with extinction by invasive alien species. Invasive alien species including purple loosestrife (*Lythrum salicaria*), common carp (*Cyprinus carpio*), and reed canary grass (*Phalaris arundinacea*) threaten the northern leopard frog (*Rana pipiens*), northern red-legged frog (*Rana aurora*), northern ribbon snake (*Thamnophis sauritus*), Oregon spotted frog (*Rana pretiosa*), and the Pacific pond turtle (*Clemmys marmorata*) (Stronen 2002). A later paper by Venter et al. (2006) also using COSEWIC data as well as Canadian Wildlife Service reports concluded that invasive species affect 22% of Canada's endangered species.

The impact invasive species have on species extinctions are debated in the literature. Some studies suggest that there is no evidence to suggest that any invasive plant have led to the extinction of another species and that such statements are based upon only on simple observational assessments (Davis 2003, Sagoff 2005). Gurevitch and Padilla (2004) for example, suggested the notion of species extinctions by invasive species is unproven. However, Clavero and Garcia-Berthou (2005) re-analyzed the data used by Gurevitch and Padilla (2004), and concluded that invasive species are the leading cause of extinction in birds in North America.

2.4 Economic Costs of Invasive Plants

The economic costs of a biological invasion may be the single most important factor for biosecurity agencies in determining a regulatory response. The economic costs of many pest invasions are thought to be immense; however few studies have attempted to quantify the economic impacts of invasive plants employing a true empirical scientific approach (Schlaepfer et al 2010). The most obvious economic impacts are direct, quantifiable costs such as measurable losses in agricultural crop output or the costs of biological or herbicide control programs. Estimating indirect costs such as losses of ecosystem services, biological diversity, wetlands, recreation, the interactive effects between invasive and native species (Mooney et al. 2005), and land value, is a more difficult exercise. In most cases economic data is difficult, if not impossible to ascertain (Colautti et. al 2006, Duncan et al. 2004). Quantifying economic costs also becomes increasingly complex when an invasive plant affects both natural and agricultural systems. To characterize the economic impact of invasive plants I will provide a review of some of the more often cited studies and government reports, which interestingly all conclude there is a general scarcity of economic data.

Two of the most widely cited contributions to date have been the papers by Pimentel et al. (2000, 2005) which estimated the economic costs of invasions in the US. In their 2000 paper, they reported that about 50,000 alien invasive species have been introduced into the US of which 5,000 were invasive plants that have escaped cultivation and now exist in US natural ecosystems spreading at rate of 700,000 ha/year (Pimentel et al. 2000). They estimated the economic costs of invasive plants to the US economy to be about \$34 billion per year, which was comprised of the costs associated with purple

loosestrife (*Lythrum salicaria*) (\$45 million), aquatic weeds (\$110 million), melaleuca tree (*Melaleuca quinquenervia*) (\$3-6 million), weeds in crops (\$26,400 million), weeds in pastures (\$6,000 million) and weeds in lawns, gardens, golf courses (\$1,500 million). Five years later, they estimated the total economic damages from invasive species to be \$120 billion US annually (Pimental et al. 2005). They estimated that purple loosestrife (*Lythrum salicaria*) alone invades about 115,000-ha annually of wildlife and wetland habitat with economic costs of \$45 million US annually in control costs and habitat loss. The economics provided by Pimental et al. (2000, 2005) have been debated. Sagoff (2009) challenged that many of the inputs used were poorly estimated, for example, the cost of \$30 allocated to a bird eaten by a feral cat, or \$9 per pigeon, and the use of data from no longer existing web pages. He further suggested invasive economics are often exaggerated to leverage political support for research. While Sagoff (2009) challenged Pimental's estimates, he didn't provide any alternative estimates. While the economic estimates of Pimental et al. (2001, 2005) maybe speculative and not based on a rigorous scientific approach, they provide us with creditable estimates and further illustrate the challenges involved in quantifying the costs of invasions.

Invasive plants incur significant economic costs in many countries. For example, Powell (2004) reported that the United States Department of Agriculture (USDA) has an annual budget of over \$500 million to deal with invasive species, and a substantial portion goes towards addressing invasive plants. It has been estimated that 79 alien species have cost the US economy an estimated \$97 billion from 1906 to 1991 (Stein and Flack 1997). Both these reports provide useful economic information but are not based on empirical field data. In a more rigorous study, the total economic losses caused by

invasive species in China was estimated at \$14.45 billion US annually, with 16% being direct costs and 84% being indirect cost (Xu et al. 2006). Wilgen et al. (2001) reviewed numerous papers and found that the economic consequences of plant invasions in South Africa are in the billions of dollars annually, however a comprehensive figure of total costs was not possible pending a thorough economic assessment. In Australia, the economic impact of weeds was estimated to be \$4 billion dollars annually, and it was suggested that if there were no weeds, incomes to agricultural producers and benefits to consumers of food would rise by \$3.9 billion dollars (Sinden et al. 2005). In Canada, the economic damages of invasive alien species on the forestry and agriculture sectors have been estimated to be \$7.5 billion annually (Dawson 2002). Critically these figures were calculated using data from the Pimentel et al. (2000) papers and substituting them with Canadian values, hence lacking empirical data. Two Government of Canada reports have estimated invasive species have resulted in economic costs as high as \$34.5 billion annually (Canada 2004), and that in the Great Lakes and St. Lawrence River Basin regions of Canada \$500 million is spent annually on control costs (Government of Canada 2001). While it may be argued that these reports are not based on studies that adopted a true scientific approach, they do however document that the economic costs of invasive species in Canada are significant.

Authors have attempted to use empirical models to estimate economic impacts. For example, Colautti et al. (2006) characterised the economic costs to Canada's fisheries, agriculture and forestry resource sectors, finding that 11 invasive alien species alone cost Canada \$187 million per year. When accounting for all invasive species the invisible taxes climbed dramatically to \$16.6 billion per year. They characterised the

economic impact of purple loosestrife at \$210,000 per year, leafy spurge \$96,000 per year, and knapweed at \$479,000 per year. While the study provided much needed Canadian data, critically I found significant data was missing. For example, the purple loosestrife economic assessment was comprised of data from Alberta (i.e., control costs), Saskatchewan (i.e., eradication program) and Ontario (i.e., biological control program) and failed to include data from similar programs in Manitoba or the Atlantic Provinces. Colautti et al. (2006) did acknowledge that their estimates were conservative reporting that there was a severe dearth of available data. I would argue that with some species (e.g., purple loosestrife) the data was available however a more rigorous, comprehensive effort was required.

Invasive plants impact Canada's agricultural sector and these costs are generally borne by farmers and consumers. Swanton et al. (1993) estimated the average annual loss by weeds in 58 commodities in four general groups (e.g., hay, field crop, fruits and vegetables, or fruit trees) were \$984 million, with losses of \$372 million in eastern Canada and \$612 million in western Canada. Leeson et al. (2006) reported that annual economic impact on invasive weeds in spring wheat, barley, and canola in the Canadian Prairie Provinces alone to be over \$1 billion dollars annually (Figure 2.1). The report indicated that 98% of herbicide application costs were attributed to the control of invasive weeds in crops and that the top weeds responsible for yield loss were wild oats, Canada thistle, volunteer wheat and green foxtail. Critically, this estimate was based upon herbicide application costs and did not consider indirect losses such as dockage, quality loss and interference with the harvest which would increase the overall estimate..

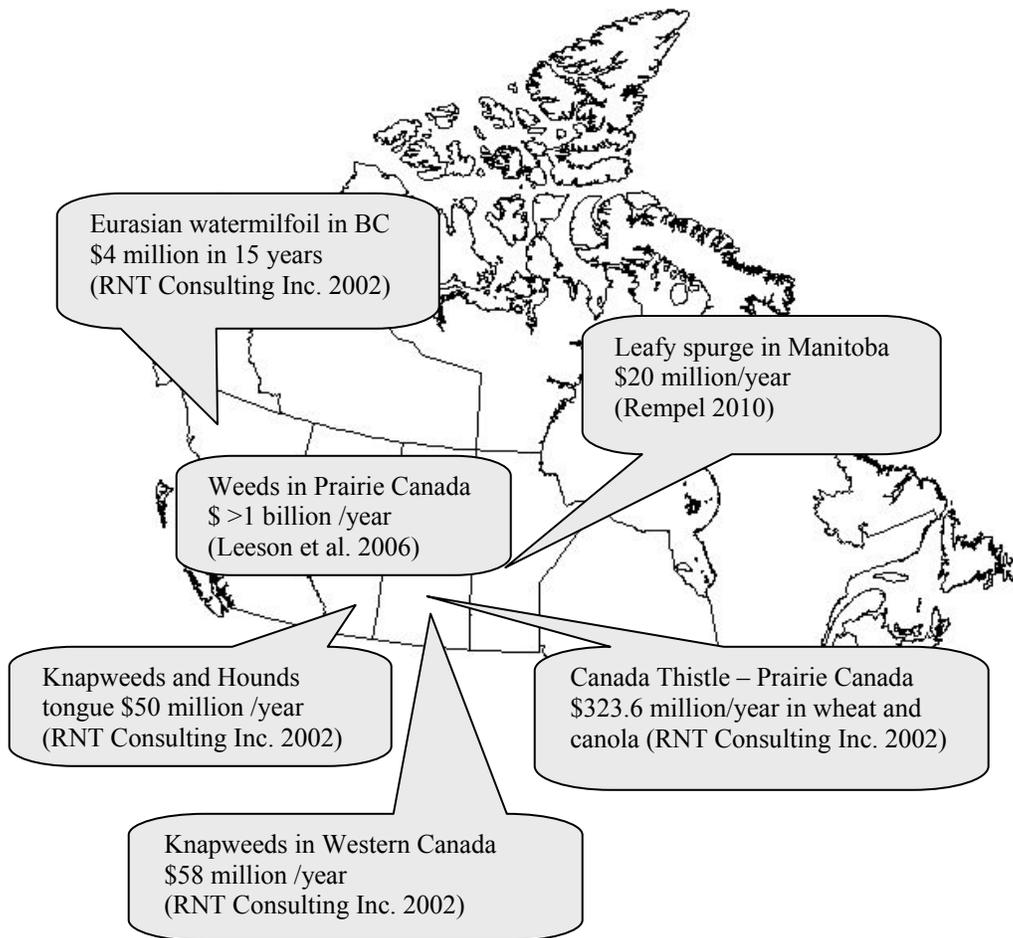


Figure 2.1 Invasive plants cost the Canadian economy billions of dollars annually. Examples include leafy spurge in Manitoba, knapweeds in British Columbia, and Canada thistle in wheat and canola.

Economic data is available for some invasive plants at regional levels. An example of an agricultural invader where rigorous economic data is available is leafy spurge (*Euphorbia esula*) (Figure 2.2). In Manitoba, the economic costs of leafy spurge were estimated at \$19 million annually; \$16 million in impacts on grazing, public land \$2.5 million, and \$0.4 million on rights of way (Rempel 2010). In the Northern Great Plains region (i.e., Montana, North Dakota, South Dakota, and Wyoming) the total impact of leafy spurge was estimated to be \$130 million/year; where direct costs were estimated at

\$40 million annually (i.e., costs to growers, landowners and business were estimated at \$37.1 million/year and \$3.4 million/year to wild lands) and secondary costs were estimated at \$82.6 million/year (Leitch et al. 1994, Leistriz et al. 2004). The costs of leafy spurge invasions in these regions alone have been significant and continue to rise. Harris and Cranston (1979) provided an economic evaluation for diffuse and spotted knapweed (*Centaurea diffusa* and *C. maculosa*) in western Canada concluding that the annual loss in hay production in British Columbia cost \$350,000 annually and this would rise to \$13 million dollars with range extension.



Figure 2.2 A leafy spurge infestation along a rail line in West St Paul, Manitoba. Leafy spurge costs Manitoba as much as \$19 million dollars annually.

Invasive plants such as saltcedar alter the capacity of ecosystems to deliver goods and services (Richardson and Wilgen 2004). Zavaleta (2000) estimated that saltcedar (*Tamarix spp.*) costs the western US an estimated \$127-291 million US annually in lost

ecosystem services which included impacts on water supplies for municipalities, farmers, hydropower generation, and on flood control. This study is one of the few studies that incorporated ecosystem services into their economic estimate. Wilgen et al. (2008) attempted to assess biome-scale impacts on ecosystem services concluding that impacts were low however likely underestimated, and that future impacts will be substantial leading to significant economic consequences and reductions in biodiversity. It should be noted however, that in some cases, invasive species may actually provide ecosystem services (Gleditsch and Carlo 2011). It is evident that more research is needed to assess the impacts of invasive plants on ecosystem services and functions (Richardson and Wilgen 2004, Liebhold et al. 2012).

Finally, there is a general lack of studies evaluating the costs associated with the seeds of invasive plants that regularly contaminate shipments of agricultural commodities. A contaminated commodity can result in the destruction of the entire shipment or a container ship being turned away at a port of entry and millions of dollars of trade being lost. Economic assessments of seeds as contaminants in soil, on vehicles, or machinery are generally lacking. The high volumes of global trade in cereals has resulted in a large amount of invasive plant seeds being introduced into grain importing countries annually (Shimono and Konuma 2008), yet there is a scarcity of quantitative economic data to characterize the impact.

2.5 Impacts on Human Health

Invasive plants have deleterious impacts on human health. Groves (2002) summarized some of the physiological reactions people have to invasive plants that

affect their general well-being and quality of life. Parthenium weed (*Parthenium hysterophorus*) causes allergic dermatitis in humans, patterson's curse (*Echium plantagineum*) as well as species of nettles (*Urtica spp.*), brassicas (*Brassica alba* and *B. napus*), stinkweed (*Inula graveolens*) and some garden plants, causes skin irritations and allergic rhinitis. Ragweeds (*Ambrosia spp.*) cause hay fever and asthma as a result of people inhaling allergenic pollen, and some invasive plants such as hemlock (*Conium maculatum*) contain poisonous compounds that may lead to illness or death. Blueweed (*Echium vulgare*) which is widely distributed across Canada is known to cause skin irritations and has pyrrolizidine alkaloids that may affect both human and animal health. The sap of the giant hogweed (*Heracleum mantegazzianum*) plant sensitizes humans to ultraviolet radiation. Stinging nettle (*Urtica dioica*) has some introduced subspecies in Canada that cause skin irritation. Groves (2002) also noted that numerous invasive plants impact animal health through the ingestion of deleterious chemicals after they invade pasture and rangelands. In Canada invasive plants such as leafy spurge and hound's-tongue (*Cynoglossum officinale*) may poison livestock which graze on them.

In New Zealand, a voluntary National Pest Plant Accord between industry and government prevents the sale of unwanted organisms including those invasive plants that have potential human health impacts (Derraik 2007). Examples include giant hogweed (*H. mantegazzianum*), a popular garden plant that has escaped cultivation and become a public health threat (i.e., the sap contains psoralens that cause dermatitis) and *Toxicodendron succedaneum*, a small tree whose the sap contains urushiols that are potent sensitizers leading to allergic reactions (Derraik 2007). These types of accords should be developed by other counties to protect human health.

2.6 Conclusions

In conclusion, it is evident that some plants become invasive and impact our economy, environment, and society thus becoming biosecurity concerns. While some will argue that these impact statements are frequently over-exaggerated in the literature and in some cases not based upon data generated by employing an empirical approach, there are a plethora of studies that do provide data generated through scientific approaches that support these impact statements. With continued increases in international trade importing countries can expect to see more introductions of new invasive plants. Biosecurity agencies have obligations to prevent the introductions of invasive plants as pests in international trade. In the following chapters, I will explore how biosecurity agencies can address invasive plants using spatial predictive modelling.

2.7 References

- Anderson, R.P., D. Lew and A.T. Peterson. 2003. Evaluating predictive models of Species' distributions: criteria for selecting optimal models. *Ecological Modelling* 162:211-232.
- Anderson, M.G. 1995. Interactions between *Lythrum salicaria* and native organisms; a critical review. *Environ. Manage.* 19:225-231.
- Bangsund, D.A., F.L. Leistritz and J.A. Leitch. 1999. Assessing economic impacts of biological control of weeds: The case of leafy spurge in the northern Great Plains of the United States. *Journal of Environmental Management* 56:35-43.
- Bradley, B.A., M. Oppenheimer and D.S. Wilcove. 2009. Climate change and plant invasions: restoration opportunities ahead? *Global Change Biology* 15:1511-1521.

- Bradley, B.A., D. Blumenthal, R. Early, E. Grosholz, J. Lawler, L. Miller, C. Sorte, C. D'Antonio, J. Diez, J. Dukes, I. Ibanez and J. Olden. 2012. Global change, global trade, and the next wave of plant invasions. *Front. Ecol. Environ.* 10:20-28.
- Canada. 2004. *An Invasive Alien Species Strategy for Canada*. Ottawa, Canada. 2004. 40 pp.
- Carroll, S.P. 2011. Conciliation biology: the eco-evolutionary management of permanently invaded biotic systems. *Evolutionary Applications* 4:184-199.
- CBD. 1992. *Convention on Biological Diversity*. United Nations Environment Programme, Rio de Janeiro.
- Clavero, M. and E. Garcia-Berthou. 2005. Invasive species are a leading cause of animal extinctions. *Trends in Ecology and Evolution* 20:110.
- Clout, M. 2001. Where protection is not enough: active conservation in New Zealand. *Trends in Ecology & Evolution* 16:415-416.
- Colautti, R., S. Bailey, C. van Overdijk and K. Amundsen. 2006. Characterized and projected costs of nonindigenous species in Canada. *Biological Invasions* 8:45-59.
- Combella, J.H. 1987. Weeds in cropping – their costs to the Australian economy. *Plant Protection Quarterly* 24:2.
- Dawson, M. 2002. Plant Quarantine: Preventing the introduction and spread of alien species harmful to plants. In *Alien Invaders in Canada's Waters, Wetlands, and Forests*. R. Claudi, P. Nantel and E. Muckle-Jeffs (Eds.). Canadian Forest Service Natural Resources Canada, Ottawa. 320 pp.
- Davis, M.A. 2003. Biotic globalization: does competition from introduced species threaten biodiversity? *BioScience* 53:481-489.

- Davis, M.A. 2011. Do native birds care whether their berries are native or exotic? No. *BioScience* 61:501-502.
- Derraik, J.G. 2007. *Heracleum mantegazzianum* and *Toxicodendron succedaneum*: plants of human health significance to New Zealand and the National Pest Plant Accord. *The New Zealand Medical Journal* 120: Viewed online at: <http://www.nzma.org.nz/journal/120-1259/index.shtml>
- Dextrase, A.J. and N.E. Mandrak. 2006. Impacts of alien species on freshwater fauna at risk in Canada. *Biological Invasions* 8:13-24.
- Ding, J.R., P. Mack, P. Lu, M. Ren and H. Huang. 2008. China's booming economy is sparking and accelerating biological invasions. *BioScience* 58:317-324.
- Duncan, C.A., J.J. Jachetta, M.L. Brown, V.F. Carrithers, J.K. Clark, J.M. DiTomaso, R.G. Lym, K.C. McDaniel, M.J. Renz and P.M. Rice. 2004. Assessing the economic, environmental, and societal losses from invasive plants on rangeland and wildlands. *Weed Technology* 18:1411-1416.
- FAO (Food and Agriculture Organization). 2007. International Standards for Phytosanitary Measures (ISPM No. 2): Framework for Pest Risk Analysis. Secretariat of the International Plant Protection Convention.
- Gleditsch, J.M. and T.A. Carlo. 2011. Fruit quantity of invasive shrubs predicts the abundance of common native avian frugivores in central Pennsylvania. *Diversity and Distributions* 17:244-253.
- Groves, R.H. 2002. The impacts of alien plants in Australia. In *Biological Invasions: Economic and environmental costs of alien plant, animal, and microbe species*. D. Pimentel (ed.). CRC Press. Washington, D.C. 369 pp.

- Gurevitch, J and D.K. Padilla. 2004. Are invasive species a major cause of extinctions? Trends in Ecology and Evolution 19:470-474.
- Harris P. and R. Cranston. 1979. An economic evaluation of control methods for diffuse and spotted knapweed in western Canada. Can. J. Plant Science 59:375-382.
- Haywood, V. and S. Brunel. 2009. Code of conduct on horticultural and invasive alien species. Nature and Environment No. 155. Council of Europe Publishing, Strasbourg.
- Hedley, J. 2004. Chapter 7: The International Plant Protection Convention and invasive species. Pp. 185-201. In: Miller, M.L. and R.N. Fabian (eds), Harmful Invasive Species: Legal Response. Environmental Law Institute, Washington, D.C., USA.
- Hejda, M. Pysek and V. Jarosik. 2009. Impact of invasive plants on the species richness, diversity and composition of invaded communities.
- Hewitt, C.L., R.A. Everett and N. Parker. 2009. Examples of current international, regional and national regulatory frameworks for preventing and managing marine bioinvasions. In Biological Invasions in Marine Ecosystems, G. Rilov and J.A. Cook (eds.). Springer-Verlag Berlin Heidelberg.
- Hovick, S.M., D.E. Bunker, C.J. Peterson and W.P. Carson. 2011. Purple loosestrife suppresses plant species colonization far more than broad-leaved cattail: experimental evidence with plant community implications. Journal of Ecology 99:225-234.
- Hulme, P. 2006. Assessing the impact of *Impatiens glandulifera* on riparian habitats: partitioning diversity components following species removal. Journal of Applied Ecology 43:43-50.
- Hulme, P. 2009. Trade, transport and trouble: managing invasive species pathways in an era of globalization. Journal of Applied Ecology 46:10-18.

- IPPC. 1997. International Plant Protection Convention, new revised text. FAO. Rome.
- IPPC Secretariat. 2005. Identification of risks and management of invasive alien species using the IPPC framework. Proceedings of the workshop on invasive alien species and the International Plant Protection Convention, Braunschweig, Germany, 22-26 September, Rome, Italy FAO. 301 pages.
- ISPM. 2004. Guidelines for Pest Risk Analysis, International Standard for Phytosanitary Measures Publication No. 2. FAO, Rome.
- ISPM. 2007. Pest Risk Analysis for Quarantine Pests. International Standard for Phytosanitary Measures Publication No. 11. FAO. Rome.
- Government of Canada. 2004. An Invasive Alien Species Strategy for Canada. Ottawa, Ontario. 46 pages.
- Koul, O., G.S. Dhaliwal and G.W. Cuperus. 2004. Integrated pest management: potential, constraints, and challenges. Oxfordshire, UK, CABI Publishing.
- Lavoie, C. 2010. Should we care about purple loosestrife? The history of an invasive plant in North America. *Biological Invasions* 12:1967-1999.
- Leeson, J., A. Thomas and J. O'Donovan. 2006. Economic Impact of Alien Weeds on Wheat, Barley and Canola Production. Canadian Weed Science Society Meeting, November 27-29, 2006. Victoria, BC.
- Liebholt, A.M., E.G. Brockerhoff, L.J. Garret, J.L. Parke and K.O. Britton. 2012. Live plant imports: the major pathway for forest insect and pathogen invasions in the US. *Front. Ecol. Environ.* 10:135-143.
- Leistritz, F.L., D.A. Bangsund and N.M. Hodur. 2004. Assessing the economic impact of invasive weeds: The case of Leafy Spurge. *Weed Technology* 18:1392-1395.

- Leitch, J.A., F.L. Leistritz and D.A. Bangsund. 1994. Economic effect of leafy spurge in the upper Great Plains: methods, models, and results. North Dakota State University Agric. Econ. Re. 316. 8 pages.
- Levine, J.M. and C.M. D'Antonio. 2003. Forecasting biological invasions with increasing international trade. *Conservation Biology* 17:362-370.
- Leopold, A. 1949. *A Sand County Almanac*. New York: Oxford University Press.
- Lonsdale, W.M. 1994. Inviting trouble: introduced pasture species in northern Australia. *Austral. J. Ecol.* 19:345-354.
- Ludsin, S.A. and A.D. Wolfe. 2001. Biological Invasion Theory: Darwin's contributions from the Origin of Species. *BioScience* 51:780-789.
- Magarey, R.D., M. Colunga-Garcia and D.A. Fiesemann. 2009. Plant biosecurity in the United States: roles, responsibilities, and information needs. *BioScience* 59:875-884.
- McNeely, J. 2001. Invasive species: a costly catastrophe for native biodiversity. *Land Use and Water Resources Research* 1:1-10.
- Meyerson, L.A. and J.K. Reaser. 2002. A unified definition of biosecurity. *Science* 295: 44.
- Mooney, H.A., R.N. Mack, J.A. McNeely, L.E. Neville, P. Johan Schei and J.K. Waage. 2005. *Invasive Alien Species: A new synthesis*. Island Press, London. 368 pp.
- Mullin, B.H., W.J. Anderson Lars, J.M. DiTomaso, R.E. Eplee and K.D. Getsinger. 2000. *Invasive Plant Species*. Issue Paper Number 13. Report published by the Council for Agricultural Science and Technology. February 2000. 18 pages.
- Meyerson, L.A. and J.K. Reaser. 2002. A unified definition of biosecurity. *Science* 295:44.

- Office of the Auditor General of Canada. 2002. Report of the Commissioner of the Environment and Sustainable Development to the House of Commons 2002: Chapter 4: Invasive Species. Minister of Public Works and Government Services Canada 2002.
- Pimental, D., L. Lach, R. Zuniga and D. Morrison. 2000. Environmental and Economic Costs of Nonindigenous Species in the United States. *BioScience* 50:53-65.
- Pimentel, D. 2002. Introduction: non-native species in the world. In *Biological Invasions economic and environmental costs of alien plant, animal, and microbe species*. D. Pimentel (editor). CRC Press, Washington, D.C. 369 pages.
- Pimentel, D., R. Zuniga and D. Morrison. 2005. Update on the environmental and economic costs associated with alien-invasive species in the United States. *Ecological Economics* 52:273-288.
- NAPPO. 2008. Pest Risk Assessment for Plants for Planting as Quarantine Pests. The Secretariat of the North American Plant Protection Organization, Ottawa, Canada.
- Rahel, F. and J. Olden. 2008. Assessing the effects of climate change on aquatic invasive species. *Conservation Biology* 22:521-533.
- Rempel, K. 2010. Economic impact assessment of leafy spurge in southern Manitoba Final Report. Rural Development Institute, Brandon University. 43 pages.
- Richardson, D.M., P. Pysek, M. Rejmanek, M.G. Barbour, F.D. Panetta and C. West. 2000. Naturalization and invasion of alien plants: concepts and definitions. *Diversity and Distribution* 6:93-107.
- Richardson, D.M. and B. W. van Wilgen. 2004. Invasive alien plants in South Africa; how well do we understand the ecological impact? *South African Journal of Science*

- 100:45-52.
- RNT Consulting Inc. 2002. Environmental and economic costs of alien invasive species in Canada. Report prepared for the Canadian Information System for the Environment. Penticton, Ontario.
- Sagoff, M. 2005. Do non-native species threaten the natural environment? *J. Agric. Environ. Ethics* 18:215-236.
- Sagoff, M. 2009. Environmental Harm: political not biological. *J. Agric. Environ. Ethics* 22:81-88.
- Schlaepfer, M.A., D.F. Sax and J.D. Olden. 2011. The potential conservation value of non-native species. *Conservation Biology* 25:428-437.
- Shimono, Y. and A. Konuma. 2008. Effects of human-mediated processes on weed species composition in internationally traded grain commodities. *Weed Research* 48:10-18.
- Shine, C. 2007. Invasive species in an international context: IPPC, CBD, European Strategy on Invasive Alien Species and other legal instruments. *OEPP/EPPO Bulletin* 37:103-113.
- Sinden, J., R. Jones, S. Hester, D. Odom, C. Kalisch, R. James and O. Cacho. 2005. The economic impact of weeds in Australia, CRC for Australian Weed Management, Technical Series No. 8, Adelaide. 39 pages.
- Smith, C.S., W.M. Lonsdale and J. Fortune. 1999. Risk, self-protection, and ex-ante economic value. *Journal of Environmental Economics and Management* 10:1-15.
- Stein, B.A. and S.R. Flack. 1997. Species Report Card: The State of U.S. Plants and Animals. The Nature Conservancy, Arlington, Virginia. 26 pages.

- Stronen, A.V. 2002. Impacts on Canadian Species at Risk from Invasive Alien Species. Canadian Wildlife Service Report, Environment Canada, 2002.
- Swanton, C.J., K.N. Harker and R.L. Anderson. 1993. Crop losses due to weeds in Canada. *Weed Technology* 7:537-542.
- U.S. Congress, Office of Technology Assessment. 1993. Harmful Non-Indigenous Species in the United States, OTA-F-565 Washington, DC: U.S. Government Printing Office.
- Venette, R., D. Kriticos, D. Magarey, F. Koch, R. Baker, S. Worner, N. Raboteau, D. McKenny, E. Dobesberger, D. Yemshanov, P. De Barro, W. Hutchison, G. Fowler, T. Kalaris and J. Pedlar. 2010. Pest risk maps for invasive alien species: a roadmap for improvement. *BioScience* 60:349-362.
- Venter, O., N. Brodeur, L. Nemiroff, B. Belland, I. Dolinsek and J. Grant. 2006. Threats to endangered species in Canada. *BioScience* 56:903-910.
- Westhal, M.I., M. Brown, K. MacKinnon, K. and I. Noble. 2008. The link between international trade and the global distribution of invasive alien species. *Biological Invasions* 10:391-398.
- White, D.J. and E. Haber. 1992. Invasive Plants of Natural Habitats in Canada. Report prepared for the Canadian Wildlife Service, March 1992.
- Wilcove, D.S., D. Rothstein, J. Phillops and E. Losos. 1998. Quantifying threats to imperilled species in the United States. *BioScience* 48:607-615.
- Wilgen, B.W., D.M Richardson, D.C. Le Maitre, C. Marais, and D. Magadlela. 2001. The Economic Consequences of Alien Plant Invasions: examples of impacts and approaches to sustainable management in South Africa. *Environment*,

- Development and Sustainability 3:145-168.
- Wilgen, B.W., B. Reyers, D. Le Maitre, D.M. Richardson and L. Schonegevel. 2008. A biome-scale assessment of the impact of invasive alien plants on ecosystem services in South Africa. *Journal of Environmental Management* 89:336-349.
- Williamson, M. 1996. *Biological Invasions*. Chapman & Hall, London.
- Williamson, M. and A. Fitter. 1996. The varying success of invaders. *Ecology* 77:1661-1666.
- Wittenberg, R., M. Kenis, T. Blick, A. Hanggi, A. Gassmann and E. Weber. 2005. An inventory of alien species and their threat to biodiversity and economy in Switzerland. CABI Bioscience Switzerland Centre report to the Swiss Agency for Environmental, Forests and Landscapes. The environment in practise no. 0629. Federal Office for the Environment, Bern. 155 pages.
- Work, T., D. McCullough, J. Cavey and R. Komsa. 2005. Arrival rate of nonindigenous insect species into the United States through foreign trade. *Biological Invasions* 7:323-332.
- Xu, H., H. Ding, M. Li, S. Quang, J. Guo, Z. Han, Z. Huang, H. Sun, S. He, H. Wu and F. Wan. 2006. The distribution and economic losses of alien species invasion to China. *Biological Invasions* 8:1495-1500.
- Zavaleta, E. 2000. The economic value of controlling an invasive shrub. *AMBIO: A Journal of the Human Environment* 29:462-467.

CHAPTER 3 - BIOSECURITY POLICY AND THE USE OF SPATIAL PREDICTIVE TOOLS TO ADDRESS INVASIVE PLANTS: THE NEED TO UPDATE THE RISK ANALYSIS TOOL BOX

ABSTRACT. International and National biosecurity policies consider risk assessment a critical component of overall plant health risk analysis. The Agreement on the Application of Sanitary and Phytosanitary measures, the International Plant Protection Convention, and the Convention on Biological Diversity all provide guidelines and recommendations on how to use risk assessment. This chapter discusses how these instruments address risk assessment and makes recommendations on how the process needs to incorporate spatial predictive modelling and geographic information systems into the plant health biosecurity risk analysis tool box.

KEY WORDS: Risk analysis, plant health biosecurity, invasive plants

3.1 Introduction

Biosecurity is the array of strategies and policies that assess and manage the risks of infectious diseases, pests, living modified organisms, and biological weapons in natural and managed systems (Myerson and Reaser 2002, Heikkila 2010). It is comprised of a myriad of activities including off-shore mitigation, pre and post border inspections, domestic surveys, quarantine measures, eradication and management programs (Magarey et al. 2009). Biosecurity is a holistic concept that encompasses all activities, including policies and regulations aimed at preventing and managing invasive species (FAO 2007,

Khetarpal and Gupta 2007, Hulme 2011). Plant health biosecurity programs have traditionally focused on pests of the agriculture and forestry sectors, or pests of plants. Over the past five years however, we have seen efforts to expand and enhance the scope of plant health biosecurity policy to also address plants as pests, or invasive plants, and extending protection to non-agricultural or unmanaged systems.

Invasive plants threaten croplands, rangelands, aquatic areas, and natural areas. They degrade the productivity and biological diversity of all ecosystems, have deleterious economic and social impact, and affect international trade. The number of new plant incursions and their impacts have increased rapidly over the past 30 years due to a) the increased frequency and speed at which commodities and people traverse the globe, b) increased numbers of ports of entry, c) increased exports and imports into new international markets, d) increased interest in the use of new exotic plants for gardening and landscaping and, e) increased access to foreign ecosystems (Mullen et al 2000). This increased risk has challenged plant health biosecurity organizations to develop new programs and measures to protect the economy, environment, and human health from invasive plants (Hewitt et al. 2009).

There are nearly 50 international biosecurity instruments, and numerous more national and regional strategies that deal with or influence some aspect of plant health biosecurity (Shine 2007). They provide various measures, rules, definitions, standards, and guidelines. They foster program development as well as outline general obligations and commitments in responding to the risks of invasive plants. Determining risk through a risk assessment is at the heart of contemporary biosecurity (Brunel et al. 2009). The objective of this paper is to discuss the major biosecurity policy instruments that have

influenced plant health responses (e.g. risk assessment) to invasive plants, and to make recommendations as to how to incorporate current geospatial predictive science and geographic information systems into the plant health biosecurity risk analysis tool box.

3.2 International Plant Biosecurity

Overall policy context for international trade is set by the World Trade Organization (WTO). Formed in 1995, essentially its purpose is to liberalize trade by limiting tariff and non-tariff barriers (Brunel et al. 2009). However, trade liberalization in turn, increases biosecurity risk. The WTO administers two agreements that have implications for plant health biosecurity. The WTO's General Agreement on Trade in Services (GATS) allows countries to take measures to protect human, animal or plant life, and this may include measures to prevent the introductions of invasive pests. The WTO Agreement on the Application of Sanitary and Phytosanitary measures (SPS Agreement) discusses how these measures may be applied. The SPS Agreement allows countries to set their own plant health standards, however it requires that these must be based on a scientifically justifiable and appropriate risk assessment (WTO 1994, Shine 2007). It is argued that the WTO has functioned in such a way that makes trade barriers a last resort increasing the risks of invasive plant introductions (WTO 1994). However, these agreements are important in discussions on the application of risk assessment.

The SPS Agreement entered into force January 1, 1995, replacing the General Agreement on Tariffs and Trade (Gruszczynski 2006). The intention of the SPS Agreement is to ensure that global commercial trade (e.g., in plants) is not hindered by artificial barriers (Brasier 2008), and that measures are based on international standards.

Article 2 notes that members shall ensure that phytosanitary measures are science-based and are not maintained without sufficient scientific evidence. Article 5 states that phytosanitary measures shall be based on an assessment¹ that uses the most appropriate scientific evidence. In assessing the risk to plant life and determining the measure to be applied, assessment may take into account, among other things, the spread of a pest (see Article 5.3). While the text does not explicitly discuss how the geospatial risk profile of an invasive pest should be determined, it can be argued that the SPS Agreement provided the impetus for the development of current day biosecurity risk analysis frameworks.

3.3 International Plant Protection Convention

The SPS Agreement provides rules for the development of international standards and guidelines and it recognizes the International Plant Protection Convention (IPPC) as the only acceptable international standard setting body with regards to plant health biosecurity. The IPPC has been described as an inter-governmental biosecurity network (Gruszczynski 2006). It is a legally binding international agreement that develops standards (see below) for addressing world phytosanitary concerns (Schrader 2003). It was first developed in 1929, established in 1952, and the most recent revisions were adopted at the Food and Agricultural Organizations (FAO) conference in 1979 (IPPC 1997). The IPPC aims to ensure common and effective action for preventing the spread

¹ Annex A of the SPS Agreement defines *Risk assessment* as the evaluation of the likelihood of entry, establishment or spread of a pest or disease within the territory of an importing Member according to the sanitary or phytosanitary measures which might be applied, and of the associated potential biological and economic consequences; or the evaluation of the potential for adverse effects on human or animal health arising from the presence of additives, contaminants, toxins or disease-causing organisms in food, beverages or feedstuffs.

and introduction of pests of plants and plant products and promoting measures for their control (IPPC 2005).

The IPPC has addressed invasive species since 1951 (Shrine 2007). The IPPC defines a pest as any species, strain or biotype of plant, animal or pathogenic agent injurious to plants or plant products, and a quarantine pest as a pest of potential economic importance to the area, endangered thereby and not yet present there, or present but not widely distributed and being officially controlled (FAO 2007). Recently, the IPPC expanded its scope to include measures to protect the natural environment and marine flora from invasive plant introductions (IPPC 2005, Hewitt 2009). It is important to note here that the scope of the IPPC includes pests such as invasive plants that may directly or indirectly affect agriculture or the environment (Hedley 2004). The concept of protecting the natural environment from pests such as invasive plants, or plants as pests, is relatively new for the IPPC.

As a specific principle of plant quarantine, the IPPC states that in determining which pests are quarantine pests countries shall use risk analysis following an IPPC framework (FAO 2004). In the eyes of the IPPC, risk analysis is comprised of initiation, risk assessment, and risk management (FAO 2007). For example, once an invasive plant is recognized as a potential threat to a country the scientific justification for its biosecurity regulation (e.g., prohibiting or allowing import) should be based upon pest risk analysis² (PRA). Two International Standards for Phytosanitary Measures (ISPMs) have been developed by the IPPC that provide guidance on risk analysis and risk

² The IPPC defines pest risk analysis as the process of evaluating biological or other scientific and economic evidence to determine whether a pest should be regulated and the strength of any phytosanitary measures to be taken against it.

assessment, and these influence national and regional biosecurity policy and regulations. The ISPM No. 2 “*Guidelines for Pest Risk Analysis*”, endorsed in 1995, provides the general requirements for a PRA to determine if a pest is a quarantine pest or not (FAO 2007). It notes that in assessing establishment and spread potential, expert judgement should be used. Here, the IPSPM fails to recognize how geospatial predictive modelling could be incorporated into PRA process. Geospatial predictive modelling would be valuable in assessing not only the spread potential of a pest, but also the potential economic damage to areas that are determined to be suitable for a pest incursion. For example, in determining economic damage to agricultural crops, environmental areas, or to society and human health, or if in fact the pest has any plant health biosecurity importance.

The next IPPC standard that addresses PRA is ISPM No. 11 “*Pest Risk Analysis for Quarantine Pests including Analysis of Environmental Risks and Living Modified Organisms*” (Clut and Poorter 2005). Endorsed in 2001, this standard along with ISPM No. 2 are important as PRA has been adopted by the WTO as the basis under which countries may restrict trade for biosecurity reasons (WTO 1994) and they underlie plant biosecurity import standards (NAPPO 2008). In 2003, the IPPC endorsed a supplement to ISPM No. 11 (Annex 1) that clearly articulated that the scope of the IPPC (i.e., and the PRA process) extends beyond pests of plants and includes plants as pests (e.g., weeds or invasive plants) as they impact the environment, biological diversity, ecosystems and wild flora. For the purposes of this perspective, ISPM No. 11 is significant in that it is the first standard that specifically references invasive plants and PRA together. It is the first standard that states that factors in the environment including climate, soil, and pest

and host competition need to be identified when assessing suitability of the environment, and that climatic modelling systems can be used to compare the known distribution of the pest to the area at risk. With references to invasive plants, predictive modelling, and risk assessment, two important points are drawn from ISPM No. 11. First, it becomes evident that from this point forward invasive plants are clearly recognized as within the scope of international biosecurity policy. Second, although only briefly alluded to, climatic modelling is noted as a potential PRA tool. The standard however, fails to elaborate on how geospatial predictive modelling might be used to support decision making?

At a regional level, the IPPC also allows for the development of Regional Standards for Phytosanitary Measures (RSPMs). Of interest to this discussion is RSPM No. 32, endorsed in 2008, "*Pest Risk Assessment for Plants for Planting as Quarantine Pests*", that provides guidelines for screening plants prior to import (NAPPO 2008). The RSPM further supports and extends the concept that a plant itself may be a pest (e.g., invasive plants). It also suggests that climate matching and climatic modelling systems may be used to compare climatic and ecological data of invaded and non invaded areas, and notes that soil, topography, elevation, and land cover are parameters a PRA may consider. The RSPM is significant in that it builds upon the text found in ISPM No. 2 and ISPM No. 11, and continues to suggest modelling as a tool that should be used in PRA's. However, the RSPM fails in that it does not suggest any modelling methods that maybe required supporting a risk assessment.

3.4 United Nations Convention on Biodiversity

Another international instrument that has influenced biosecurity policy is the United Nations Convention on Biodiversity (CBD) which entered into force in 1993 (i.e., ratified by Canada in 1992) (CBD 1992). It is an international legally binding treaty for the protection of biodiversity (Hewitt et al. 2009). Currently the convention has been signed by 190 contracting parties and provisions for invasive species have been included in many programmes established by the Conference of the Parties (Shine 2007). Signatory parties have explicit obligations to manage alien species (CBD 1992). The CBD defines an invasive alien species as a species, subspecies or lower taxon, introduced outside its natural past or present distribution; includes any part, gametes, seeds, eggs, or propagules of such species that might survive and subsequently reproduce. The CBD, as an international instrument, has challenged biosecurity decision makers to consider the protection of natural areas and biodiversity when forming biosecurity policy and regulations.

Within the text of the CBD, Article 8(h) specifically addresses invasive alien species. It states that each contracting party shall prevent the introduction of, control or eradicate those alien species which threaten ecosystems, habitats or species. It is the only global instrument that mandates prevention and mitigation measures for all invasive alien species categories (Mooney et al 2005). The Conference of the Parties to the CBD further recognized that there is an urgent need to address the impact of invasive alien species through a three-stage hierarchical approach where priority is given to preventing new introductions, early detection and rapid response, followed by eradication, containment and long-term management efforts (Mooney et al 2005).

In 2002, the Conference of Parties of the CBD further identified 15 non-binding guiding principles for the prevention, introduction and mitigation of invasive species (Shine 2007, Hewitt et al. 2009). There are a number of guiding principles that reference risk analysis. For example guiding principle number seven states that states should implement border control and quarantine measures that are based upon risk analysis, and guiding principle number 10 states that intentional introductions need to be considered within a risk analysis framework. While these principles do provide guidance from which governments may develop strategies against invasive species, they do not provide the how to details. One impact of the CBD has been to challenge plant health biosecurity agencies to recognize that invasive plants (i.e., plants as pests) that impact biological diversity need to be addressed in biosecurity policy and regulations. In addition, the CBD has resulted in signatory countries developing national biodiversity strategies, which further address invasive pests and PRA. For example, in ratifying the CBD, Canada became obligated to prepare a national biodiversity strategy. The Canadian Biodiversity Strategy was released in 1995 as Canada's response to the CBD. The Strategy recognizes that alien species impact biological diversity through species displacement and habitat destruction and defines alien organisms as those species which enter ecosystems beyond their natural range through deliberate or inadvertent introduction by humans. Interestingly, organisms that have extended their natural range without human help are not considered alien. The Strategy suggests that Canada should take all necessary steps to prevent the introduction of harmful alien organisms and to mitigate or eliminate their adverse effects by monitoring, prioritizing species for resources action based upon their impact on native biodiversity, eliminating common

sources of unintentional introductions, developing national and international databases, ensuring adequate legislation and enforcement and enhancing public education and awareness. It states that to prevent the introduction of harmful alien organisms, prevention mechanisms such as risk assessment need to be improved (e.g., see Strategic Direction 1.81). Although the Canadian Biodiversity Strategy provides many strategic directives, it falls short in that details on how to improve risk assessment are lacking, it fails to appreciate that risk assessment is a component of a risk analysis process, and does not discuss how geospatial predictive science could be used to protect biological diversity from invasive pests.

3.5 Updating the Biosecurity Risk Analysis Tool Box

There is a need to re-evaluate the current biosecurity risk analysis toolbox in light of the magnitude of new and emerging risks associated with the growing international trade of plants, some of these invasive. There is a need to modernize risk analysis processes which are being challenged by globalization as policy decisions depend upon accurate spatial and temporal characterizations of pest risk (Venette et al. 2010). Tools that predict potential spatial patterns of pest invasions before they occur need to be incorporated into the risk analysis toolbox, and these are required to support and modernize plant health biosecurity policy. The plant biosecurity toolbox needs to be restocked.

Geographic information systems (Jarnevich et al. 2010) (GIS) and ecological niche modeling (Stockwell and Noble 1992, Stockwell and Petters 1999) are tools that biosecurity risk assessments need to further embrace. For example, ecological niche

modelling has been described as a geospatial predictive tool that models potential niche space available to an invasive pest (Pheloung et al 1999, McClay et al. 2010). It can be used to develop strategies for avoiding species invasions (Peterson and Vieglais 2001), and it can be used in weed risk assessments that support biosecurity policy. Predictive risk maps also provide a policy analyst, or risk manager, with an illustrative tool that enhances risk communication.

While weed risk assessment tools are currently being developed and/or used by organizations in Canada (McClay et al. 2010), Australia (Pheloung et al. 1999), Hawaii (Daehler et al. 2004), Florida (Gordon et al. 2008) and the Czech Republic (Krivanek and Pysek 2006), critically they all have elected not to incorporate either GIS or predictive approaches such as ecological niche modelling. The above weed risk assessments for invasive plants are generally qualitative in nature (FAO 2007), arriving at a determination of risk by assigning subjective scores using a questionnaire-based approach. These approaches could easily integrate geospatial predictive modelling which would enhance the current biosecurity weed risk assessment process. For example, if we examine the system developed by Pheloung et al. (1999), on which many of the above approaches are based on, geospatial predictive modelling could be incorporated into Section A or the Biogeography section, that addresses risk based upon distribution and weediness elsewhere.

It is also recommended that either an ISPM or RSPM be developed to provide plant health biosecurity with clear guidelines on how to use predictive modelling and GIS in the PRA process. Similarly, Venette et al. (2010) called for the development of a best-practice guide for building risk models and creating risk maps. It is suggested that a

new ISPM or RSPM be developed that would provide guidance for NPPOs on (1) how to effectively use geospatial predictive tools, (2) how to incorporate geospatial predictive modeling into pest risk analysis, and (3) how to use modelling and GIS tools to assess risk to a PRA area. General provisions might consider which biotic or abiotic variables should be considered in building the predictive model, what are the important assumptions of the modelling approach, what are the most appropriate sources of training and test data (e.g., NPPO survey data) and where these data can be found, and how might the model accuracy and predictive power be assessed. Figure 3.1, adapted from ISPM No. 2, provides a conceptual illustration of where in the PRA process predictive modelling and GIS might be incorporated. Alternatively, guidelines on how to incorporate geospatial predictive modelling into the PRA process could be considered as a supplement to ISPM No. 2 (see Chapter 8 for further discussion).

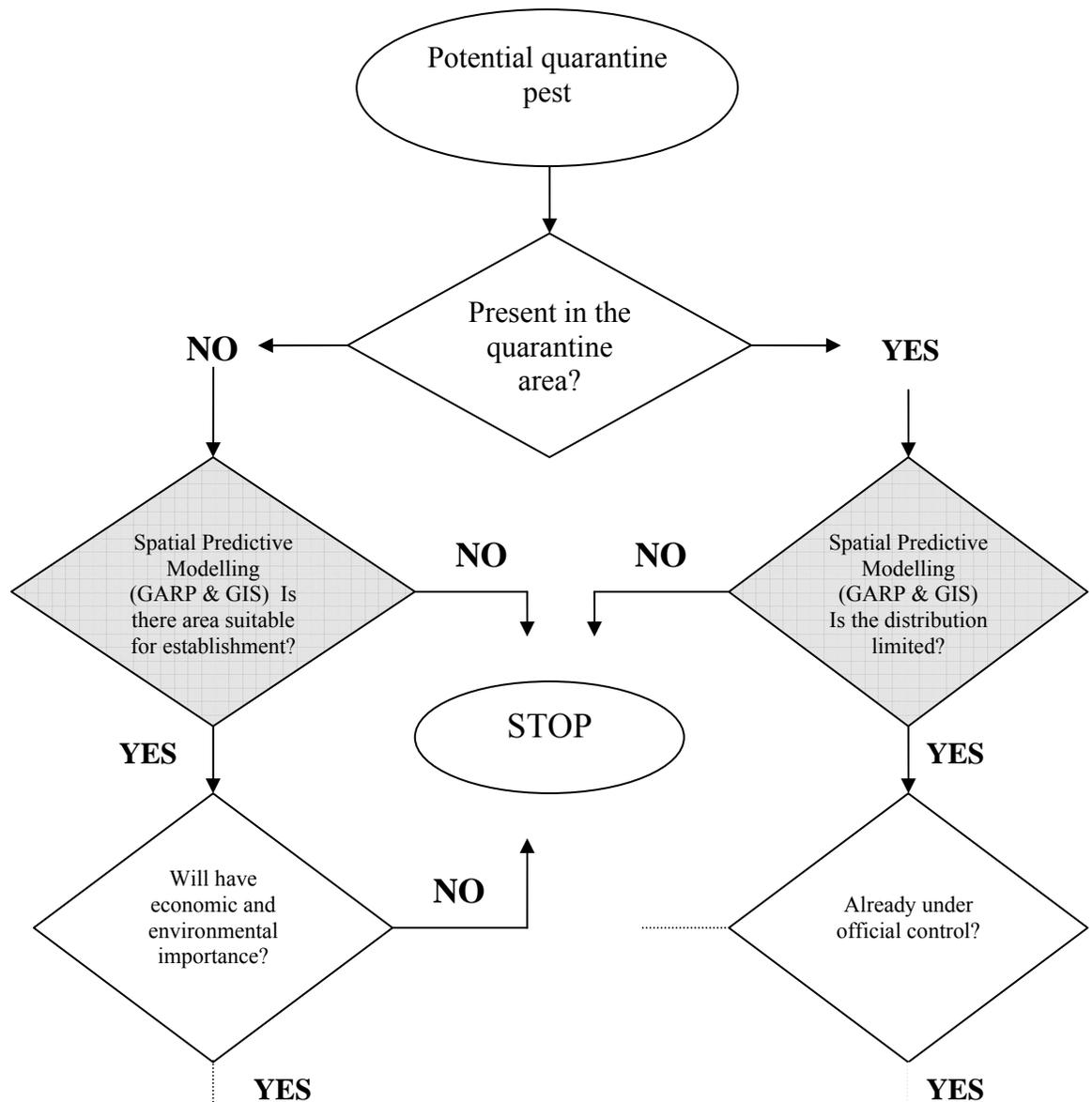


Figure 3.1 Spatial predictive modelling and geographic information systems (grey shaded triangles) can be incorporated into the risk analysis toolbox. The flowchart was adapted from Figure 2 in ISPM No. 2 (FAO 2006).

3.6 Conclusions

Advances in spatial predictive modelling and GIS technologies have provided powerful new tools that are not being used in current biosecurity risk analysis

approaches. By not using these tools a weak link has been created in risk-based biosecurity frameworks. Spatial predictive modelling can play an important role in risk analysis (Stohlgren and Schnase 2006) and hence there is a need to adapt and utilize these new tools and methods (Anderson et al. 2004). Predicting the potential distribution of a pest represents a shift in the biosecurity paradigm from a reactive to proactive approach which anticipates new emerging pests. This paradigm shift is critical as governments are continuing to reprioritize limited biosecurity resources towards prevention policies. It is recognized that prevention policies using predictive tools are the most cost effective strategy to addressing invasive pests. It is recommended that new spatial predictive tools be incorporated into the biosecurity toolbox. In the next chapter I will critically review commonly used spatial predictive tools and discuss their advantages and disadvantages.

3.7 References

- Andersen, M.C., H. Adams, B. Hope and M. Powell. 2004. Risk assessment for invasive Species. *Risk Analysis* 24:787–793.
- Brasier, C.M. 2008. The biosecurity threat to the UK and global environment from international trade in plants. *Plant Pathology* 57:792-808.
- Brunel, S., F. Petter, E. Fernandez-Galiano and I. Smith. 2009. Approach of the European and Mediterranean plant protection organization to the evaluation and management of risks presented by invasive alien plants. In: Inderjit, editor. *Management of Invasive Weeds*, Springer. Netherlands, p. 319-343.
- CBD. 1992. Convention on Biological Diversity. United Nations Environment

- Programme, Rio de Janeiro.
- Clout, M.N. and M. Poorter. 2005. International initiatives against invasive alien species. *Weed Technology* 19:523-527.
- Daehler, C.C., J.S. Denslow, S. Ansari and H. Kuo. 2004. A risk-assessment system for screening out invasive pest plants from Hawaii and other Pacific Islands. *Conservation Biology* 18:360-368.
- FAO. 1993. ISPM No. 1 Principles of plant quarantine as related to international trade. International Standards for Phytosanitary Measures. Secretary of the International Plant Protection Convention. Rome, Italy.
- FAO. 2004. ISPM No. 11 Pest Risk Analysis for Quarantine Pests including Analysis of Environmental Risks and Living Modified Organism. Secretary of the International Plant Protection Convention. Rome, Italy.
- FAO. 2007. Biosecurity Toolkit. FAO, Rome, Italy.
- Gordon, D.R., D.A. Onderdonk, A.M. Fox, R.K. Stocker and C. Gantz. 2008. Predicting Invasive Plants in Florida Using the Australian Weed Risk Assessment. *Invasive Plant Science and Management* 1:178-195.
- Gruszczynski, L. 2006. The role of science in risk regulation under the SPS Agreement. EUI Working Papers Law 2006/03. European Institute University Department of Law.
- Hager, H.A. and K.D. McCoy. 1998. The implications of accepting untested hypotheses: a review of the effects of purple loosestrife (*Lythrum salicaria*) in North America. *Biodiversity and Conservation* 7:1069-1079.
- Hedley, J. 2004. Chapter 7: The International Plant Protection Convention and

- invasive species. In: Miller ML, Fabian RN, editors, Harmful Invasive Species: Legal Response. Environmental Law Institute, Washington, D.C., USA. p. 185-201.
- Heikkila J. 2011. Economics of biosecurity across levels of decision-making: a review. *Agronomy for Sustainable Development* 31:119-138.
- Hewitt, C.L, R.A. Everett and N. Parker. 2009. Examples of current international, regional and national regulatory frameworks for preventing and managing marine bioinvasions. In: Rilov G, Cook JA, editors. *Biological Invasions in Marine Ecosystems*, Springer-Verlag Berlin Heidelberg.
- Hulme, P.E. 2011. Biosecurity: the changing face of invasion biology In: *Fifty Years of Invasion Ecology – The Legacy of Charles Elton*. In: Richardson DG, editor. Blackwells, p. 301-314.
- IPPC. 1951. *International Plant Protection Convention*. Food and Agriculture Organization of the United Nations, Rome, Italy.
- IPPC. 1997. *International Plant Protection Convention*. New revised text approved by the FAO Conference at its 29th Session – November 1997. Food and Agriculture Organization of the United Nations, Viale delle Terme di Caracalla, Rome, Italy.
- IPPC. 2005. Identification of risks and management of invasive alien species using the IPPC framework. In *Proc. Workshop in Braunschweig, Germany 22-26 September 2003*. Rome, Italy: International Plant Protection Convention Secretariat, FAO.
- Jarnevich, C.S., T.R. Holmcombe, D.T. Barnett, T.J. Stohlgren and J.T. Kartesz. 2010. Forecasting weed distributions using climate data: A GIS early warning tool. *Invasive Plant Science and Management* 3:365-375.

- Khetarpal, R.K. and K. Gupta. 2007. Plant biosecurity in India – Status and Strategy. Asian Biotechnology and Development Review 9:83-107.
- Krivanek, M. and P. Pysek. 2006. Predicting invasions by woody species in a temperate zone: a test of three risk assessment schemes in the Czech Republic (Central Europe). Diversity and Distributions 12:319-327.
- Magarey, R.D., M. Colunga-Garcia and D.A. Fieselmann. 2009. Plant biosecurity in the United States: roles, responsibilities, and information needs. BioScience 59: 875-884.
- McClay, A, A. Sissons, C. Wilson and S. Davis. 2010. Evaluation of the Australian weed risk assessment system for the prediction of plant invasiveness in Canada. Biological Invasions 12:4085-4098.
- Meyerson, L.A. and J.K. Reaser. 2002. Biosecurity: moving towards a comprehensive approach. BioScience 52:593-600.
- Mooney, H.A., R.N. Mack, J.A. McNeely, L.E. Neville, P. Johan Schei and J.K. Waage. 2005. Invasive Alien Species: A New Synthesis. Island Press, London. 368 pp.
- Mullin, B.H., W.J. Anderson Lars, J.M. DiTomaso, R.E. Eplee and K.E. Getsinger. 2000. Invasive Plant Species. Issue Paper Number 13. Report published by the Council for Agricultural Science and Technology.
- NAPPO. 2008. Pest risk assessment for plants for planting as quarantine pests (RSPM No. 32). The Secretariat of the North American Plant Protection Organization. Ottawa, Ontario.
- Peterson, A.T. and D.A. Vieglais. 2001. Prediction species invasions using ecological niche modeling: new approaches from bioinformatics attach a pressing

- problem. *Bioscience* 51:363-371.
- Pheloung, P.C., P.A. Williams and S.R. Hallory. 1999. A weed risk assessment model for use as a biosecurity tool evaluation plant introductions. *Journal of Environmental Management* 57:239-251.
- Schrader, G. and J. Unger. 2003. Plant quarantine as a measure against invasive alien species: the framework of the International Plant Protection Convention and the plant health regulation in the European Union. *Biological Invasions* 5:357-364.
- Shine C. 2007. Invasive species in an international context: IPPC, CBD, European Strategy on Invasive Alien Species and other legal instruments. *OEPP/EPPO Bulletin* 37:103-113.
- Stockwell, D. 1997. Generic predictive systems: An empirical evaluation using the learning base system (LBS). *Expert Systems with Applications* 12:301-310.
- Stockwell, D. and I.R. Noble. 1992. Induction of sets of rules from animal distribution data: a robust and informative method of data analysis. *Mathematics and Computers in Simulation* 33:385-390.
- Stockwell, D. and D. Peters. 1999. The GARP modeling system: problems and solutions to automated spatial prediction. *International Journal of Geographical Information Science* 13:143-158.
- Stohlgren, T.J. and J.L. Schnase. 2006. Risk analysis for biological hazards: What we need to know about invasive species. *Risk Analysis* 26:163–173.
- Venette, R., D. Kriticos, D. Magarey, F. Koch, R. Baker, S. Worner, N. Raboteau, D. McKenny, E. Dobesberger, D. Yemshanov, P. De Barro, W. Hutchison, G. Fowler, T. Kalaris and J. Pedlar. 2010. Pest risk maps for invasive alien species:

a roadmap for improvement. *BioScience* 60:349-362.

Waage, J.K. and J.D. Mumford. 2007. Agricultural Biosecurity. *Philosophical Transactions of the Royal Society* 363:863-876.

WTO. 1994. Description of the agreement on the application of SPS measures. Geneva: World Trade Organization.

CHAPTER 4 – SPATIAL PREDICTIVE MODELLING LITERACY

One of the most interesting aspects of bioclimatic analysis is the forecasting of the potential distribution of insect species into uninfested areas. Such forecasting attempts are particularly important in cases of foreign insect pests against which quarantine measures have been directed (Messenger 1959).

4.1 Spatial Predictive Modelling and Niche Space

Researchers have been wondering about why species are where they are for over 100 years and most likely much longer outside of the published scientific literature. For example, as early as 1917 Joseph Grinnell pondered the above geographic question, and made spatial predictions by comparing environments inside and outside of a species distribution. Spatial predictive modelling is also about where species are, and where they are not. The concept of the ecological niche, which defines where, and where not, a species can survive, is critical in understanding and interpreting spatial predictive modeling approaches. Spatial predictive modelling, its assumptions and interpretations of results, are conceptualized by the ecological niche (Pearson and Dawson 2003), hence a review of niche concepts follows.

4.2 Why Are Species Where They Are?

There have been numerous contributors to the evolving concept of the ecological niche. Joseph Grinnell may have pioneered the term niche in his 1917 paper that described the niche relationships of the California thrasher (*Toxostoma redivivum*)

(Grinnell, 1917a, Wiens and Graham, 2005). The concept of the Grinnellian Niche was believed to arise from Grinnell wondering about why species are where they are, and why they are not where they are not, and Grinnell arriving at spatial predictions by comparing environments inside and outside of a species distribution (Peterson 2006). Grinnell (1917a) postulated that physiological and psychological variables were critical conditions that constrained spatial distributions. He concluded that the range of *T. redivivum* was constrained by climate (i.e., temperature) and faunal (i.e., habitat) conditions, both parameters that comprised the associational niche for the species. Grinnell (1917b) described the niche as a set of tolerances or limits that defined where a species may survive, and where it may not. Hence, the Grinnellian niche was based upon broad abiotic landscape variables and was not affected by variables such as species density (Hirzel and Le Lay 2008).

The Grinnellian niche was later expanded upon by Charles Elton (1927), a British ecologist, who described the niche as a functional unit describing a species place in its biotic environment. The Eltonian niche included fine-scale variables that may be consumed by a species (Hirzel and Le Lay 2008). Zoologist G. Evelyn Hutchinson (1957) further characterized the ecological niche as a set of biotic and abiotic conditions in which a species is able to survive and propagate. Hutchinson (1957) introduced the term hypervolume, a multi-dimensional space of resources including light, nutrients, and structure available to an organism. The niche then becomes a subset of environmental dimensions that limit or restrict an organism's survival. Hutchinson (1957) further distinguished between a fundamental niche that includes all abiotic conditions under which an organism can survive and a realized niche which is the narrower niche the

organism adapts to in the presence competition from other species (Kearney 2006).

Fundamental niche space is characterized by climatic conditions assuming that climate is the only limiting factor, while realized niche space is the range of climate conditions that are actually occupied (Webber et al. 2011).

Around the same time that Joseph Grinnell was developing his theories on the concept of the niche, William Cook, an entomologist at the Montana Agricultural Experimental Station in the United States, was also advancing similar theories that addressed the question of what limits a species distribution. Cook (1924) developed climograph curves to estimate the spatial distribution of the pale western cutworm (*Porosagrotis orthogonia*), a pest of grain. The climograph plotted monthly values of temperature and precipitation on a graph where these variables formed the axes, then connected the points for successive months by a line that revealed the direction of the annual cycle. He suggested that the climograph could be used to determine the spatial distribution for any species of life living in the soil. Cook (1924, 1925) further postulated that climographs could be used to determine the economic distribution of a species, and this would be of considerable value in studies of invasive species.

In 1929, Cook further expanded his theories on biogeographical distributions. Cook produced climatographs, by superimposing responses of the alfalfa weevil (*Hypera postica*) to climate onto locational graphs of temperature and relative humidity, creating bioclimatic zonations that predicted spatial distribution. He distinguished between absolute and economic distributions, where the absolute distribution considers all known occurrences of an insect while the economic distribution is a smaller region within the absolute distribution where an insect causes economic damage to crops. He suggested

that there are three zones or degrees of destructiveness within the area of economic distribution (1) a zone of normal abundance where a pest is able to sustain a permanent population, there are no limiting conditions and outbreaks are frequent, (2) a zone of occasional abundance where a pest is held to a small population by climatic conditions and only occasionally is able to become destructive, and (3) a zone of possible abundance that includes areas not in the former two zones, and where it is climatically possible for outbreaks to occur and a pest to become destructive, but where it cannot sustain a permanent population. Cook (1931) concluded that geographical distributions are limited by climatic conditions, and that climatic conditions are generally stable, hence it is possible to map future spatial distributions. This remains an important assumption underlying present spatial predictive modelling studies.

Cook's studies may have been the first that identified the importance of spatial predictive modelling in risk decision making. Cook's use of climatic data to predict a pest's potential spatial distribution is similar to modern day spatial predictive modeling studies as well as biosecurity risk assessment (e.g., probability of establishment). His theories on the importance of economic distributions of a pest outbreak are similar to present day concepts of regulated areas and quarantine zones (e.g., risk management). William Cook used climatic data from a pest's native range to predict future invasions in an effort to support, what he referred to as intelligent quarantines.

Cook recognized that spatial predictive modelling was challenged by the accuracy of the data, that available distributional data sets are usually unsatisfactory, and that results are at a coarse scale. He noted that climatic data, for example, are available only from a small number of stations which are widely separated; hence local conditions

are often overlooked when making spatial predictions of distributions (Cook 1929, Messenger 1959). These challenges are identical to those identified in present day spatial predictive modelling studies.

Climate matching is the “basis for intelligent quarantines, which will not hinder commerce between the infested area and those regions where no damage is expected. There is no use in maintaining quarantine against an insect that would do very little damage if introduced” (Cook 1931).

Hutchinson, Grinnell, Cook, and Elton all recognized that abiotic and biotic conditions determined the spatial distributions of plants and animals, and that abiotic variables could be used to predict potential distributions by comparing these variables from the native area of a pest to a novel area. Cook (1931) postulated that the climatic analysis of insect distributions was a new promising field and one in which advances are certain to be made in the near future.

The work of Grinnell, Cook, Elton and Hutchinson provided the foundations for present day spatial predictive modelling studies. For example, using environmental variables to predict species distributions is seen as an operational application of the ecological niche (Hirzel and La Lay 2008). A species realized niche is the space where it is excluded from parts of its fundamental niche as a result of biotic factors such as competition (Pearson and Dawson 2003). As predicted by Cook (1931), advances have been made in the climatic analysis of species distributions, mostly as a result of advances in computer technology and geographic information systems (GIS) (Madsen 1999, Daehler and Carino 2000, Welk et al. 2002, Peterson et al. 2003). Species distribution models are now commonly used for predicting the potential range of an invasive species

and should be considered as an important component of a biosecurity risk assessment (Webber et al. 2011), and a powerful tool for biogeographers (Babar et al. 2012). A discussion on types of spatial predictive models follows.

4.3 Types of Spatial Models

Variables that determine a species distribution are (1) conditions in the local environment (i.e., climate), (2) biotic interactions with other species, and (3) the ability of a species to disperse (Hirzel and Le Lay 2008, Webber et al. 2011). As biotic interactions and dispersal events may change rapidly due to anthropogenic influences, predictive modelling subsequently explores habitat suitability as it is determined by climate (Webber et al. 2011). Numerous models and approaches are available that predict potential species distributions. The types of models can be categorized based upon either the general methods used (i.e., correlative, mechanistic) or the type of data used (i.e., presence, absence).

Models can generally be categorized as those that use presence-only data, or presence-absence data (i.e., at each sample site it is known with certainty whether the species is present or absent (Hirzel et al. 2006, Tsoar et al. 2007)). In most cases modellers have access to presence only data, such as museum or herbarium records, and in rare cases validated field collected survey data. Examples of models that use presence only data are BIOCLIM (Busby, 1986; Nix, 1986) and GARP (Stockwell and Peters 1999). Absence data is rarely available and when available it is important to consider if the habitat truly cannot support the species or alternatively has the species just not arrived (i.e., dispersed) there yet. Collecting absence data is also time-consuming and

resource-consuming (Raimundo et al. 2007). Some modelling approaches, such as GARP, generate pseudo-absence data by selecting points at random from the geographic space in the study where the species has not been recorded, however these points are not true absence points and may actually have populations (Stockwell and Peters 1999, Raimundo et al. 2007).

Spatial predictive models can also be categorized as being either correlative or mechanistic (Beerling et al. 1995, Robertson 2003, Kearney and Porter 2009, Webber et al. 2011). Correlative models, which are commonly used, are based upon relationships between the species and climate, while mechanistic models evaluate climate in terms of ecophysiological constraints/tolerances (i.e., growing degree-days, heat, cold, frost) and resource limitations (i.e., water, light, nutrients) that determine distribution (Webber et al. 2011, Yates et al. 2000). Correlative models use predictor variables such as climate that are associated with distribution records to classify the predictor variable into presence-absence regions projected onto spatial maps (Robertson et al. 2003). For example, the georeferenced locality record indicates that the species was able to survive, establish, and successfully reproduce at that specific location, which has an associated suite of multivariate spatial conditions defining suitable environmental space (Kearney and Porter 2009). In terms of ecological niche modelling, the results of correlative modelling are thought to reflect a species realized distribution niche (Rodda et al. 2011).

Mechanistic models attempt to simulate the mechanisms that underlie the observed correlations with environmental variables using life-history attributes (Beerling et al. 1995). A species then becomes not a point on a map, but rather represented by a set of behavioural, morphological and physiological traits (Kearney and Porter 2009).

Mechanistic models have also been referred to as ecophysiological models or process models (Robertson et al. 2003). Stephenson (1998) also referred to mechanistic models as ecophysiological (i.e., those based on detailed knowledge of physiology and life-history traits of plants), and that in many cases ecophysiological studies depend on correlations to determine quantitative relationships between physiologically variables and plant distributions. Mechanistic models do not use variables associated with distribution records but use those associated with resource gradients and are more proximal, while predictor variables in correlative models tend to be more distal (Robertson et al. 2003). In terms of ecological niche modelling, the results of mechanistic models reflect a species fundamental niche (Rodda et al. 2011).

The decision to adopt either a correlative or mechanistic approach will largely depend on the purpose of the study as both approaches have advantages and disadvantages. It has been suggested that in some cases mechanistic models out perform correlative models because of the additional physical realism incorporated, however where data is limited correlative models are preferred (Yates et al. 2000). Critically, disadvantages of mechanistic models is that they are expensive, time consuming, require a greater knowledge of species biology, and require more data as compared to correlative approaches (Robertson et al. 2003, Kearney and Porter 2009, Webber et al. 2011). One possible solution towards producing more robust prediction maps maybe a strategy that incorporates both correlative and mechanistic approaches (Kearney and Porter 2009).

4.4 Spatial Predictive Modelling Approaches

Spatial predictive modelling approaches can be simple indices that allow geographical comparisons, sophisticated computer systems, or software and algorithms that assess environmental parameters to predict a species geographic distribution. The principle assumptions with predictive modeling systems are that (1) species distributions is determined largely by climate (Andrewartha and Birch 1954), and biotic interactions are unimportant and constant over space and time, (2) evolutionary changes happen very slowly and the genetic composition of species is constant over space and time, and (3) species can occur at all locations where climate is favourable and nowhere else (i.e., dispersal is unlimited) (Jeschke and Strayer 2008). Predictive models are thus pragmatic approaches for assessing the potential establishment of an invasive pest (Jarvis and Baker 2001) where the actual distribution of a pest will be determined by its ability to disperse with or without human assistance, and its interactions with other species (Sutherst et al. 2011).

Spatial predictive modelling systems are used by a wide variety of practitioners including geographers, land managers, national science organizations, biological control practitioners, and by biosecurity organizations (i.e., pest risk analysts). However, the use of spatial predictive models can be controversial (Jeschke and Strayer 2008) in that there are many types of approaches each with different assumptions, advantages and disadvantages, costs, and resource needs. It is difficult to identify one single modelling approach that consistently outperforms all other for all types of data and species (Babar et al. 2012). I will provide a comparative review of three commonly used modelling approaches (1) BIOCLIM, (2) CLIMEX and (3) GARP. All three approaches use

presence only data which, in most cases, is all that is available to inform a biosecurity risk assessment. Table 4.1 summarizes these three approaches.

Table 4.1 Comparative summary of common spatial predictive modeling approaches.

MODEL	Type	Data	Founder
CLIMEX	Correlative	Presence Only	R.W. Sutherst and G.F. Maywald - Australia
BIOCLIM	Correlative	Presence Only	H.A. Nix, J.R. Busby and M.F. Hutchinson - Australia
GARP	Genetic Algorithm	Presence Only (pseudo-absence)	D. Stockwell – United States

4.4.1 BIOCLIM

BIOCLIM is a correlative modelling approach that uses presence only and environmental data to form a profile for a species (Manning et al. 2005, Barry and Elith 2006). It was the first computer based system for predicting species distributions (Kriticos and Randall 2001). Developed by H.A Nix, J.R. Busby and M.F. Hutchinson, it became available for general use in 1984. It is a module of ANUCLIM bioclimatic prediction system (Hutchinson et al. *n.d.*, Booth et al. 1988) that is used by Australian State and Federal governments in pre-border weed risk assessments (Brown 2006). Guisan and Zimmermann (2000) described BIOCLIM as a boxcar approach that creates environmental envelopes using one-by-one degree latitude-longitude grid cells. It interpolates up to 35 surrogate climatic layers for known occurrence points using monthly or weekly values of (1) maximum temperature, (2) minimum temperature, (3) rainfall, (4) radiation, and (5) evaporation (Hutchinson et al. *n.d.*, Beaumont et al. 2005). Nix and Switzer (1991) summarized BIOCLIM as using a three step process (1) the

estimation of climate for the species location record, (2) matching the bioclimatic profile with other locations with similar conditions, and finally (3) mapping of predicted bioclimatic areas to produce a predicted potential distribution map. Similarly, Beaumont et al. (2005) noted that BIOCLIM describes the environment in which a species has been recorded, identifies other locations where it may reside, and then identifies where it may occur under alternative climate scenarios. BIOCLIM predicts species occurrences in categories along environmental dimensions, trims marginal portions of distributions, and takes the niche as the conjunction of the trimmed ranges (Peterson et al. 2002).

Critically BIOCLIM has a number of disadvantages. It suffers in efficacy when many environmental dimensions are included (Peterson et al. 2002). For example, the use of all 35 parameters leads to over-fitting the model and thus to inaccurate representations of potential distributions (Beaumont et al. 2005, Chen 2008). Inclusion of unnecessary predictive parameters may also result in increased errors of omission (i.e., where habitat being identified as climatically unsuitable when in fact the species could occur there) and selection of too few parameters leads to increased commission errors (i.e., false positives) (Beaumont et al. 2005). Practitioners using BIOCLIM need to consider that using too many parameters or too few parameters may result in incorrect predicted distributions, and that expert opinion and knowledge of the biology of the species will help guide the appropriate selection of parameters (Beaumont et al. 2005).

BIOCLIM predicts where a species does not occur, not where it does occur often resulting in false predictions of occurrence (i.e., commission errors) (McNyset 2005, Kriticos and Randall 2002). Peterson (2001) also noted that BIOCLIM generally has high rates of commission error or overprediction. Another criticism is that at the

distributional margins where sites of known suitable habitat are indicated as marginal, unsuitable sites may be predicted as suitable (Kriticos and Randall 2001). For example, Chen (2008) used BIOCLIM to predict the potential distribution of the yellow crazy ant (*Anoplolepis gracilipes*) finding that it under-predicted (i.e., high omission errors) the potential distribution in New Zealand. Manning et al. (2005) also concluded that BIOCLIM has many disadvantages but noted it is a useful starting point for further geographic investigations. Tsoar et al. (2007) suggested that BIOCLIM is one of the simplest modelling approaches in that it is based on creating a rectilinear environmental envelope, noting that a disadvantage is that it cannot deal with correlations or interactions between the environmental factors. BIOCLIM is available for purchase from the Australian National University limiting the use of the modelling approach to only those that can afford to purchase.

Applications

BIOCLIM has been used to predict animal and plant distributions. For example, Beaumont et al. (2005) used BIOCLIM to predict the geographic distributions of 25 species of butterflies from five biogeographic zones in Australia. It has been used to predict the impact of climate change on the distribution of 42 fauna species in south-eastern Australia (Brereton et al. 1995), to define the potential geographical limits of the Australian distribution of the leadbeater's possum (*Gymnobelideus leadbeateri*) by creating a bioclimatic profile (Lindermayer et al. 1991), and to define the bioclimatic range of the superb parrot (*Polytelis swainsonii*) in Australia (Manning et al. 2005). Manning (2010) used BIOCLIM to identify possible locations of Scots pine (*Pinus sylvestris*) in Scotland.

4.4.2 CLIMEX

CLIMEX is a second example of a climate-based correlative modeling approach. It was developed by R.W. Sutherst and G.F. Maywald as a computerized system for matching climates in ecology (Sutherst and Maywald 1985, Hearne Scientific Software 2007). It was developed at the Commonwealth Scientific and Industrial Research Organization (CSIRO), Australia's national science agency (note that CSIRO is not a biosecurity agency with an obligation to conduct pest risk analysis, it contributes CLIMEX analyses to risk assessments done by others such as Biosecurity Australia and Biosecurity New Zealand). Sutherst et al. (2000) stated that CLIMEX differs from all other modelling approaches as it uses both simulation modelling and an inference approach to estimate a species response to climate. It has been described as a process-oriented climatic niche model (Watt et al. 2010), a process-oriented ecophysiological niche model (Webber et al. 2011), a mechanistic niche model, as well as a tool for comparing the relative potential for growth and persistence of populations of poikilothermic organisms at different times and places (Sutherst and Maywald 1985, Taylor 2012). It is based on the assumption that climate determines a species distribution, and it is commonly used in the fields of biological control, climate change and pest risk assessment (Sutherst 2003).

The CLIMEX model is based on the concept that there are two types of seasons in each year, one with population growth (i.e., a growth season) and another with population decline (i.e., a stress season) (Sutherst 2003). It is based upon a mechanistic eco-physiological growth model that assumes that a population experiences a favourable

season with positive growth, and an unfavourable season (i.e., based upon cold, wet, hot and dry stressors) with negative growth (Sutherst et al. 2007). It uses a combination of growth and stress indices to describe responses over a full range of climatic conditions that occur in different seasons in different locations (Sutherst et al. 2000). Using meteorological data and an estimate of a species response to temperature (i.e., average maximums and minimums), moisture (i.e., rainfall and relative humidity) and day length (i.e., seasonal phenology), an annual ecoclimatic index (EI) is derived to describe the suitability of a given location for a species (Sutherst and Mayward 1985, Sutherst and Bourne 2009, Taylor et al. 2012). The overall climatic suitability is provided by a single number referred to as the ecoclimatic index (EI) (i.e., scaled from 0 to 100), that describes the favourability of each location for a species. The EI describes the overall climatic suitability on a scale from 0 (i.e., no growth) to 100 (i.e., optimal growing conditions), establishment is only possible with $EI > 0$, and an EI value of 100 signifies ideal growth conditions year-round (Sutherst 2003). A population's response to climate in its geographic range is then used to map potential range in new regions, and range boundaries are mostly defined by climatic stresses (Sutherst 2003).

Disadvantages of using CLIMEX include the need for detailed knowledge of a species response to environmental parameters and in obtaining required detailed climatic records (Carpenter et al. 1993). The CLIMEX model does not consider non-climatic factors that also determine habitat suitability such as local hydrology, soil type, or land use and disturbance (Kriticos et al. 2003). Fitting parameters in CLIMEX is labour-intensive and requires considerable skill and extensive training. In addition, the accurate interpolation of results requires considerable modelling experience; hence it is frequently

misused (Kriticos and Randall 2001, Webber et al. 2011). An economic disadvantage is that CLIMEX software is expensive to purchase and requires annual upgrades and maintenance packages which additionally need to be purchased. A single license can be purchased through Hearne Scientific Software at an initial cost of about \$2,300 dollars.

Applications

CLIMEX has been used widely by Australian practitioners to assess the potential distribution of many species as well as to assess potential distributions under climate change scenarios (Kriticos et al. 2005, Watt et al. 2009, Taylor et al. 2012). For example, Kriticos et al. (2003) used CLIMEX to model the potential of the invasive plant prickly acacia (*Acacia nilotica* spp. *indicat*) to invade Australia based on its distribution outside of Australia under both current and estimated climate change. Watt et al. (2010) used CLIMEX to identify climatically suitable areas for the highly invasive weed butterfly bush (*Buddleja javidii*) in efforts to support the selection of new sites for tree plantations under changing climate conditions in New Zealand. Dunlop et al. (2006) used CLIMEX to model the distribution of *Senna obtusifolia*, an aggressive invasive agricultural weed in Australia. Olfert and Weiss (2006) used CLIMEX to develop bioclimatic models for three pest species of Canada, the cabbage seed pod weevil (*Ceutorhynchus obstrictus*), the rape blossom beetle (*Meligethes viridescens*), and the cereal leaf beetle (*Oulema melanopus*) under climate change estimates. Olfert et al. (2006) used CLIMEX to predict the potential range of the swede midge (*Contarinia nasturtii*), an invasive pest in Canada. Goolsby (2004) used it to predict the potential distribution of a fern (*Lygodium microphyllum*) in North America and to determine its ecoclimatic boundaries. CLIMEX

has been used by the European and Mediterranean Plant Protection Organization (EPPO) in risk assessments of a fruit fly (*Bactrocera invadens*) (EPPO 2010), an aquatic invasive plant water hyacinth (*Eichhornia crassipes*) (EPPO 2008) and an aquatic invasive plant marsh pennywort (*Hydrocotyle ranunculoides*) (EPPO 2009).

4.4.3 GARP

The Genetic Algorithm for Rule-set Production (GARP), developed by David Stockwell at the San Diego Supercomputer Center, is a modeling approach that allows for the prediction of species distributions (Stockwell, 1997). It is a learning algorithm that uses rule-sets to predict species distributions (Peterson 2001, Crossman and Bass 2008). Genetic algorithms are computer programming strategies that evolve by mimicking natural selection hence they can solve complex problems that even their creators do not fully understand (Holland 1992). John Holland and colleagues at the University of Michigan are considered the fathers of genetic algorithms and published his landmark book entitled *Adaptation in Natural and Artificial Systems* in 1975 (Sumida et al. 1990). Genetic algorithms have been used in modeling and problem solving in robot learning, economic studies, immune system models, population genetics, stock market prediction, scheduling at airports, and in engineering.

Genetic algorithms are based on evolutionary concepts that suggest that random chance of variation coupled with the law of selection, can be an effective problem solving technique (Marczyk 2004, Ruxton and Beauchamp 2008). They mimic evolutionary processes of natural selection and sexual reproduction in machine language. The algorithms are genetic in the sense that they use mating, mutation, and crossover to

arrive at a solution (Sumida et al. 1990). They compare the relative performance of solutions (i.e., fitness) arrived at through operators such as mutation and recombination. Solutions with high fitness are kept and allowed to reproduce; these digital offspring go on to the next generation and are subjected to further fitness evaluation. Random variations may occur that may improve fitness and provide an optimized solution. Overall fitness or the solution is increased each round. In spatial predictive modelling genetic algorithms provide a heuristic solution to a geographic question by scanning broadly across the search space and refining solutions that show high values of fitness (Anderson et al. 2003).

In developing predictive models GARP applies a genetic algorithm that takes the form of rule-sets or if-then statements (Stockwell and Peterson 2002, Stockwell and Peters 1999). Stockwell and Peters (1999) provided the following description of GARP. It is comprised of eight programs each within one the four groups (1) data preparation, (2) model development, (3) model application and (4) communication. The model is developed by the central program called EXPLAIN which is composed of a set of rules or if-then relationships. A rule has preconditions that determine when it can be applied, and when the conditions are not met, the rule is developed through evolutionary refinement, through testing and selecting rules on random subsets of training data. Stockwell and Peters (1999) provided an example of an envelope rule (note that GARP also uses atomic and logit rules) that might be used by GARP:

Rule: if annual temperature (TANN) falls between 23° and 29° C, and the annual rainfall (RANN) falls between 609 and 1420mm, and the value of the category (GEO) falls in the range 6 to 244, then the rule predicts the species as present

Or: IF TANN=(23,29)degC AND RANN=(609,1420)mm AND GEO=(6,244)c THEN SP=PRESENT).

After obtaining a first rule-set GARP allows rules to evolve by a number of processes that metaphorically mimic DNA evolution including mutations, deletions and recombination (Raimundo et al. 2007). The change in predictive accuracy (i.e., fitness) of a rule from one iteration to the next is used to evaluate if a rule should be retained in the model (Raimundo et al. 2007). The goal of GARP is to maximize significance and predictive accuracy of rules without overfitting or overly specializing rules. The modules search for non-random associations between ecological characteristics of an area containing known occurrence points (Ganeshaiha et al. 2003).

Oberhauser and Peterson (2003) described how GARP approximates ecological niche space. It samples known occurrence points and pseudo-absence points (e.g., sites where the species is not known to occur) randomly with replacement to create training and test data sets of up to 1,250 points each. It works in an iterative process to develop rules that identify key niche parameters, evaluates their importance and predictivity, and either incorporates them into the model or rejects them. The algorithm evaluates the fitness of a rule-set using test data, then evolves that rule-set through a series of perturbations. Rule-sets showing improved fitness are retained and those where fitness is reduced are eliminated. Changes in predictive accuracy from one iteration to the next are used to evaluate whether a rule should be incorporated into the model. It identifies ecological niche space projected onto binary maps that identify potential distributions.

Kriticos and Randall (2003) suggested that one of the disadvantages of GARP as a biosecurity risk assessment tool is that it does not produce global or large scale international predictions. Arguably, this is not the case as GARP is capable of using global data to make international projections. Some studies have found that the algorithm

overpredicted the potential distribution. For example, Larson et al. (2009) found that it overpredicted the potential range of mosquitoes in Iowa, and Elith and Graham (2009) also found that GARP overprediction. However, depending upon what your using the algorithm for, overprediction can be an advantage. I would argue that overprediction may be an advantage in (1) modelling an invasive species where the species is continuing to invade new geographic space at a rapid rate, (2) where conservative models may lead to unwanted economic risk, or (3) where overprediction may account for evolutionary change or ecological processes not captured by the predictive spatial model. It is likely the case that GARP should not be used to model the distributions of endangered species, for example, where overprediction might lead to inflated conclusions (Stockman et al. 2006). However, Babar et al. (2012) successfully used GARP to predict the potential range of the endangered plant (*Pterocarpus santalinus*).

Stockman et al. (2006) stated that based upon the area under the curve (AUC) scores, their GARP model failed miserably and performed no better than flipping a coin, while comparatively their BIOCLIM model performed with much greater accuracy. They concluded that their GARP model suffered from a high degree of comission error or overprediction, and that in general GARP was more difficult to implement, more computationally intensive, and the results impossible to interpret when compared to BIOCLIM. However, McNyst and Blackburn (2006) challenged that Stockman et al. (2006) used highly unusual methods in their modelling study and simply misused the GARP algorithm by using a single data point to create predictive models. McNyst and Blackburn (2006) replicated the Stockman et al. (2006) study using 42 occurrence points in their model building producing an accurate GARP model with 0% omission. In this

case the GARP algorithm did not fail, the modelling practitioners did. I would argue that developing a spatially predictive model based upon only a single occurrence point would most likely produce an inaccurate model using any modelling approach.

4.4.4 Why use GARP?

The use of GARP has been promoted over other modelling approaches as it is considered a superset of other approaches and hence it has greater predictive ability than any one individual approach (Peterson 2001). It has successfully produced robust predictive models under a wide variety of situations (Anderson et al. 2003). Peterson and Vieglais (2001) and Vieglais (2001) suggested that other modelling approaches, including logistic regression and BIOCLIM, suffer from greater errors of omission and commission. An additional advantage is that GARP creates pseudo-absence points by resampling in areas of the study where the species has not been detected, a strategy not employed by other presence-only approaches (Stockwell and Peters 1999). Peterson (2003) stated that GARP can be used to predict independent test-occurrence data sets with precision.

In this thesis, I selected GARP as a spatial predictive modelling tool because (1) it is an algorithm that has the advantage of an inherent mechanism for iteratively evaluating and improving on prediction rules, (2) it allows the user to use expert knowledge to set parameters to optimize model performance based on omission and commission errors, (3) it has been used successfully by a wide variety of practitioners across a number of disciplines, (4) its application has not been explored as a biosecurity risk assessment tool, and (5) it is freely available. Access is critical as it allows

practitioners to conduct modelling exercises that support biosecurity regulations without the prohibitive costs associated with similar approaches. In addition, access allows others to critically scrutinize risk maps produced by others rather than just being presented with results that cannot be replicated (Kriticos and Randall 2001). From a biosecurity perspective, it is particularly important for countries that are signatory to the International Plant Pest Convention and thus have obligations to conduct science-based risk assessments, however, do not have the resources to purchase or update other expensive modelling approaches.

Applications

There are many examples of GARP being used as a tool to predict species invasions however its use has yet to be extended to biosecurity risk analysis. Peterson and Vieglais (2001) predicted the potential invasions by cattle egrets (*Bubulcus ibis*), house finches (*Carpodacus mexicanus*), Asian longhorn beetles (*Anoplophora glabripennis*), and the Japanese white-spotted citrus longhorn beetle (*Anoplophora malasiaca*) suggesting that ecological niche models can be used develop strategies for preventing species invasions. Peterson and Scachetti-Pereira (2004) used 40 hand-georeferenced Asian occurrence points (i.e., demonstrating GARP functions well with small sample sizes) for the Asian longhorned beetle (*Anoplophora glabripennis*) to predict potential invasions into North America. They concluded that management priority should be directed to areas of the eastern United States that are most vulnerable to invasion.

The algorithm has been used to predict distributions of aquatic invasive species. Drake and Bossenbroek (2004) forecasted the potential distribution of Eurasian zebra mussels (*Dreissena polymorpha*) in the United States concluding they are not likely to invade areas west of 100° W and hence management efforts should be concentrated at points of entry to western river basins. Herborg et al. (2007) used GARP modeling to assess the risk of invasion from the Chinese mitten crab (*Eriocheir sinensis*). GARP has been used to model potential distributions of invasive plants. Schussman et al. (2006) modeled the potential distribution of the alien grass *Eragrostis lehmanniana* in Arizona and New Mexico, Evangelista et al. (2008) modeled *Tamarix chinensis* and *Bromus tectorum* distributions in Utah. Welk et al. (2002) used Eurasian data to predict the invasion of garlic mustard (*Alliaria petiolata*) across North America. Peterson et al. (2003) used ecological niche models to predict the invasion of garlic mustard (*Alliaria petiolata* Bieb), Russian olive (*Elaeagnus angustifolia* L.), hydrilla (*Hydrilla verticillata* Royle) and sericea lespedeza (*Lespedeza cuneata* G. Don) across North America using native range occurrence data. They concluded that predictive models were able to predict spatial invasions with high accuracy.

The algorithm has been used to assess the risk of forest and agricultural invaders. Kluza et al. (2007) and Kelly et al. (2007) both used spatial predictive modeling to assess the potential distribution of an invasive forest pathogen, *Phytophthora ramorum*, a causal agent for sudden oak death (SOD) in the United States. Ganeshaih et al. (2003) used GARP to predict the potential spread of the woolly aphid (*Ceratovacuna lanigera* Zehntner), a pest of sugarcane in India, concluding GARP can be used as an important tool in fighting outbreaks of pests and diseases in crops. It has been used to

geographically explore human health issues such as the distribution of fleas in California that are potential vectors for the bacterial plague *Yersinia pestis* (Adjemian et al. 2006) and the *Anopheles gambiae sensu lato* mosquito complex in the fight against malaria in Africa (Levine et al. 2004).

4.5 Challenges in Spatial Predictive Modelling

Selecting which modelling approach to employ and then interpolating the results presents many challenges to risk analysts and practitioners (Venette et al. 2010). In developing spatial predictive models there are multiple steps in the process where risk analysts and practitioners are required to make informed decisions. These include selecting the most appropriate model, interpolating the results, evaluating data quality, evaluating model performance, validating the model and then testing the model. There are numerous modelling approaches available and without an understanding of how each approach should be used and its inherent challenges, useful models cannot be developed. For example, in many cases modelling practitioners have never been in the field and hence do not have the necessary knowledge on either the biology or geography of the species they are modelling to make informed decisions as to if their model is realistic or not. This leads to models that then mislead decision makers. A review of some of the more common challenges in spatial predictive modelling follows.

4.5.1 Choosing the Appropriate Model - All Things are Not Equal

Each modelling approach has a different suite of underlying assumptions and methods. In addition, different modelling approaches, using the same response and predictor variables, often yield different results (Araujo and Guisan 2006, Elith et al. 2006, Webber et al. 2011) and produce different mapped projections (Elith and Graham 2009). The underlying assumptions of BIOCLIM are that the abundance of a species is determined by climatic limits (Nix 1986). A risk analyst needs to ask what the right model to use is. Indiscriminate model selection may cause incorrect estimates of potential distributions and hence lead to inaccurate assessments of pest risk (Venete et al 2010). While there is substantial information available on modeling approaches and systems, there is no clear practicum for selecting relevant models and practitioners need to ask what methods are suitable for the intended use (Elith and Graham 2009).

Biosecurity decisions arrived at using erroneous models may cost stakeholders millions of dollars in the form of incorrect management options. Models must be selected based upon their assumptions (i.e., use of presences vs absence data) and objectives. In addition, risk analysts and biosecurity decision makers need to understand that no models take into account all realities. Once a practitioner produces a risk map there are a series of questions that should be considered. Does the model make sense intuitively? Does the model mimic reality? How well does the risk map speak to the question of quarantine biosecurity? Do I understand the results? Does it fit with my sense of reality? Is it believable? Can I defend it? It is also critical that those involved in a biosecurity risk analysis are able to understand which model to use and why, as they might have to defend a biosecurity policy decision in court.

4.5.2 Estimating Prediction Error (Omission and Commission)

Prediction errors are inevitable (Venette et al. 2010). In spatial predictive modelling errors of omission and commission are possible (Peterson 2001, Anderson 2003). Fielding and Bell (1997) described these errors as either false positives (i.e., commission error or overprediction) or false negatives (i.e., omission error or underprediction). Peterson et al. (2002) described omission errors as leaving out areas actually inhabited and commission error as including areas not actually inhabited. Omission errors are also referred to as Type I errors while commission errors are also referred to as or Type II errors (Figure 4.1). Omission error occurs when known occurrence points are not included in the model representing a failure of the model to extend to areas where the species is known to maintain a population.

It is important to note that errors of commission and omission should not be treated equally in biosecurity risk analyzes. If the precautionary principle is adhered to, spatial risk models that overpredict rather than underpredict are preferred. In selecting models, omission errors are then more important than commission error in determining good from bad models (Raxworthy et al. 2003, Peterson et al. 2008). Regulatory decisions based upon models that underpredict potential distributions could have potentially dire economic consequences. Hence, in predicting the distributions of invasive plants omission errors are considered more serious than commission errors. With invasive species commission error, for example, may represent area where a species has not yet invaded and hence becomes a necessary part of niche modelling (Peterson 2003, Jimenez-Valverde et al. 2011).

		Actual		
		Present	Absent	Total
Predicted	Present	A True positives	b False positives (commission error – pixels incorrectly predicted absent by model) Type I errors	$a+b$ <i>Number of predicted presences</i>
	Absent	c False negatives (omission error – pixels of known distribution predicted absent by model) Type II errors	d True negatives	$c+d$ <i>Number of predicted absences</i>
	Total	$a+c$ <i>Number of observed presences</i>	$b+d$ <i>Number of observed absences</i>	N = total number of observations

Figure 4.1 The 2 x 2 confusion matrix. Elements of a confusion matrix are used to measure the performance of spatial predictive models including sensitivity, specificity, kappa, the odds ratio, omission and commission error.

4.5.3 Measuring Model Accuracy and Performance

The quality of a predictive model is usually measured by its accuracy and there are many choices of measure (Fielding and Bell 1977). A challenge to spatial predictive modellers is employing the most appropriate measure of accuracy (Guisan and Thuiller 2005, Allouche et al. 2006) keeping in mind that there is no single best approach (Peterson et al. 2011). In addition, different approaches measure different aspects of performance, so careful consideration must be given to the selection of the most appropriate measure or statistic (Elith and Graham 2009).

Measures of model performance include sensitivity (i.e., the proportion of observed presences that are predicted as such, and therefore quantifies omission errors) and specificity (i.e., the proportion of observed absences that are predicted as such and therefore quantifies commission errors) (Allouche et al. 2006, Fielding and Bell 1997). These measures are calculated from the confusion matrix (Figure 4.2). Sensitivity is measured as $a/(a+c)$, which is also referred to as the true positive fraction (TPF); and specificity is measured as $b/(b+d)$, which is also referred to as the false positive fraction (FPF), which is also 1-specificity (Fielding and Bell 1997). The intrinsic omission error is the proportion of pixels that fall outside the predicted region while the intrinsic commission index is the proportion of pixels predicted present by the model (Anderson et al. 2003). Low omission error is a general condition of a good model (Peterson et al. 2011).

The area under the receiver operating characteristic curve (ROC), developed during World War II to assess the performance of radar receivers in signal detections, is

commonly used as a method to assess accuracy of spatial predictive models (Fielding and Bell 1977, Swets 1988, Lobo et al. 2007). ROC curves plot proportion of true positives (sensitivity) against the corresponding proportion of false positives (equal to 1 – specificity) and have been considered a highly effective measure of model performance (Allouche et al. 2006, Fielding and Bell 1977). The AUC ranges from 0 to 1, where 1 indicates perfect accuracy and 0.5 indicates results are generally no better than flipping a coin. As such the area under the ROC function (AUC) is between 0.5 (i.e., scores for two groups do not differ) and 1.0 (i.e., no overlap in distributions of scores), where a value of 0.8 means that for 80% of the time a random selection from the positive group will have a score greater than a random selection from the negative class (Fielding and Bell 1977). Lobo et al. (2007) presented five arguments as to why AUC is not a good measure of accuracy in spatial predictive modelling exercises, and suggested that sensitivity and specificity should also be reported. Peterson et al. (2008) suggested that ROC analysis is limited as it systematically undervalues models that do not provide predictions across the entire spectrum of proportional areas in the study area, and that it does not distinguish between different meanings of absence in modelling approaches. They suggested using a modified approach that examines partial-area ROC curves.

Another popular measure of accuracy is Kappa. Allouche et al. (2006) described Kappa as a simple measure ranging from -1 to +1 (i.e., perfect performance) that corrects the overall accuracy of model predictions by the accuracy expected to occur by chance, and provides one parameter that accounts for commission and omission errors. However McPherson et al. (2004) suggested that Kappa maybe an inappropriate statistic as it is inherently sensitive to prevalence.

To arrive at measures of error, models are developed using a generally large proportion of the data (training data) and tested against a smaller subset (test data) of the available data to arrive at measures of accuracy (Anderson et al. 2003, Fielding and Bell 1997). This allows for robust assessments of the accuracy of a model by using independent data. Hence, omission error is the proportion of the test data not predicted as present. Peterson et al. (2002) suggested that that commission error is more difficult to measure.

Model performance can also be evaluated by partitioning point occurrence data into training data and independent (i.e., extrinsic) testing data. A one-tailed X^2 -statistic can then be used to determine if test points fall into regions of predicted presence more often than expected by chance, given the proportion of pixels predicted present (Peterson et al. 1999, Anderson et al. 2003). Anderson et al. (2003) noted that X^2 -significance values represent reliable measures of model performance. A limitation of this approach is that a portion of the data is with-held from model development which may or may not impact the robustness of the final model. However, with large datasets, removing a small percentage of the data should not impair model development.

4.5.4 Data Quality

A major challenge of predictive modelling is the lack of quality data on which to build models (e.g., testing and training data) especially localized models (Welk et al. 2002). In most cases data is not available or difficult to access (Peterson and Vieglais 2001) or not comprehensive for a region (Peterson 2001, Venette et al. 2010). Predictive models are often developed using non-validated point occurrence data gathered through

sources such as web sites, personal communications or in some cases herbariums. In many cases herbaria and museum data are collected opportunistically as a result of ad hoc surveys leading to incomplete datasets for modelling (Stockwell and Peters 1999). In other cases modellers use data from websites that is inaccurate which leads to inaccurate models. For example, the United States Department of Agriculture plants database indicates that the invasive plant yellow star-thistle (*Centaurea solstitialis*) is in Alberta, Saskatchewan, and Manitoba, when in reality it is not.

Some published papers present maps based upon inaccurate data (e.g., see Welk (2004) who used spatially incorrect data points for purple loosestrife's distribution in Manitoba) or data for the wrong species (Webber et al. 2011). Data are also often incomplete and biased (Araujo and Guisan 2006). Some pest risk maps illustrate distributions based upon herbarium records which do not accurately communicate if the pest has established or is still present. Some risk maps are developed using data from maps published in another study, effectively generating second hand maps (see Welk 2004). West et al. (2011) categorized data quality as being either low (e.g., anecdotal information from ad hoc sources), medium (e.g., expert knowledge from local specialists based upon observations), or high (scientific data from field surveys). While there are continued advances in GIS tools, computer speed, storage, and capacity, modeling ultimately requires good validated data. Good data leads to informed biosecurity decisions, and obtaining comprehensive accurate datasets is a challenge.

4.5.5 Can Models Account for Biotic Interactions?

A challenge to spatial predictive models is that they do not account for biotic interactions such as predation or interspecific and intraspecific competition (Pearson and

Dawson 2003, Guisan and Thuiller 2005, Kearney and Porter 2009, Venette et al. 2010). Biotic interactions vary in space and time which is opposed to one of the basic assumptions of spatial modelling. Biotic factors that influence spatial distributions cannot yet be incorporated leaving models based upon abiotic variables only. For example, abiotic competition or a predator in a habitat will influence the spatial distribution of a species, and alternatively, as is the case with invasive plants the lack of competition or predators favours establishment into new habitats. Examples of biotic variables that can determine the geographic distribution of an invasive plant include herbivores, fire, nutrients, ornamental plantings, beautification projects, and other unpredictable stochastic events. In spatial predictive modelling the realized niche is the area where a species is excluded from parts of its fundamental niche by biotic interactions such as competition (Guisan and Zimmerman 2000). Thus, in interpreting a model, risk analysts need to consider that the model only represents a portion of the risk reality. Spatial predictive models that include biotic variables are not common as biotic data on diversity and population dynamics is not generally available over large geographic scales (Venette et al. 2010). It is unclear as to how biotic interaction, if at all, can be incorporated into current modelling approaches. Biotic datasets are required and these will be resource intensive to collect.

4.5.6 Spatial Autocorrelation

Spatial autocorrelation (i.e., variables at locations at certain distance apart take on values that are more similar than expected from random – positive autocorrelation) is a challenge to spatial predictive modelling as it may impair the ability to conduct standard statistical tests of hypotheses and it violates the assumption of independently and

identically distributed errors and hence inflates type I errors (Dorman et al. 2007, Legendre 1993). Results from spatial predictive modelling can be compromised because of spatial autocorrelation of species occurrence data (Segurado et al. 2006). If data was collected using a spatially autocorrelated approach, then test and training data used to validate models are not independent (Segurado et al. 2006, Veloz 2009, Naimi et al. 2011). Spatial autocorrelation, where each site is sampled much closer than would be expected if all sites were sampled randomly, may lead to inaccuracy in model prediction and evaluation (Veloz 2009). However, spatial autocorrelation may occur in species distribution data simply because of parameters that limit species mobility or dispersal, or make one area more suitable than another, resulting in aggregated populations (Dorman et al. 2007). When projecting species distributions into new geographic areas addressing spatial autocorrelation becomes problematic if not impossible (Dorman et al. 2007). Ferrier et al (2002) noted that in the natural environment species do exhibit spatial pattern or autocorrelation and that this cannot be explained by correlations with environmental variables hence incorporating spatial autocorrelation into spatial predictive modelling is a challenge.

4.5.7 Dispersal

Dispersal plays a determining role in species distributions and incorporating variables that estimate movement or dispersal is a challenge in spatial predictive modelling. Dispersal can be gradual along the front of an invasion as well as by stochastic jumps where new populations are established far from the leading edge. Bogich and Shea (2008) referred to this type of dispersal as stratified diffusion where a

pest spreads through both local growth of the main infestation and growth and dispersal of new infestations ahead of the main infestation. Most spatial predictive modelling approaches do not account for dispersal events especially stochastic movements. An example might be an ornamental planting of an invasive plant far removed from the main infestation that escapes and naturalizes in a new area. For invasive plants, one novel solution maybe to add garden centers that are far removed from the invasive front that are known to retail the plant as an occurrence point.

4.5.8 Modelling Fundamental vs. Realized Niche Space

A challenge to spatial predictive modelling is that models generally estimate only a portion of the potential distribution. Biotic, abiotic, movement variables characterize the functional relationship between niche space and spatial predictive modelling (Soberon and Peterson 2005, Soberon 2010, Barve et al. 2011, Jimenez-Valverde et al. 2011). Species are present in areas where (1) abiotic conditions (e.g., climate) are favourable, (2) interspecific biotic interactions (e.g. competition, predators) are favourable, and (3) where it is able to disperse or move into (Soberon and Peterson 2005, Peterson 2011). The potential distribution of a species, also referred to as the fundamental niche, is illustrated by the area intersected by abiotic and biotic variables. Within this area, there is smaller area that is inaccessible owing to dispersal barriers. The actual area a species can inhabit, referred to as the realized niche, is then an area where abiotic and biotic variables are suitable and the species can disperse into. Most spatial predictive models estimate the area constrained by abiotic and biotic variables as variables predicting dispersal are in most cases lacking (Soberon and Peterson 2005).

4.6 Conclusion

There have been numerous contributors to the concept of the niche. Grinnell (1917) discussed the importance of abiotic conditions, Elton (1927) discussed the importance of biotic variables, and Hutchinson (1957) distinguished between the fundamental and realized niche. The conceptual niche can be used help understand where species are where they are with respect to spatial predictive modelling studies. Modelling approaches range from simple maps and indices to sophisticated computer programs. For example, as early as 1924 William Cook (1924) used simple climographs to model potential distributions noting that these provided the bases for intelligent quarantines. The GARP algorithm, CLIMEX and BIOCLIM are all examples of commonly used modelling approaches. The GARP algorithm has several advantages over the other approaches was hence selected as the modelling approach for this dissertation. In the next chapter, I present new field data for the invasive plant purple loosestrife, data that can be used in spatial predictive modelling.

4.7 References

- Adjemian, J., Girvetz, E. Beckett, L. and J. Foley. 2006. Analysis of genetic algorithm for rule-set production (GARP) modeling approach for predicting distributions of fleas implicated as vectors of plague, *Yersinia pestis*, in California. *J. Med. Entomology* 43: 93-103.
- Allouche, O., Tsoar, A. and R. Kadmon. 2006. Assessing the accuracy of species

- distribution models: prevalence, kappa and the true skill statistic. *Journal of Applied Ecology* 43:1223-1232.
- Anderson, R.P., D. Lew and A.T. Peterson. 2003. Evaluating predictive models of species' distributions: criteria for selecting optimal models. *Ecol. Model.* 162:211-232.
- Andrewartha, H.G. and L.E. Birch. 1954. *The Distribution and Abundance of Animals*. University of Chicago Press, Chicago, 782 pp.
- Araujo, M.B. and A. Guisan. 2006. Five (or so) challenges for species distribution modelling. *Journal of Biogeography* 33:1677-1688.
- Aspinall, R. 1992. An inductive modeling procedure based on Bayes Theorem for analysis of pattern in spatial data. *Int. J. Geogr. Inf. Syst.* 6:105-121.
- Austin, M. 2002. Case Studies of the Use of Environmental Gradients in Vegetation and Fauna Modeling: Theory and Practice in Australia and New Zealand. Pages 73-82 In *Predicting Species Occurrences: Issues of Accuracy and Scale*. J. Scott, P. Heglund, M. Morrison, J. Haufler, M. Raphael, W. Wall and F. Samson (Eds.). Island Press. Washington USA..
- Austin, M.P. and J.A. Meyers. 1996. Current approaches to modelling the environmental niche of eucalypts: implication for management of forest biodiversity. *Forest Ecology and Management* 85:95-106.
- Babar, S., G. Amarnath, C. Reddy, A. Jentsch and S. Sudhakar. 2012. Species distribution models: ecological explanation and prediction of an endemic and endangered plant species (*Pterocarpus santalinus* L.f.). *Current Science* 102:1157-1165.

- Baker, R., R. Cannon, P. Bartlett and I. Barker. 2005. Novel strategies for assessing and managing the risks posed by invasive alien species to global crop production and biodiversity. *Annals of Applied Biology* 146:177-191.
- Barry, S. and J. Elith. 2006. Error and uncertainty in habitat models. *Journal of Applied Ecology* 43:413-423.
- Beaumont, L.J., L. Hughes and M. Poulsen. 2005. Predicting species distributions: use of climatic parameters in BIOCLIM and its impact on predictions of species' current and future distributions. *Ecological Modelling* 186:250-269.
- Beerling, D.J., B. Huntley and J.P. Bailey. Climate and the distribution of *Fallopia japonica*: use of an introduced species to test the predictive capacity of response surfaces. *Journal of Vegetation Science* 6:269-282.
- Bogich, T. and K. Shea. 2008. A state-dependent model for optimal management of an invasive metapopulation. *Ecological Applications* 18:748-761.
- Booth, T.H., H.A. Nix, M.F. Hutchinson and T. Jovanovic. 1988. Niche analysis and tree species introduction. *Forest Ecology and Management* 23:47-59.
- Brereton, R., S. Bennett and I. Mansergh. 1995. Enhanced greenhouse climate change and its potential effect on selected fauna of south-eastern Australia: A trend analysis. *Biological Conservation* 72:339-354.
- Brookman, D.A. 2004. Remote sensing and predictive modeling of saltcedar (*Tamarix*) in the Northern Great Plains. Master of Thesis, University of North Dakota, Grand Forks, North Dakota.
- Brown, L., B. Simon, D. Cunningham and M. Bomford. 2006. Current practice in applying CLIMATE for weed risk assessment in Australia. Pages 703-706 in the

- Proceedings of the Fifteenth Australian Weeds Conference. September 24-28, 2006.
Adelaide Convention Centre, Adelaide, South Australia.
- Busby, J.R. 1991. BIOCLIM – a bioclimate analysis and predictive system. In: Nature Conservation: Cost Effective Biological Surveys and Data Analysis (eds Margules, C.R. & Austin, M.P.). CSIRO, Melbourne, pp. 64-68.
- Carpenter, G., A.N. Gillison and J. Winter. 1993. DOMAIN: a flexible modelling procedure for mapping potential distributions of plants and animals. *Biodiversity Conservation* 2:667-680.
- Chen, Y. 2008. Global potential distribution of an invasive species, the yellow crazy ant (*Anoplolepis gracilipes*) under climate change. *Integrative Zoology* 3:166-175.
- Cook, W.C. 1925. The distribution of the alfalfa weevil (*Phytonomus pesticus* Gyll.); a study in physical ecology. *J. Agricultural Research* 30:479-491.
- Cook, W.C. 1929. A bioclimatic zonation for studying the economic distribution of injurious insects. *Ecology* 10:282-293.
- Cook, W.C. 1931. Notes on predicting the probable future distribution of introduced insects. *Ecology* 12:245-247.
- Crossman, N. and D. Bass. 2008. Application of common predictive habitat techniques for post-border weed risk management. *Diversity and Distributions* 14:213-224.
- Daehler, C.C and D.A. Carino. 2000. Predicting invasive plants: prospects for a general screening system based on current regional models. *Biological Invasions*, 2:93-102.
- Diniz-Filho, J. and P. DeMarco. 2010. How many studies are necessary to compare niche-based models for geographic distributions? Inductive reasoning may fail at the end. *Braz. J. Biol.* 70:263-269.

- Dormann, C.F., J.M. McPherson, M.B. Araujo, R. Bivand, J. Bollinger, G. Carl, R. Davis, A. Hirzel, W. Jetz, W. Kissling, I. Kuhn, R. Ohlemuller, P.R. Peres-Neto, B. Reineking, B. Schroder, F.M. Schurr, and R. Wilson. 2007. Methods to account for spatial autocorrelation in the analysis of species distributional data: a review. *Ecography* 30:609-628.
- Drake, J.M. and J.M. Bossenbroek. 2004. The potential distribution of zebra mussels in the United States. *BioScience* 54:931-941.
- Elith, J. and C.H. Graham. 2009. Do they? How do they? WHY do they differ? On finding reasons for differing performances of species distribution models. *Ecography* 32:66-77.
- Elton, C. 1927. *Animal Ecology*. MacMillian. New York. London. 209p.
- Elton, C. 1958. *The Ecology of Invasions by Animals and Plants*. The University of Chicago Press. Chicago.
- EPPO. 2010. Pest Risk Analysis for *Bactrocera invadens*. European and Mediterranean Plant Protection Organization, Paris.
- EPPO. 2008. Pest Risk Analysis for *Eichhornia crassipes*. European and Mediterranean Plant Protection Organization, Paris.
- EPPO. 2009. Pest Risk Analysis for *Hydrocotyle ranunculoides*. European and Mediterranean Plant Protection Organization, Paris.
- Evangelista, P., S. Kumar, T. Stohlgren, C. Jarnevich, A. Crall, J. Norman III and D. Barnett. 2008. Modelling invasion for a habitat generalist and a specialist plant species. *Diversity and Distributions* 14:808-817.
- Fielding, A.H. and J. F. Bell. 1997. A review of methods for assessment of prediction

- errors in conservation presence/absence models. *Environmental Conservation* 24:38-49.
- Ferrier, S. 2002. Mapping spatial pattern in biodiversity for regional conservation planning: where to from here? *Systematic Biology* 51:331-363.
- Ferrier, S., G. Watson and J. Pearce. 2002. Extended statistical approaches to modelling spatial pattern in biodiversity in northeast New South Wales. I. Species-level modelling. *Biodiversity and Conservation* 11:2275-2307.
- Ganeshiah, K.N, N. Barve, N. Nath, K. Chandrashekara, M. Swamy and R. Uma Shaanker. 2003. Predicting the potential geographic distribution of the sugarcane woolly aphid using GARP and DIVA-GIS. *Current Science* 85:1526-1528.
- Gjullin, C.M. 1931. Probable distribution of the Mediterranean fruit fly (*Ceratitidis capitata* Weid.) in the United States. *Ecology* 12:248-258.
- Goolsby, J.A. 2004. Potential distribution of the invasive old world climbing fern, *Lygodium microphyllum* in North and South America. *Natural Areas Journal* 24:351-353.
- Grinnell, J. 1917. The niche-relationships of the California thrasher. *The Auk* 34:427-433.
- Grinnell, J. 1917a. Field tests of theories concerning distributional control. *American Naturalist* 51:115-128.
- Guisan, A. and W. Thuiller. 2005. Predicting species distribution: offering more than simple habitat models. *Ecology Letter* 8:993-1009.
- Guisan, A. and N.E. Zimmerman. 2000. Predictive habitat distribution models in ecology. *Ecological Modelling* 13:147-186.

- Herborg, M.L., C.L. Jerde, D. Lodge, G.M. Rutz and H.J. MacIsaac. 2007. Predicting invasion risk using measures of introduction effort and environmental niche models. *Ecological Applications* 17:663-674.
- Hijmans, R.J., L. Guarino, M. Cruz and E. Rojas. 2001. Computer tools for spatial analysis of plant genetic resources data: 1. DIVA-GIS. *Plant Genet. Resour. Newsl.* 127:15-19.
- Hirzel A.H, G. Le Laya, V. Helfera, C. Randina and A. Guisana 2006. Evaluating the ability of habitat suitability models to predict species presences *Ecological Modeling* 199:142-152.
- Hirzel, A.H. and G. Le Lay. 2008. Habitat suitability modelling and niche theory. *Journal of Applied Ecology* 45:1372-1381.
- Hirzel, A.H., J.D. Hausser, D. Chessel and N. Perrin. 2002. Ecological-niche factor analysis : how to compute habitat-suitability maps without absence data? *Ecology* 83:2027-2036.
- Holland, J. H. 1992. Genetic Algorithms. *Scientific American*, July:66-72.
- Holland, J. H. 1975. *Adaptation in natural and artificial systems*. Ann Arbor, MI: University of Michigan Press.
- Holdridge, L.R. 1947. Determination of world formations from simple climatic data. *Science* 105:367-368.
- Hutchinson, G.E. 1957. *A Treatise on Limnology*. New York: Wiley & Sons. 1015 pp.
- Hutchinson, M.F., H.A. Nix, D.J. Holder and J.P. McMahon. n.d. ANUCLIM Version 1.8 User Guide. Center for Resource and Environmental Studies, The Australian National University, Canberra.

- Intergovernmental Panel on Climate Change. 2001. Climate data archive. IPCC, Geneva, Switzerland. Available from <http://www.ipcc.ch/> (accessed August 2008).
- Jarvis, C.H. and R.H. Baker. 2001. Risk assessment for nonindigenous pests: I. Mapping the outputs of phenology models to assess the likelihood of establishment. *Diversity and Distributions* 7:223-235.
- Jeschke, J.M. and D.L. Strayer. 2008. Usefulness of bioclimatic models for studying climate change and invasive species. *Ann. N.Y. Acad. Science* 1134:1-24.
- Jimenez-Valverde, A., A.T. Petersoin, J. Soberon, J.M. Overton, P. Aragon and J.M. Lobo. 2011. Use of niche models in invasive species risk assessments. *Biological Invasions* 13:2785-2797.
- Kearney, M. and W. Porter. 2009. Mechanistic niche modelling: combining physiological and spatial data to predict species' ranges. *Ecology Letters* 12:334-350.
- Kelly, M., Q. Guo, D. Liu and D. Shaari. 2007. Modeling the risk for a new invasive forest disease in the United States: An evaluation of five environmental niche models. *Computers, Environment and Urban Systems* 31:689-710.
- Kluza, D.A., D.A. Vieglais, J.K. Anderson and A.T. Peterson. 2007. Sudden oak death: geographic risk estimates and predictions of origins. *Plant Pathology* 56:580-587.
- Kriticos, D.J., R.W. Sutherst, J.R. Brown, S.W. Adkins and G.F. Maywald. 2003. Climate change and the potential distribution of an invasive alien plant: *Acarica nilotica* ssp. *indica* in Australia. *Journal of Applied Ecology* 40:111-124.
- Kriticos, D.J., T. Yonow and R.E. McFadyen. 2005. The potential distribution of *Chromolaena odorata* (Siam Weed) in relation to climate. *Weed Research* 45:246-254.
- Larson, S.R., J.P. DeGroot, L.C. Bartholomay and R. Sugumaran. 2009. Ecological

- niche modeling of potential West Nile virus vector mosquito species in Iowa. *Journal of Insect Science* 10:1-17.
- Legendre, P. Spatial autocorrelation: trouble or new paradigm? *Ecology* 74:1659-1673.
- Lehmann, A, J.M. Overton and J.R. Leathwick. 2002. GRASP: generalized regression analysis and spatial prediction. *Ecol. Model* 157:189-207.
- Levine, R., A. T. Peterson and M. Benedict. 2004. Geographic and ecologic distributions of the *Anopheles gambiae* complex predicted using a genetic algorithm. *Am. J. Trop. Med. Hyg.* 70:105-109.
- Lindenmayer, D., H. Nix, J. McMahon, M. Hutchinson and M. Tanton. 1991. The conservation of Leadbeater's possum, *Gymnobelideus leadbeateri* (McCoy): a case study of the use of bioclimatic modelling. *Journal of Biogeography* 18:371-383.
- Lindgren, C.J. 2003. A brief history of Purple Loosestrife, *Lythrum salicaria*, in Manitoba and its status in 2001. *Canadian Field-Naturalist* 117:100-109.
- Lobo, J.M., A. Jimenez-Valverde and R. Raimundo. 2007. AUC: a misleading measure of the performance of predictive distribution models. *Global Ecology and Biogeography* 17:145-151.
- Madsen, J.D. 1999. Predicting the invasion of Eurasian watermilfoil into Northern Lakes. US Army Corps of Engineers Waterways Experiment Station. Technical Report A-99-2, February 1999. 36 pp
- Magarey, R.D., G.A. Fowler, D.M. Borchert, T.B. Sutton, M. Colunga-Garcia and J.A. Simpson. 2007. NAPPFAST: An internet system for the weather-based mapping of plant pathogens. *Plant Disease* 91:336-345.
- Manning, A., D. Lindenmayer, A. Nix and S. Barry. 2005. A bioclimatic analysis of

- the highly mobile Superb Parrot of south-eastern Australia. *Emu* 105:193-201.
- Manning, A.D., J. Kesteven, J. Stein, A. Lunn, T. Xu and B. Rayner. Could native Scots pines (*Pinus sylvestris*) still persist in northern England and southern Scotland. *Plant Ecology & Diversity* 3:187-201.
- Marczyk, A. 2004. Genetic algorithms and evolutionary computation. Viewed online May 2010 at: <http://www.talkorigins.org/faqs/genalg/genalg.html>
- McNyset, K.M. 2005. Use of ecological niche modelling to predict distributions of freshwater fish species in Kansas. *Ecology of Freshwater Fish* 14:243-255.
- McNyset, K.M and J.K. Blackburn. 2006. Does GARP really fail miserably? A response to Stockman et al. (2006). *Diversity and Distributions* 12:782-786. Terribile, L.C,
- Messenger, P.S. 1959. Bioclimatic studies with insects. *Annual Reviews Entomol.* 4:183-206.
- Mullin, B., L. Anderson, J. DiTomaso, R. Eplee and K. Getsinger. 2000. Invasive Plant Species. Issue paper for the Council for Agricultural Science and Technology. Number 13. Ames, Iowa.
- Naimi, B., A.K. Skidmore, T.A. Groenk, and N.A. Hamm. 2011. Spatial autocorrelation in predictors reduces the impact of positional uncertainty in occurrence data on species distribution modelling. *Journal of Biogeography* 38:1497-1509.
- Nix, H. 1986. A biogeographical analysis of Australian Elapid snakes. In: Longmore, R. (Ed.), *Snakes: Atlas of Elapid snakes of Australia*. Bureau of Flora and Fauna, Canberra, pp. 4-10.
- Nix, H.A. and M.A. Switzer (Eds) 1991. *Rainforest Animals: Atlas of Vertebrates Endemic to Australia's Wet Tropics*. Kowari 1. Australian National Parks and

- Wildlife Service, Canberra.
- Oberhauser, K. and A.T. Peterson. 2003. Modelling current and future potential wintering distributions of eastern North American monarch butterflies. Proceedings of the National Academy of Sciences of the United States of America. Published online November 11 2003 at: www.pnas.org/content/100/24/14063.full.pdf
- Olfert, O. and R.M. Weiss. 2006. Impact of climate change on potential distribution and relative abundances of *Oulema melanopus*, *Meligethes viridescens*, and *Ceutorhynchus obstrictus* in Canada. Agriculture, Ecosystems, and Environment 113: 295-301.
- Olfert, O., R. Hallett, R. Weiss, J. Soroka and S. Goodfellow. 2006. Potential distribution and relative abundance of swede midge, *Contarinia nasturtii*, an invasive pest of Canada. Entomologia Experimentis et Applicata 120:221-228.
- Peterson, A.T. and D. Vieglais. 2001. Prediction species invasions using ecological niche modeling: new approaches from bioinformatics attach a pressing problem. Bioscience 51:363-371.
- Peterson, A.T. 2001. Predicting species' geographic distributions based on ecological niche modeling. The Condor 103:599-605.
- Peterson, A.T., M. Papes and D. Kluza. 2003. Predicting the potential invasive distributions of four alien plant species in North America. Weed Science 51:863-868.
- Peterson, A.T. 2003. Predicting the geography of species' invasions via ecological niche modeling. The Quarterly Review of Biology 78:419-433.
- Peterson, A.T. 2011. Ecological niche conservatism: a time structured review of

- evidence. *Journal of Biogeography* 38:817-827.
- Peterson, A.T., J. Soberon, R.G. Pearson, P. Anderson, E. Martinez-Meyer, M. Nakamura, and M. Bastos Araujo. 2011. *Ecological Niches and Geographic Distributions*. Princeton University Press, Princeton, New Jersey. 316 pp.
- Pearson, R.G., T.P. Dawson, P.M. Berry and P.A. Harrison. 2002. SPECIES: a spatial evaluation of climate impact on the envelope of species. *Ecol. Model* 154:289-300.
- Phillips, S.J., M. Dudik and R.E. Schapire. 2005. Maximum entropy modeling of species geographic distributions. In: *Twenty-first International Conference on Machine Learning*.
- Prentice, C., C. Wolfgang, S.P. Harrison, R. Leemans, R.A. Monserud and A.M. Solomon. 1992. A global biome model based on plant physiology and dominance, soil properties and climate. *Journal of Biogeography* 19:117-134.
- Raimundo, R.L., R.L. Fonseca, R. Schachetti-Pereira, A.T. Peterson and T.M. Lewinshohn. 2007. Native and exotic distributions of siamweed (*Chromolaena odorata*) modeled using the genetic algorithm for rule-set production. *Weed Science* 55:41-48.
- Ricklefs, R.E. and R.E. Latham. 1992. Intercontinental correlation of geographical ranges suggests stasis in ecological traits of relict genera of temperate perennial herbs. *Am. Nat.* 139:1305–1321.
- Robertson, M.P., C.I. Peter, M.H. Villet and B.S. Ripley. 2003. Comparing models for predicting species' potential distributions: a case study using correlative and mechanistic predictive modelling techniques.
- Rodda, G.H., C.S. Jarnevich and R.N. Reed. 2011. Challenges in identifying sites

- climatically matched to the native ranges of animal invaders. PLoS ONE 6:1-18.
- Ruxton, G.D. and G. Beauchamp. 2008. The application of genetic algorithms in behavioural ecology, illustrated with a model of anti-predator vigilance. *Journal of Theoretical Biology* 250:435-448.
- Sax, D.F. 2001. Latitudinal gradients and geographic ranges of exotic species: implications for biogeography. *Journal of Biogeography* 28:139-150.
- Scachetti-Pereira, R. 2001. Desktop GARP. www.lifemapper.org/desktopgarp.
- Schussman, H., E. Geiger, T. Mau-Crimmins and J. Ward. 2006. Spread and current potential distribution of alien grass, *Eragrostis lehmanniana* Nees, in southwestern USA: comparing historical data and ecological niche models. *Diversity and Distributions* 12:582-592.
- Segurado, P., M.B. Araujo and W.E. Kunin. 2006. Consequences of spatial autocorrelation for niche-based models. *Journal of Applied Ecology* 43:433-444.
- Soberon, J. and A.T. Peterson. 2005. Interpretation of models of fundamental ecological niches and species distributional areas. *Biodiversity Informatics* 2:1-10.
- Soberon, J.M. 2010. Niche and area of distribution modeling: a population ecology perspective. *Ecography* 33:159-167.
- Stephenson, N.L. 1998. Actual evapotranspiration and deficit: biologically meaningful correlates of vegetation distribution across spatial scales. *Journal of Biogeography* 25:855-870.
- Stockman, A.K., D.A. Beamer and J.E. Bond. 2006. An evaluation of a GARP model as an approach to predicting the spatial distribution of non-vagile invertebrate species. *Diversity and Distributions* 12:81-89.

- Stockwell, D. 1997. Generic predictive systems: An empirical evaluation using the learning base system (LBS). *Expert Systems With Applications* 12:301-310.
- Stockwell, D. and D. Peters. 1999. The GARP modelling system: problems and solutions to automated spatial prediction. *International Journal of Geographical Information Science* 13:143-158.
- Stockwell, D. and D. Peters. 1999. The GARP modelling system: problems and solutions to automated spatial prediction. *Int. J. Geogr. Inf. Sci.* 13:143-158.
- Stockwell, D. and A.T. Peterson. 2002. Effects of sample size on accuracy of species distribution models. *Ecological Modelling* 148:1-13.
- Sutherst, R.W. and G.F. Mayward. 1985. A computerized system for matching climates in ecology. *Agriculture, Ecosystems and Environment* 13:281-299.
- Sutherst, R.W. 2003. Prediction of species geographical ranges. *Journal of Biogeography* 30:805-816.
- Sutherst, R.W. and A.S. Bourne. 2009. Modelling non-equilibrium distributions of invasive species: a tale of two modelling paradigms. *Biological Invasions* 11:1231-1237.
- Sutherst, R.W., F. Constable, K. Finlay, R. Harrington, J. Luck, and M.P. Zalucki. 2011. Adapting to crop pest and pathogen risks under a changing climate. *Climate Change* 2:220-237.
- Sudima, B.H., A.I. Houston, J.M. McNamara and W.D. Hamilton. 1990. Genetic algorithms and evolution. *Journal of Theoretical Biology* 147:59-84.
- Swets, J.A. 1988. Measuring the accuracy of diagnostic systems. *Science* 240:1285-1293.

- Taylor, S., L. Kumar, N. Reid and D. Kriticos. 2012. Climate change and the potential distribution of an invasive shrub, *Lantana camara* L. PLoS ONE 7:1-14.
- Thompson, D.Q., R.L. Stuckey and E. Thompson. 1987. Spread, Impact and Control of Purple Loosestrife (*Lythrum salicaria*) in North American Wetlands. U.S. Fish and Wildlife Service, Fish and Wildlife Research, 2, 55.
- Thuiller, W. 2003. BIOMOD – optimizing predictions of species distributions and projecting potential future shifts under global change. Glob. Change Biol. 9:1353-1362.
- Tsoar, A., O. Allouche, O. Steinitz, D. Rotem and R. Kadmon. 2007. A comparative evaluation of presence-only methods for modelling species distribution. Diversity and Distribution 13:397-405.
- Veloz, S.D. 2009. Spatially autocorrelated sampling falsely inflates measures of accuracy for presence-only niche models. Journal of Biogeography 36:2290-2299.
- Watt, M.S., D.J. Kriticos and L.K. Manning. 2009. The current and future potential distribution of *Melaleuca quinquenervia*. Weed Research 49:381-390.
- Watt, M.S., D.J. Kriticos, K.J. Potter, L.K. Manning, N. Tallent-Halsell and G.W. Bourdot. 2010. Using species niche models to inform strategic management of weeds in a changing climate. Biological Invasions 12:3711-725.
- Webber, B.L., C.J. Yates, D. Le Maitre, J.K. Scott, D.J. Kriticos, N. Ota, A. McNeill, J. Le Roux and G.F. Midgely. 2011. Modelling horses for novel climate courses: insights into projecting potential distributions of native and alien Australian acacias with correlative and mechanistic models. Diversity and Distributions 17:978-1000.
- West, P., L. Brown, C. Auricht and Q. Hart. 2011. Mapping actual and predicted

- distribution of pest animals and weeds in Australia. Pages 91-128 in S.A. Clay (ed.) GIS Applications in Agriculture Volume Three: Invasive Species. CRC Press, Boca Raton, Florida.
- Wiens, J.J. and C.H. Graham. 2005. Niche Conservatism: Integrating Evolution, Ecology, and Conservation Biology Annual Review of Ecology, Evolution, and Systematics 36:519-539.
- Welk, E., K. Schubert and M. Hoffmann. 2002. Present and potential distribution of invasive garlic mustard (*Alliaria petiolata*) in North America. Diversity and Distributions 8:219-233.
- White, D.J. E. Haber and C. Keddy. 1993. Invasive Plants of Natural Habitats in Canada: An integrated Review of Wetland and Upland Species and Legislation Governing their Control. Ottawa. Ontario. 121 pp.
- Westbrooks, R.G., D.C. Hayes and W.P. Gregg. 2000. National early warning and rapid response system for invasive plants – proposed strategies for early detection, reporting, rapid assessment, and rapid response to new invasive plants in the United States of America. Early Warning Sub-Committee, Federal Interagency Committee for the Management of Noxious and Exotic Weeds.
- Westbrooks, R.G. 2004. New approaches for early detection and rapid response to invasive plants in the United States. Weed Technology 18:1468-1471.
- Worrall, J. 2002. Review of systems for early detection and rapid response. Unpublished report to the National Invasive Species Council, Washington, D.C., USA.

CHAPTER 5 –ASSESSING THE SPATIAL RISK OF PURPLE LOOSESTRIFE (*Lythrum salicaria*) TO PRAIRIE CANADA USING GROWING-DEGREE DAYS AND FIELD COLLECTED DATA

ABSTRACT. Purple loosestrife (*Lythrum salicaria* L.) is an invasive plant that is of both environmental and economic concern in Prairie Canada. It invades wetlands and aquatic ecosystems deleteriously impacting wildlife habitat and biological diversity. It is currently extending its range across Prairie Canada and once established is difficult control. Although its been in Prairie Canada for many years, basic biological data is lacking especially data collected from wetlands. In this study, purple loosestrife growth dynamics and seed production were determined using actual season long field data, I statistically modelled season long growth, and developed an interpolated growing degree-day (GDD's) risk surface specific to purple loosestrife using a temperature base of 8°C. Stems emerged from perennial root stocks in late May to early June after about 45 GDD's. Stems grew prolifically from early June to late July annually averaging 15.4 cm to 25 cm of growth every ten days which decreased in early August to less than 4.4 cm every ten days. On average, stems reached 50% of their final height at about 338 GDD's, and final stem heights were reached at about 1007 GDD's. The mean number of seed capsules produced per stem was 276.4 while the mean number of seeds produced by a seed capsule was 79.4. A three parameter logistic function was a robust predictor of growth ($R^2 = 0.86$). Growing degree-days and meteorological data to geostatistically interpolate a purple loosestrife risk surface. The interpolated surface created in this Chapter indicates that GDD's are a constraining parameter for the distribution of purple

loosestrife in Prairie Canada. The results of this study contribute new biological and spatial data that can be used to support management plans, and to create effective biosecurity policy and regulations, and to refine further spatial predictive models. In Chapter 5, new unique GDD's spatial data was developed that was further extended for use in the Chapter 6.

5.1 Introduction

Purple loosestrife (*Lythrum salicaria*) is an introduced invasive plant that invades freshwater wetlands, marshes, and riparian habitats deleteriously impacting wildlife habitat and biological diversity (Thompson et al. 1987, Mal et al. 1992, Mullin 1998, Lindgren 2003). It was introduced into northeastern North America in the early 1800's and spread as far north as Manitoba by the late 1800's (Thompson et al. 1987). It has since steadily expanded its geographic range, demonstrating a tolerance of a wide range of soil and climatic conditions (Thompson et al. 1987), yet field studies characterizing its annual growth and seed production as a function of growing degree days (GDD's), as well as studies investigating its potential spatial distribution in Prairie Canada, are lacking. It is critical that we understand a plants basic growth and reproductive traits, phenology, as well as any constraints (e.g., GDD's) that may determine its spatial distribution (Bossard and Rejmanek 1994, Nagel and Griffin 2001, Ball et al. 2004), and in turn provide necessary data to inform policy makers and wetland managers.

Growth metrics are important in predicting phenological events, providing input parameters for spatial predictive modelling, determining evolutionary changes, and in helping understand life strategies and wetland dynamics. These data are equally

important to policy makers and regulators who frequently note that there is a general lack of data required to effectively assess risk and predict invasions (Rejmanek and Richardson 1996, Goodwin et al. 1999, Lindgren et al. 2010, Lindgren 2011) resulting in risk models that rely on expert opinion (Yemshanov et al. 2009). Growth and reproduction data are also important in developing management plans (Shrestha 2010, Averill et al. 2011). For example, the initiation of management strategies is often temporally planned using plant emergence data (Lawson et al. 2006). Growth data are also important in determining optimal times for herbicide applications (Knezevic et al. 2002, Dillehay et al. 2011) or in developing integrated purple loosestrife control strategies (Henne et al. 2004). Studies describing plant growth and seed production also provide important data in agriculture, horticulture, silviculture, forestry (Hassan et al. 2007), and in the epidemiology of diseases and pests (Crepinsek et al. 2006).

A literature search revealed that there is no field data available to statistically model purple loosestrife's season long growth. In this chapter, I present the results of a field study that statistically and phenologically described the growth dynamics and seed production of purple loosestrife in the Netley-Libau Marsh, Manitoba (MB). There are no studies that model the growth of purple loosestrife using growing degree-days.

One determinate of the spatial distributions of plants is temperature (Patterson et al. 1999). Temperature may be the critical determining variable for wetland plants such as purple loosestrife when for example, water and nutrients are not limited. Temperature may constrain the spatial distribution of purple loosestrife as laboratory studies have determined that purple loosestrife seed will not germinate below 14°C, and that growth is restricted by temperatures below 8°C (Shamsi and Whitehead 1974a; 1974b). There is no

information on the functional relationship between purple loosestrife growth dynamics and temperature using a growing degree-day (GDD's) model that might predict where, and where not, purple loosestrife may grow. The use of GDD's has been referred to as a biophysical approach to modeling that uses basic thermodynamic principles to model selected physiological responses such as growth (Lati et al. 2011; Sutherst et al. 2011). The value of characterizing the functional relationship and assessing spatial risk using GDD's is that (1) GDD's are a biologically relevant parameter that has been used to spatially predict distributions (Woodward 1987, Crepinsek et al. 2006, Yang et al. 2006, Magarey et al. 2011), (2) GDD's have been successfully used as a spatially dynamic variable to characterize biological events including stem growth and seed production in invasive plants (Bailey et al. 2003, Ball et al. 2004, Yang et al. 2006, Hassen et al. 2007, Schwinghamer and Van Acker 2008, Shrestha et al. 2010, Wu 2010), and (3) GDD's are a useful spatial predictive variable as the number of GDD's required by a plant to complete its development is constant at temperatures above a critical threshold (Yang et al. 2006). With regards to this study, the important assumption is that while local growing conditions will vary across broad landscapes, the number of GDD's required to complete various life stages should remain constant and allow for spatial predictions.

Growing degree-days have been successfully used to model the emergence and growth of invasive plants for a variety of purposes. Berti and Johnson (2008) reported a positive linear relationship between cuphea (*Cuphea viscosissima* Jacq. X *C. lanceolata* W.T. Aiton, PSR23) plant height and accumulated GDD's in studies in North Dakota and Minnesota, USA. Recasens et al. (2005) used cumulative GDD's to determine emergence of *Abutilon theophrasti*, an exotic invasive weed of agroecosystems. Shrestha

et al. (2010) utilized GDD's to assess the growth and phenology of *Conyza canadensis* in determining its competitive ability. Other examples include Eizenberg et al. (2005) who developed a predictive model for *Orobanche minor* parasitism in red clover to determine optimal timing for surveys and herbicide control applications, and Schwinghamer and Van Acker (2008) who also used GDD's to model *Kochia scoparia* phenology in Manitoba. Growing degree-days then, should also be valuable in assessing the spatial risk of purple loosestrife to Prairie Canada.

In invasive plant/weed studies that develop GDD's models, various base temperatures are used with 0°C being the most commonly used (Hacault and Van Acker 2006). For purple loosestrife I found one study by Katovich et al. (2003) that used a base temperature of 10°C to estimate the overwinter survival of seedlings, however they inappropriately selected the base temperature by using surrogate data from other weedy species. A previous study by Shamsi and Whitehead (1974a) determined that the correct base temperature for purple loosestrife is 8°C. The functional relationship between purple loosestrife growth and temperature using GDD's has not been investigated using a 8°C base temperature, a base temperature previously found to be specific to purple loosestrife (Shamsi and Whitehead 1974a). In this study, I further used the GDD's data to interpolate a GDD's risk surface, again using a species specific temperature base. The spatial distribution of purple loosestrife has not been assessed using actual season long field data, GDD's, and accurate georeferenced occurrence data.

Growing degree-days can be spatially interpolated using a variety of geostatistical approaches including kriging (Rossi et al. 1992, Cousens et al. 2002, Hijmans et al. 2005, Jodoin et al. 2008, Hlasny et al. 2011). Kriging is a geostatistical

tool that produces a predictive surface interpolating patterns across broad landscapes (Jarvis and Stuart 2001, Cousens et al. 2002, Kleijnen 2009). The spatial distribution of GDD's, as interpolated using species specific data and thresholds, provides critical information for risk analysts and wetland managers. Specifically, the interpolated GDD's surface can be used to estimate areas where purple loosestrife can, or can not grow.

Basic biological data regarding growth dynamics, seed production, and physiological tolerances to climate are found to be lacking for purple loosestrife. These data are critical in modeling its potential spread and in understanding its invasiveness especially considering future climate change. In this paper I present the results of a multi-year field study that collected season long data on the growth and seed production of purple loosestrife, and developed a refined GDD's model using a base temperature of 8°C. I further interpolated the model across Prairie Canada to produce a pest risk map. This paper is the first step in a refined modeling approach that provides a tool for policy makers for use in preventing and/or managing species invasions.

5.2 Materials and Methods

Studies were conducted in the Netley-Libau Marsh which is an area of 26,000-ha of freshwater coastal wetlands (Grosshans et al. 2004) located at the southern end of Lake Winnipeg, approximately 65-km north of Winnipeg, Manitoba (Figure 6.1). The marsh is located in the Boreal Plains Ecozone of Canada. The land around the marsh is characterized by little topographic relief dominated by grasslands and mixed deciduous and coniferous forests (Cicek et al. 2006). The marsh is a complex of lakes and streams whose water levels are influenced by Lake Winnipeg and is an important waterfowl

nesting and staging habitat. Major emergent plant species are cattail (*Typha latifolia* and *T. angustifolia*), giant reed grass (*Phragmites australis*), awned sedge (*Carex atherodes*), reed canary grass (*Phalaris arundinacea*), willow (*Salix* spp.) and bulrush (*Scirpus acutus* and *S. validus*), and the predominant vegetation in the Marsh being *Typha* spp. (Grosshans et al. 2004). Purple loosestrife most likely was established in the study area in the late 1940's to early 1950's (Ottenbreit, 1991). A vegetation survey carried out by D. Hinks (1936) under the authority of the Winnipeg Game and Fish Association, examined thirteen waterbodies in the Netley-Libau Marsh and did not identify any purple loosestrife incursions. Surveys conducted by Verbiwski (1986), Ruta et al. (1999), and Lindgren (2003) reported purple loosestrife as prevalent and invasive in the marsh.

In the study area, mean monthly temperatures at the Selkirk weather station (1971-2000) ranged from -17.5°C to +19.8°C, and mean monthly precipitation ranged from 11.3-mm to 93.0-mm (Environment Canada 1981). The study area has an average frost-free period of 128 days (Land Resource Unit 1999) and the growing season from 170 to 180 days (Pratt et al. 1961). The soils in the flooded and waterlogged areas of the marsh are poorly drained organic muck overlying high content silt and clay ranging from sandy loam to silty clay (Verbiwski 1986, Grosshans et al. 2004). Soils are Fyala, Osborne, Morris and Libau, and slightly stony (Verbiwski 1986), and are of medium texture, clayey lacustrine (Luvisols and Dary Gray Chernozems) and clayey lacustrine (Gleysols) and imperfectly drained (Land Resource Unit 1999).

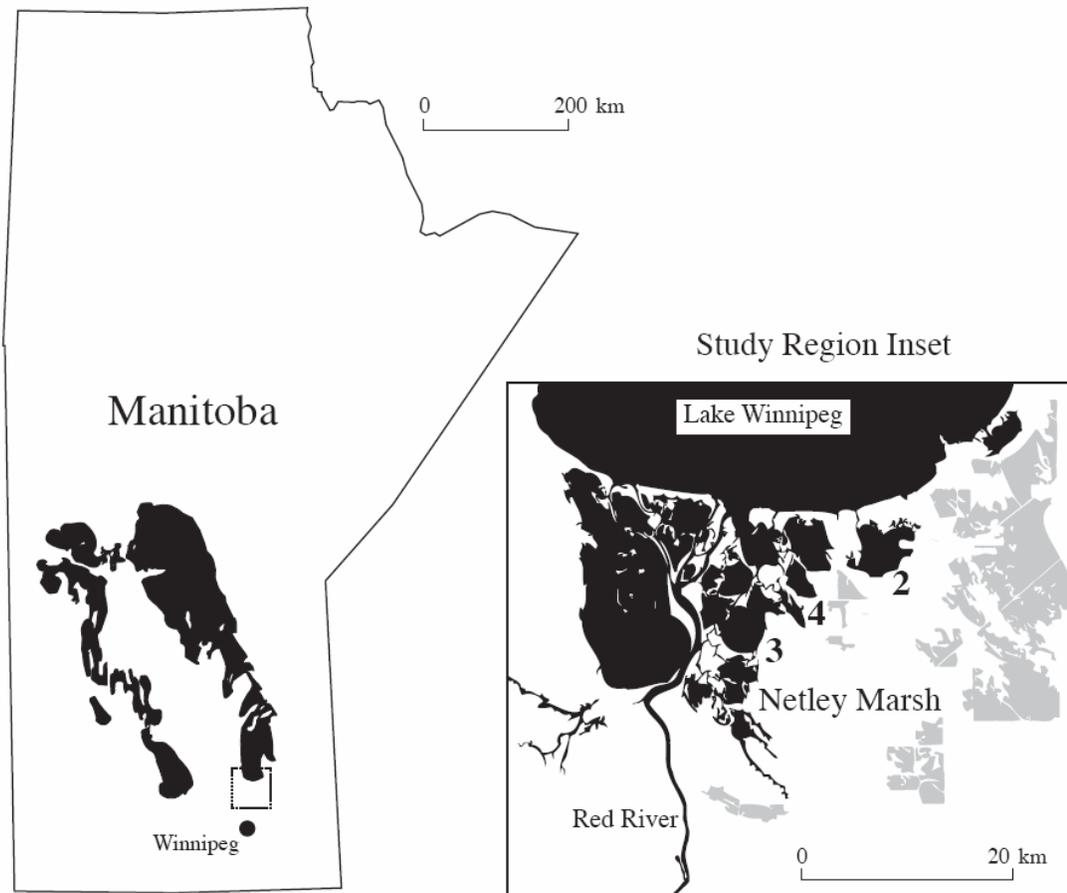


Figure 5.1 The Netley-Libau Marsh field study area. The locations of the three fixed monitoring stations (FMS) are identified by numbers 3, 4 and 5 in the map on the right. Season long field data on growth and was collected between 1995 and 1997 from each FMS.

Data Collection Methods. Data were collected from three fixed monitoring stations (FMS) located in the Netley-Libau Marsh in south central Manitoba. Data was collected from 1995 to 1997. Libau #2 FMS was located south of Folsters Lake ($50^{\circ} 20''\text{N}$; $96^{\circ} 39''\text{W}$), Libau #3 FMS was located west of Lower Devil Lake ($50^{\circ} 18''\text{N}$; $96^{\circ} 44''\text{W}$), and Libau #4 FMS was located in the south basin of Parisian Lake ($50^{\circ} 21''\text{N}$; $96^{\circ} 42''\text{W}$). A stratified random sample design was used. Each FMS was 10-m long by 5-m

wide and divided into 1-m² sampling units. From each of the 10 strata that represented the long axis of the FMS, a 1-m² sampling unit was randomly selected and permanently marked with steel rebar. In each sampling unit, three purple loosestrife stems were randomly selected, tagged with orange flagging tape, and numbered for identification. Consequently, data were collected from thirty tagged stems in each FMS annually. Data were not collected on the same stem or plant through consecutive sampling years. Stems were selected as the sampling unit as it is very difficult to define an individual purple loosestrife plant without digging up the root system. From late May to early September of each year, data were collected about every 10 days from tagged stems. Stem heights were recorded using a 1.25-cm PVC pipe demarcated to 200-cm. Stem height was recorded from the base of the stem at ground level to tallest part of the stem. In September of 1996 and 1997, seed capsules from 30 tagged stems in each FMS were removed, counted, and placed into plastic zip-lock bags. To determine the number of seeds per seed capsule, three seed capsules were randomly selected from each zip-lock bag, and the numbers of seeds per capsule were counted under a dissecting microscope.

Calculating Growing Degree-Days. To calculate GDD's, the following equations were used:

$$\text{GDD}_{\text{daily}} = (T_{\text{max}} + T_{\text{min}})/2 - T_{\text{base}} \text{ and}$$

$$\text{Cumulative GDD} = \sum \text{GDD}_{\text{daily}}$$

where T_{max} is the maximum daily temperature, T_{min} is the minimum daily temperature, and T_{base} is the base temperature (T_{base}) where purple loosestrife growth and development

is not deemed to occur (McMaster and Wilhelm 1997, Miller et al. 2001, Ball et al. 2004, Laswon et al. 2006, Shrestha et al. 2010). In this study I used a T_{base} of 8°C. Cumulative GDD's were calculated by summing those daily GDD's that were above 0°C. Temperature data was obtained from from the Selkirk Manitoba weather station (Environment Canada 2011) located about 20-km south of the FMS's.

Interpolating a Growing Degree-day Surface. Temperature data from 48 weather stations that covered the geographic extend of Manitoba (N=19), Saskatchewan (N=14) and Alberta (N=15) was used to kriging a GDD's surface. Data were imported into an Excel spreadsheet for processing cumulative GDD's. I used ESRI's ArcMap Geostatistical Analyst tool to fit the surface using latitude, longitude, and the GDD's value. Kriging was used to create a smooth fitted curve to estimate the GDD's across the Prairie Provinces using a Gaussian model.

Statistical Analysis of Stem Growth. General nonlinear modeling techniques were used to analyze purple loosestrife stem growth. Contrasts were performed on statistically significant main effects. Data from all three FMS and across years were pooled to create one cumulative GDD model. To model growth using accumulated GDD, log transformed mean stem height data were nonlinear regressed using a sigmoidal logistic three-parameter function using Sigma Plot:

$$Y = a / 1 + (x/x_0)^b$$

In this study, Y is the dependent variable representing mean purple loosestrife stem heights. The nonlinear parameter estimates are a which represents the upper asymptote (i.e., maximum growth), x represents cumulative GDD, x_0 represents GDD when stem heights are 50% of the maximum growth (i.e., median), and b represents the slope at x_0 . Goodness of fit was estimated from the coefficient of determination (i.e., R^2). Sigmaplot 2001[®] was used to process the data. The fitted curve provided a statistical and biological description of growth (Brown and Mayer 1988)

5.3 Results and Discussion

Climate Trends. The long-term monthly temperature and precipitation averages for the Netley-Libau Marsh were examined to detect any significant abnormalities. Monthly mean temperatures for each month of the study were found to be similar to a 30-year average (Environment Canada 2011) (Table 5.1). Total precipitation was highest in 1996 (477.5-mm), followed by 1997 (341.6-mm), and 1995 (303.4-mm). In general, the number of cumulative GDD's increased in each year of the study with 1159, 1213, and 1293 GDD's reached in 1995, 1996 and 1997 respectively.

Table 5.1 Monthly mean temperature and total precipitation followed by 30-year average (1971-2000) in brackets. Cumulative growing degree-days (GDD's) for each month of the study period.

Year	Month	Temperature (°C)	Precipitation (mm)	GDD's
1997	April	-0.2 (4.1)	3.8 (26)	0.0
	May	11.0 (12.4)	44.2 (56.5)	79.4
	June	19.2 (17.3)	95.5 (93)	373.8
	July	20.1 (19.8)	65.6 (79.6)	739.6
	Aug	18.6 (18.7)	63.1 (74.5)	1021.1
	September	15.4 (12.5)	69.4 (54.3)	1293.9
1996	April	-0.7	0.0	0.0
	May	10.0	80.8	8.0
	June	19.0	48.4	318.4
	July	20.0	133.2	672.4
	Aug	20.1	80.4	1041.2
	September	13.8	134.7	1213.4
1995	April	0.7	8.4	0.0
	May	11.1	70.1	12.0
	June	21.0	61.8	404.4
	July	20.0	45.5	768.4
	Aug	20.1	100.2	1136.3
	September	13.1	17.4	1159.0

Stem Growth. In this study, final stem heights averaged 127.3 cm (SE=1.6, range 44-181cm). Over each field season, we found significant differences between mean stem heights at each ten day data collection period ($P > 0.001$). This would be expected as stems elongated over the course of each field season. Within the Libau #3 FMS and the Libau #4 FMS there were no significant differences between final mean stem heights. However, in the Libau #2 FMS ($F = 6.97$; $df 2,68$; $P > 0.0017$) mean stem heights were

significantly greater in 1997 (133.9 cm) when compared to 1996 (107.0 cm) and 1995 (113.9 cm) (Table 5.2). The reasons for these differences are unknown.

Table 5.2 Annual stem growth data for the Libau fixed monitoring stations (FMS). For each FMS, growing degree-days (GDD's), mean stem height, standard error (SE) and change in centimeters of growth between data collection dates (in brackets) is provided.

Date	1995	1996	1997
	GDD Mean \pm SE	GDD Mean \pm SE	GDD Mean \pm SE
FMS #2			
June 5	116.5 41.72 \pm 5.11	55.8 5.73 \pm 1.27	110.3 15.08 \pm 1.14
June 16	215.1 60.04 \pm 4.39 (18.3)	193.4 40.06 \pm 1.79 (34.4)	227.4 48.56 \pm 1.59 (33.4)
June 26	345.8 70.59 \pm 4.57 (10.5)	242 66.95 \pm 2.31 (26.8)	317.7 76.46 \pm 2.11 (27.9)
July 8	475.4 80.54 \pm 5.02 (10)	425.4 82.46 \pm 3.27 (15.5)	394.2 92.70 \pm 2.55 (16.3)
July 23	67.2 97.68 \pm 5.33 (17.1)	600 98.40 \pm 4.90 (7.3)	603 111.96 \pm 2.91 (19.2)
August 5	832 101.02 \pm 5.51 (3.3)	757.5 103.9 \pm 6.40 (8.6)	771 125.93 \pm 3.89 (13.9)
August 13	934.9 104.36 \pm 5.84 (3.4)	837.7 105.03 \pm 6.62 (1.13)	838.6 128.30 \pm 5.09 (2.36)
August 25	1072 113.95 \pm 6.14 (9.6)	974.8 107.00 \pm 6.63 (0.87)	934.1 133.86 \pm 4.14 (5.56)
FMS #3			
June 5	116.5 43.60 \pm 2.42	55.8 26.2 \pm 13.13	110.3 16.86 \pm 1.66
June 16	215.1 61.84 \pm 3.71 (18.2)	193.4 50.13 \pm 4.01 (23.93)	227.4 44.7 \pm 2.71 (27.84)
June 26	345.8 79.42 \pm 3.82 (17.62)	242 69.53 \pm 4.93 (19.4)	317.7 67.6 \pm 2.78 (22.9)
July 8	475.4 96.07 \pm 4.94 (16.65)	425.4 84.73 \pm 4.98 (15.2)	394.2 85.7 \pm 3.27 (18.1)
July 23	672.2 121.82 \pm 8.40 (25.75)	600 113.83 \pm 5.82 (29.07)	603 111.1 \pm 3.73 (25.43)
August 5	832 129.2 \pm 7.40 (7.34)	757.5 123.9 \pm 7.36 (10.1)	771 124.17 \pm 4.01 (13.03)

August 13	934.9	136.5 ± 7.43 (7.34)	837.7	129.57 ± 7.64 (5.6)	838.6	126.63 ± 4.61 (2)
August 25	1072	139.6 ± 7.73 (3.13)	974.8	132.77 ± 7.82 (3.27)	934.1	133.07 ± 4.10 (6.9)

FMS #4

June 5	116.5	23.3 ± 1.74	55.8	0 ± 0	110.3	17.96 ± 1.04
June 16	215.1	42.7 ± 3.06 (19.4)	193.4	25.9 ± 2.00 (25.9)	227.4	38.96 ± 2.20 (21)
June 23	345.8	59.6 ± 3.27 (16.9)	242	49.46 ± 2.39 (23.5)	283.4	54.1 ± 3.54 (15.14)
July 8	475.4	74.1 ± 5.48 (14.5)	425.44	69.16 ± 2.06 (19.7)	394.2	73.43 ± 3.30 (19.33)
July 15	581.8	88.62 ± 4.72 (14.5)	497.4	87.1 ± 2.69 (17.9)	496	96.96 ± 4.18 (23.53)
July 26	707.5	103.2 ± 4.76 (14.5)	630.3	103.8 ± 2.82 (16.7)	651.4	115.46 ± 4.29 (18.5)
August 8	883.3	104.1 ± 5.92(0.9)	782	118.73 ± 3.04 (14.9)	820.3	118.4 ± 3.81 (2.94)
August 13	934.9	105.0 ± 8.12 (1.8)	837.7	123.63 ± 3.18 (4.9)	838.6	120.5 ± 3.65 (2.1)
August 25	1072	109.0 ± 7.50 (4.0)	974.8	125.13 ± 3.15 (1.5)	934.1	122.8 ± 3.44 (2.3)

Stems emerged from perennating rootstocks by late May to early June each year, and were on average 20 cm in height in early June and had obtained 16% of their final heights. From early June to late July, stems grew from 14.5 to 25.9 cm every ten days at Libau FMS #4, 7.3 to 34.4 cm in the Libau FMS #2, and 15.2 to 29.1 cm in the Libau FMS #3. During this period stems grew an average of 2.3 cm a day and the largest amounts of growth occurred in 1996 when stems grew an average of 2.5 cm a day. Through August stem growth decreased substantially to about 0.4 cm a day. By early August stems had obtained 96% of their final height. In comparison, Rawinski (1982) reported that most plants reached 90% of their final height by the first week in August. Seasonal variations in stem growth were most likely associated with shifts in resource allocation from growth towards reproduction (Harper and Ogden 1970, Bazzaz et al.

1987). Differences between FMS's are more difficult to explain however may have been due to herbivory, competition, plasticity, or an unknown site specific constraining resource. Variations in growth within a region are not uncommon for purple loosestrife (Olsson and Agren 2002).

Flower buds emerged in early July when stems had reached 66% of their final growth (Table 5.3). Most stems had flower buds and a few had open inflorescences by mid July. Basal seed capsules matured while distal inflorescences were still flowering. In 1997, some stems had developed seed capsules as early as the beginning of July, but generally seed capsules were found in late July to by early August, when stems had reached 96% of their final stem height. By mid-August stems had reached 98% of final height and all had developed seed capsules.

Table 5.3 Phenology as a function of cumulative growing degree days. Cumulative growing degree-days followed by calendar date data in brackets, followed by the mean stem height.

FMS	Year	First Buds		First Flowers		First Seeds	
		GDD (Date)	Stem Height	GDD (Date)	Stem Height	GDD (Date)	Stem Height
Libau 2	1996	391.6 (July 5)	89.7cm	618.3 (July 26)	98.4cm	760 (Aug 6)	103.9cm
	1997	422.7 (July 8)	92.7cm	631.5 (July 23)	111.9cm	799.5 (Aug 5)	125.9cm
Libau 3	1996	391.6 (July 5)	98.8cm	485.4 (July 15)	98.8cm	618.3 (July 26)	113.8cm
	1997	422.7 (July 8)	85.7cm	631.5 (July 23)	111.1cm	799.5 (Aug 5)	124.1cm
Libau 4	1996	252.8 (June 26)	87.1cm	618.3 (July 26)	103.8cm	745.5 (Aug 6)	118.7cm
	1997	422.7 (July 8)	73.4cm	631.5 (July 23)	96.9cm	799.5 (Aug 5)	115.46cm

A literature review revealed that there are no field studies that provide data on the annual season long stem growth of purple loosestrife. A few studies report final stem height information, however, there is considerable variation depending on geographic location of the study. For example, Thompson et al. (1987) reported plants grew as high as 300 cm in Nebraska, Mal et al. (1992) reported plants grew to 270 cm, Balogh (1986) reported plants ranged in height from less than 100 cm to more than 250 cm in Ohio, Mullin (1998) reported plants grew from 50 cm to 350 cm, Olsson and Agren (2002) reported plants in Sweden ranged from 15 cm to 61 cm, and Ture et al. (2004) found that stem heights ranged from 120 cm to 170 cm in Turkey. Differences in stem heights can be attributed to various biotic and abiotic variables including climatic gradients, latitude, or competition. For example, data from the Ture et al. (2004) study was likely confounded by the presence of the classical biological control agents *Galerucella californiensis*, *G. pusilla*, *Hylobius transversovittatus* and *Nanophyes marmoratus*. Bastlova et al. (2004) found that decreasing latitudes were associated with increases in stem heights. Olsson and Agren (2002) also found plants grew taller in lower latitudes in Sweden, however data were collected from seeds grown in a greenhouse where they were fertilized, thinned two weeks after planting (e.g., creating a monoculture and removing affects of competition), and then transferred to an outside garden where they were again watered and fertilized further removing the affects of competition. While the geographic extent of the plants examined in this study is relatively finite, they represent individuals that were perennial from plants that existed *in situ* for the duration of the study. The multi-year *in situ* nature of this study provided a natural dynamic impossible to characterize in greenhouse or cultivated experiments.

Seed Production. The mean number of seed capsules produced across all years of the study was 276.4 (SE±14.9; range 0-1578). We found significant differences ($P < 0.05$) between FMS's where the mean number of seed capsules produced were 255.76 (SE±24.49), 387.15 (SE±31.73) and 187.62 (SE±13.03) for Libau 2, Libau 3, and Libau 4 respectively. Unexpectedly, there were significant differences ($P < 0.05$) between study years in seed data from the Libau FMS #3 (Table 5.4). The reason for high seed capsules production in 1996 and 1997 is unknown but indicated the possible influence of an in-site variable, but surprisingly, this did not result a proportional increase in seed yield.

Overall, the mean number of seeds produced per seed capsule was 79.44 (SE±1.48). The mean number of seeds per seed capsule at each FMS's were 79.56 (SE±2.76), 73.51 (SE±2.70), and 85.15 (SE±2.01) for Libau #2, Libau #3 and Libau #4 respectively. At the Libau #4 FMS significantly ($P < 0.0167$) more seeds per capsule were found in 1996 when compared to 1995 and 1997. Similarly, in the Libau #2 FMS significantly ($P < 0.0009$) more seeds per capsule were produced in 1996 as compared to 1995 and 1997. These differences may be attributed to precipitation as substantially more precipitation as received in 1996 as compared to 1995 and 1997 (see Table 5.1).

Table 5.4 Purple loosestrife seed production. Mean number of seed pods per stem and mean number of seeds per pod, followed by the standard error in brackets, and range.

FMS	Year	No. Seed Pods (SE) range	Mean No. Seeds per Pod
Libau 2	1997	293.33 ^a (± 41.58) 26-877	73.02 ^a (± 5.61) 0-119
	1996	234.06 ^a (± 42.18) 2-1025	93.70 ^b (± 4.11) 52-155
	1995	234.80 ^a (± 41.14) 13-883	71.95 ^a (± 3.41) 29-98
Libau 3	1997	195.76 ^a (± 34.39) 0-948	64.90 ^a (± 6.19) 0-134
	1996	444.23 ^b (± 47.46) 113-1128	80.33 ^a (± 3.27) 45-117
	1995	521.46 ^b (± 61.94) 1-1577	75.32 ^a (± 3.73) 26-105
Libau 4	1997	167.53 ^a (± 26.05) 0-780	81.29 ^a (± 4.07) 0-116
	1996	221.46 ^a (± 20.02) 76-471	93.18 ^b (± 3.04) 58-124
	1995	173.86 ^a (± 20.91) 34-501	80.95 ^a (± 2.83) 39-109

^a Means within a column and a FMS, followed by the same superscripted letter are not different (Student's *t* test at $P = 0.05$).

The mean number of seeds per seed capsule produced by Netley-Libau plants was slightly lower than data presented in other studies (Table 5.5). These differences may be attributed to biotic or abiotic variables. For example, Ture et al. (2004) found a linear relationship ($r^2 = 0.92$) where plants produced more seeds and grew taller in environments with lower amounts of light. Others suggest that plants that have been introduced and considered invasive, produce more seeds than plants in their native range

(Crawley 1987, Edwards et al. 1998, Blossey and Notzold 1995). In this study, seed production in the invasive Netley-Libau plants was not substantially greater than native European populations. Prolific seed production, as well as the relatively small seed size, contributes to invasive ability of purple loosestrife (Baker 1965, Rejmanek and Richardson 1996). Small seeds are able to disperse naturally through both terrestrial and aquatic pathways, as well as by human assisted pathways, and seed size is a life history trait that contributes to purple loosestrife's invasive success. Prolific seed production also results in the formation of large seed banks that allow for rapid recovery after events such as marsh draw downs or droughts (Van der valk and Davis 1978).

Modelling Stem Growth. While there are studies that provide limited data on purple loosestrife growth, there are none that statistically model its growth under actual field conditions or investigate stem growth as a function of GDD's. Purple loosestrife log transformed mean stem height data were nonlinear regressed to cumulative GDD's using a three-parameter logistic function (Brown and Mayer 1988). A sigmoid shape relationship was observed between stem growth and cumulative GDD's ($Y = 150.3/(1 + (x/118.52)^{-1.399})$; $P < 0.0001$) (Figure 6.2). A coefficient of determination indicated that this model provided the best fit to the data ($R^2 = 0.86$). The fitted curve provides a statistical and biological description of purple loosestrife growth. Stems did not follow a

Table 5.5 Comparative studies on purple loosestrife seed production.

Study	Source	Seeds per Seed Capsule
Edwards et al. (1998)	Czech /Slovak Republic, Europe	58 – 64 *
Edwards et al. (1998)	Indiana/Michigan, US	89 – 103
Ture et al. (2004)	Turkey, Europe	95.8 **
Shamsi and Whitehead (1974a)	England, Europe (assumed)	120
Thompson et al. (1987)	Colorado, US	83 – 130
This Study	Manitoba, Canada	79.4

* insect larvae and adult weevils present

***Galerucella* spp., *Hylobius* spp. and *Nanophyes* spp. present

constant growth rate over a field season. The relationship between stem growth and GDD's was asymmetrical with rapid growth early that slowed as plants reached a growth asymptote. Rapid growth through vegetative stages to the flowering stage is a common characteristic of an invasive weed (Baker 1965). Rapid early stem growth provides purple loosestrife with an ecologically significant advantage over slower growing native species in the competition for limited resources. By modelling purple loosestrife growth it is possible to predict emergence and growth stages providing information to land managers for example on critical times to implement control programs, herbicide applications, or when to release of biological control agents. This study provides the first statistical model of purple loosestrife growth using multi-year field data. The results are

significant as existing data has come from controlled or cultivated studies (i.e., plants have been watered and fertilized). This study further contributes a model that accurately describes when shoots began to grow, how quickly they grow, and the extent of growth. Future studies might collect similar season long field data from other geographic regions to further test and validate the statistical relationship, and further refine a spatiotemporal model.

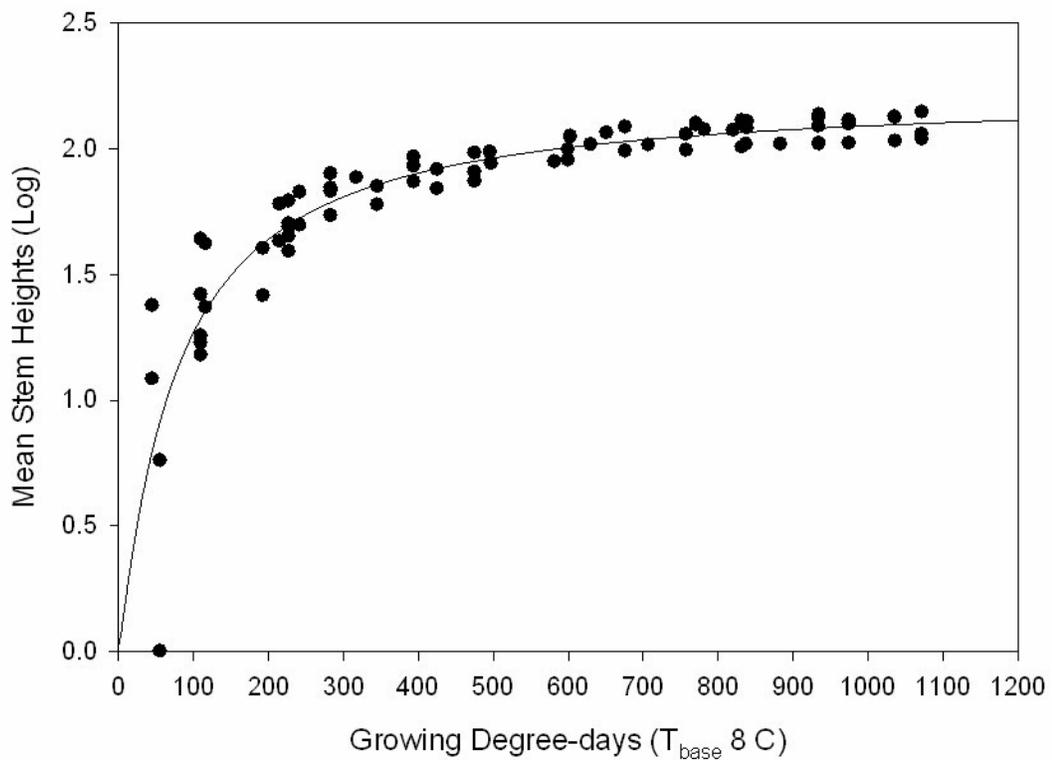


Figure 5.2 Modelling the growth of purple loosestrife using growing degree-days (GDD's). Purple loosestrife emergence and growth in the Netley-Libau Marsh characterized by cumulative (GDD's) using a T_{base} of $8^{\circ}C$ where $GDD_{daily} = (T_{max} + T_{min})/2 - T_{base}$. Circles are field data fitted to a logistic three-parameter nonlinear regression.

Growing Degree-days and Phenology. Stems emerged from root stocks at about 45 cumulative GDD's which were generally reached by the end of May in each field season (Table 2). Stems required an average of 338 GDD's to reach 50% of their end of growing season height and an average of 1007 GDD's to reach end of growing season height. Flower buds formed on average at 384 GDD's, open flowers were observed on average at 602 GDD's, and the first seed capsules were observed on average at 753 GDD's. Data presented here can be used to predict purple loosestrife growth and phenology in novel regions as development expressed in GDD's should be consistent across different spatial scales (De Corby et al. 2007) providing other constraining variables are similar. Comparative data are required from North American and European populations to further develop and refine a GDD's model for purple loosestrife. It would also be interesting to determine if invasive populations have a comparable GDD's profile when compared to native populations.

Interpolated GDD's Risk Surface. The interpolated GDD's map provides risk-based information on where and where not purple loosestrife might further establish (Figure 6.3). There is a strong northwest GDD's gradient across the Prairie Provinces with the highest values found in south-eastern Manitoba and decreasing northwest towards northern Alberta. Growing degree-days appear to constraint much of the maximal extent of the distribution of purple loosestrife in prairie Canada. For instance, the elevations of the Rocky Mountains and associated climatological barriers in western Alberta are impediments to the natural dispersal of purple loosestrife from nascent foci in the west. While in eastern Manitoba the Boreal Shield and changing landscape physiography limit

the dispersal despite largely similar climatic conditions. The northern extend of distribution seems to be broadly constrained by a GDD's threshold. The kriged map indicates that areas in Alberta around Grande Prairie, and areas east of Edmonton and Calgary are suitable for further invasions. Areas of central Saskatchewan north and west of Saskatoon, and areas in southern Saskatchewan, are also suitable for purple loosestrife establishment. In Manitoba, areas northwest of Winnipeg as well as the Interlake region provide suitable are susceptible to further purple loosestrife dispersal. It is most likely the case that purple loosestrife just has not dispersed into these areas yet, and when it does, our data indicated that there are enough GDD's to support establishment.

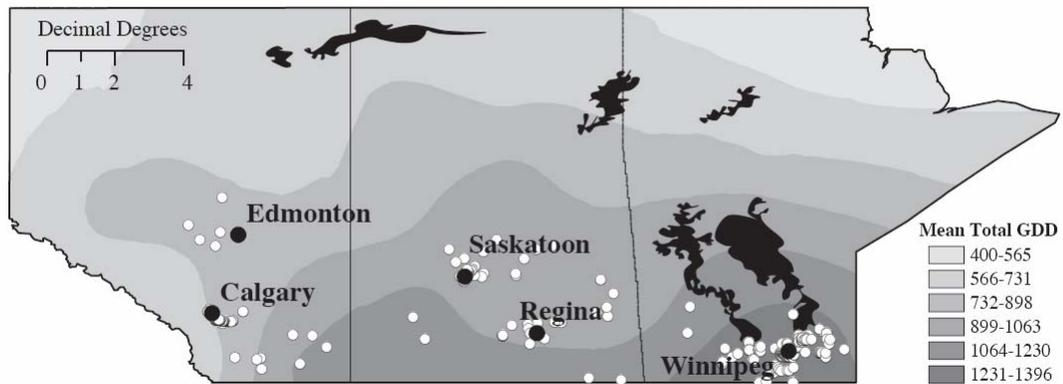


Figure 5.3 Spatial interpolation of cumulative mean growing degree-day's for Prairie Canada calculated using a T_{base} of 8°C . White circles indicate purple loosestrife occurrences with major city centres, lakes, and provincial boundaries provided for context.

Purple loosestrife is spreading across Prairie Canada in an invasion pattern that is consistent with stratified diffusion (Shigesada et al. 1995, Bogich and Shea 2008). In our study stratified diffusion consisted of 1) localized dispersal by neighborhood diffusion, and 2) human mediated dispersal through intentional garden introductions that represent long-distance diffusion into new areas where purple loosestrife could not disperse through neighborhood diffusion. Occurrence points are aggregated around major urban centers suggesting that purple loosestrife was introduced into urban areas through garden plantings, and these plantings subsequently escaped and dispersed locally (Figure 5.3). We can expect purple loosestrife to continue to spread in Prairie Canada through both local diffusion and long distance human-assisted diffusion through garden plantings.

The interpolated GDD's risk map also indicates that the prairie pothole region and its associated wetlands are suitable area for further invasion. The wetlands in this region are environmentally and economically important. However invasive plants such as purple loosestrife are replacing the indigenous vegetation in a substantial portion of these inland wetlands (Galatowitsch et al. 1999) impacting nesting waterfowl (Balogh and Bookhout 1989) and waterfowl populations (Thompson et al. 1987). Further loss or degradation of wetland habitat as predicted suitable by our GDD's risk map, would be detrimental to as wetlands in the study area are recognized as the most productive habitat for waterfowl in the world (Johnson et al. 2005).

The interpolated risk map and geographic pattern of the known occurrence points provides spatial information to support the development of regulatory policy and management plans. To manage the spread of purple loosestrife in Prairie Canada a triage-approach is recommended. First, from a policy perspective, regulations that

prevent the long distance human mediated dispersal would be effective, as many areas of prairie Canada remain free of purple loosestrife. Second, regional programs need to attempt to either eradicate or contain localized populations. Third, early detection and rapid response efforts need to be focused on areas indicated by our interpolated risk map has not having purple loosestrife yet having enough GDD's to sustain new founder populations.

5.4 Conclusions

This chapter contributes new phenological and statistical information quantitatively describing the season long growth and seed production of purple loosestrife under field conditions. An interpolated GDD's risk map indicated that purple loosestrife has not reached its potential distribution in Prairie Canada and that substantial area remains for purple loosestrife to invade. In developing invasive plant risk maps, GDD's should be included as an important predictive layer along with other abiotic variables. The results and methods presented in this chapter can support land managers in developing effective control plans or in selecting areas for early detection rapid response programs. In the next chapter, I will extend the use of GARP as a tool for biosecurity agencies to model the potential distribution of purple loosestrife in Prairie Canada.

5.5 Literature Cited

Averill, K.M., A. DiTommaso, C.L. Mohler and L.R. Milbrath. 2011. Survival,

- growth, and fecundity of the invasive swallowworts (*Vincetoxicum rossicum* and *V. nigrum*) in New York State. *Invasive Plant Sci. and Manag.* 4:198-206.
- Bailey, W.A., S.D. Askew, S. Dorai-Raj and J.W. Wilcut. 2003. Velvetleaf (*Abutilon theophrasti*) interference and seed production dynamics in cotton. *Weed Sci.* 51:94-101.
- Baker, H.G. 1965. Characteristics and modes of origin in weeds. Pages 147-172 in H. G. Baker and G. L. Stebbins, eds. *The Genetics of Colonizing Species*. New York: Academic Press.
- Ball, D.A., S.M. Frost and A.I. Gitelman. 2004. Predicting timing of downy brome (*Bromus tectorum*) seed production using growing degree days. *Weed Sci.* 52:518-524.
- Balogh, G.R. 1986. Ecology, distribution, and control of purple loosestrife (*Lythrum salicaria*) in Northwest Ohio. PhD dissertation. The Ohio State University 1986.
- Balogh, G.R and T.T. Bookhout. 1989. Purple loosestrife (*Lythrum salicaria*) in Ohio's Lake Erie Marshes. *Ohio J. Science* 89:62-64.
- Bastlova, D. and J.A. Kvet. 2004. Differences in dry weight partitioning and Flowering phenology between native and non-native plants of purple loosestrife (*Lythrum salicaria* L.). *Flora – Morphology, Distribution, Functional Ecology of Plants* 197:332-340.
- Bazzaz, F.A., N.R. Chiariello, P.D. Coley and L.F. Pitelka. 1987. Allocating resources to reproduction and defense. *BioScience* 37:58-67.
- Berti, M.T. and B.L. Johnson. 2008. Growth and development of *Cuphea*. *Industrial Crops and Products* 27:265-271.

- Bogich, T. and K. Shea. 2008. A state-dependent model for the optimal management of an invasive metapopulation. *Ecological Applications* 18:748-761.
- Bossard, C.C. and M. Rejmanek. 1994. Herbivory, growth, seed production, and resprouting of an exotic invasive shrub *Cytisus scoparius*. *Biol. Conserv.* 67:193-200.
- Blossey, B. and R. Notzold. 1995. Evolution of increased competitive ability in invasive nonindigenous plants: a hypothesis. *J. Ecol.* 83:887-889.
- Brown, R. F. and D. G. Mayer. 1988. Representing cumulative germination. 1. The use of the Weibull function and other empirically derived curves. *Ann. Bot.* 61:127-138.
- Cicek, N., S. Lambert, H. D. Venema, K. R. Snelgrove, E. L. Bibeau, and R. Grosshans. 2006. Nutrient removal and bio-energy production from Netley-Libau Marsh at Lake Winnipeg through annual biomass harvesting. *Biomass and Bioenergy* 30:529-536.
- Cousins, R.D., R.W. Brown, A.B. McBratney, B. Whelan and M. Moerkerk. 2002. Sampling strategy is important for producing weeds maps: a case study using kriging. *Weed Sci.* 50:542-546.
- Crepinsek, Z., L. Kajfez-Bogataj and K. Bergant. 2006. Modelling of weather variability effect on fitophenology. *Ecol. Modell.* 194:256-265.
- De Corby, K.A., R.C. Van Acker, A.L. Brule-Babel and L.F. Friesen. 2007. Emergence timing and recruitment of volunteer spring wheat. *Weed Sci.* 55:60-69.
- Dillehay, B.L., W.S. Curran and D.A. Mortensen. 2011. Critical period for weed control in alfalfa. *Weed Sci.* 59:68-75.
- Edwards, K.R., M.S. Adams and J. Kvet. 1998. Differences between European native

- and American invasive populations of *Lythrum salicaria*. *Appl. Vegetation Science* 1:267-280.
- Environment Canada 2011. National Climate Data and Information Archive
http://climate.weatheroffice.gc.ca/climateData/canada_e.html
- Environment Canada. 1981. Canadian climate normals 1951-1980 temperature and precipitation prairie provinces. A publication of the Canadian Climate Program. 429 pp.
- Eizenberg, H., J. Colquhoun and C. Mallory-Smith. 2005. A predictive degree-days model for small broomrape (*Orobanche minor*) parasitism in red clover in Oregon. *Weed Sci.* 53:37-40.
- Galatowitsch, S.M., N.O. Anderson and P.D. Ascher. 1999. Invasiveness in wetland plants in temperate North America. *Wetlands* 19:733-755.
- Grosshans, R.E., D.A. Wrubleski and L.G. Goldsborough. 2004. Changes in the Emergent Plant Community of Netley-Libau Marsh Between 1979 and 2001. Delta Marsh Field Station (University of Manitoba) Occasional Publication No. 4, Winnipeg, Canada. 52 pp.
- Gowdin, B.J., A J. McAllister and L. Fahrig, 1999. Predicting invasiveness of plant species based on biological information. *Conservation Biology* 13:422-426.
- Harper, J.L. and J. Ogden. 1970. The reproduction strategy of higher plants: I. The concept of strategy with special reference to *Senecio Vulgaris* L. *J. of Ecology* 58:681-698.
- Hassan, Q.K., C.P. Bourque, F. Meng, and W. Richards. 2007. Spatial mapping of growing degree days: an application of MODIS-based surface temperatures and

- enhanced vegetation index. *J. Appl. Remote Sensing* 1:1-12.
- Hassan, Q. and C. Bourque. 2009. Potential species distribution of Balsam Fir based on the integration of biophysical variables derived with remote sensing and process-based methods. *Remote Sensing* 1:393-407.
- Henne, D.C., C.J. Lindgren, T.S. Gabor, H. R. Murkin and R.E. Roughley. 2004. An integrated management strategy for the control of purple loosestrife *Lythrum salicaria* L. (Lythraceae) in the Netley-Libau Marsh, southern Manitoba. *Biol. Control* 32:319-325.
- Hearne Scientific Software. 2007. CLIMEX Software Version 3.0.2 Hearne Scientific Software Pty Ltd, Melbourne.
- Hijmans, R., S.E. Cameron, J.L. Parra, P.G. Jones and A. Jarvis. 2005. Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology* 25:1965-1978.
- Hinks, D., and R. Fryer. 1936. Aquatic plant survey 1936. Manitoba Department of Mines and Natural Resources Government Report. 32 pp.
- Hlasny, T., L. Zajickova, M. Turcani, J. Holusa and Z. Sitkova. 2011. Geographic variability of spruce bark beetle devilmnt under climate change in the Czech Republic. *Journal of Forest Science* 57:242-249.
- Javis, C.H. and N. Stuart. 2001. A comparison among strategies for interpolating maximum and minimum daily air temperatures. Part II: the interaction between number of guiding variables and the type of interpolation method. *American Meteorological Society* 40:1075-1084.
- Jimenez-Valverde, A., A.T. Peterson, J. Soberon, J.M. Overton, P. Aragon, and J.M.

- Lobo. 2011. Use of niche models in invasive species risk assessments. *Biological Invasions* 13:2785-2797.
- Jodoin, Y., C. Lavoie, P. Villeneuve, M. Theriault, J. Beaulieu and F. Belzile. 2008. Highways as corridors and habitat for the invasive common reed *Phragmites australis* in Quebec, Canada. *J. of Applied Ecology* 45:459-466.
- Johnson, W.C., B.V. Millett, T. Gilmanov, R.A. Voldseth, G.R. Guntenspergen, and N.E. Naugle. 2005. Vulnerability of Northern Prairie Wetlands to Climate Change. *BioScience* 55:863-872.
- Kirwan, M.L., G.R. Guntenspergen, and J.T. Morris. 2009. Latitudinal trends in *Spartina alterniflora* productivity and the response of coastal marshes to global change. *Global Change Biology* 15:1982-1989.
- Kleijnen, J. P. C. 2009. Kriging metamodeling in simulation: a review. *European Journal of Operational Research* 192:707-716.
- Knezevic, S.Z., S. P. Evans, E. E. Blankenship, R.C. Van Acker, and J.L. Lindquist. 2002. Critical period for weed control: the concept and data analysis. *Weed Sci.* 50:773-786.
- Land Resource Unit, 1999. Soils and Terrain. An Introduction to the Land Resource. Rural Municipality of St Clements. Information Bulletin 99-9, Brandon Research Centre, Research Branch, Agriculture and Agri-Food Canada.
- Lati, R.N., S. Filin and H. Eizenberg. 2011, Temperature and radiation-based models for predicting spatial growth of purple nutsedge (*Cyperus rotundus*). *Weed Science* 59:476-482.
- Lawson, A. N., R.C. Van Acker, and L.F. Friesen. 2006. Emergence timing of volunteer canola in spring wheat fields in Manitoba. *Weed Sci.* 54:873-882.

- Lindgren, C.J. 2003. A brief history of purple loosestrife, *Lythrum salicaria*, in Manitoba and its status in 2001. *Can. Field-Nat.* 117:100-109.
- Lindgren, C.J., C. Pearce, and K. Allison. 2010. The biology of invasive alien plants in Canada. 11. *Tamarix ramosissima* Ledeb., *T. chinensis* Lour. and hybrids. *Can. J. Plant Sci.* 90:111-124.
- Lindgren, C.J. 2011. Biosecurity policy and the use of geospatial predictive tools to address invasive plants: updating the risk analysis toolbox. *Risk Analysis* 32:9-15.
- Magarey, R.D., Borchert, D.M., Engle, J.S., M. Colunga-Garcia and F.H. Koch. 2011. Risk maps for targeting exotic plant pest detection programs in the United States. *Bulletin* 41:46-56.
- Mal. T.K., J. Lovett-Doust, L. Lovett-Doust and G. A. Mulligan. 1992. The biology of Canadian weeds. 100. *Lythrum salicaria*. *Can. J. Plant Sci.* 72:1305-1330.
- McMaster, G.S. and D.E. Smika. 1988. Estimation and evaluation of winter wheat phenology in the central Great Plains. *Agric. Forest Meteorology* 43:1-18.
- McMaster, G.S. and W.W. Wilhem. 1997. Growing degree-days: one equation, two interpretation. *Agricultural and Forest Meteorology* 8:291-300.
- Miller, P., W. Lanier and S. Brandt. 2001. Using growing degree days to predict plant stages. Montana State University Extension Service, Bozeman, Montana.
- Mullin, B.H. 1998. The biology and management of purple loosestrife (*Lythrum salicaria*). *Weed Technol.* 12:397-401.
- Nagel, J.M. and K.L. Griffin. 2001. Construction cost and invasive potential: comparing *Lythrum salicaria* (Lythraceae) with co-occurring native species along pond bank. *Am. J. Bot.* 88:2252-2258.

- Olsson, K. and J. Agren. 2002. Latitudinal population differentiation in phenology, life history and flower morphology in the perennial herb *Lythrum salicaria*. *Journal of Evol.Biol.* 15:983-996.
- Ottenbreit, K. 1991. The distribution, reproductive biology, and morphology of *Lythrum* species, hybrids and cultivars in Manitoba. M.S. thesis, University of Manitoba, Winnipeg, Manitoba.
- Patterson, D.T., J.K. Westbrook, R.J. Joyce, P.D. Lingren and J. Rogasik. 1999. Weeds, insects and diseases. *Climatic Change* 43:711-727.
- Pratt, L.E., W.R. Ehrlich, F.P. Leclaire and J.A. Barr. 1961. Report on detailed reconnaissance soil survey of Fisher and Teulon Map Sheet Area. Manitoba Soil Survey. Soils Report No. 12, Winnipeg, Manitoba and Canadian Governments, Dept. of Agriculture.
- Rawinski, T. 1982. The Ecology and Management of Purple Loosestrife (*Lythrum salicaria* L.) in Central New York. M.S. thesis. Cornell University, Ithaca, NY. 88 p.
- Recasens, J., C. Calvert, A. Cirujeda, and J.A. Conesa. 2005. Phenological and demographic behaviour of an exotic invasive weed in agroecosystems. *Biol. Invasions* 7:17-27.
- Rejmanek, M. and D.M. Richardson. 1996. What attributes make some plant species more invasive? *Ecology* 77:1655-1661.
- Rossi, R. E., D. J. Mulla, A.G. Journel and E.H. Franz. 1992. Geostatistical tools for modeling and interpreting ecological spatial dependence. *Ecological Monographs* 62:277-314.
- Ruta, T., M. Kowalchuk, and W. Neily. 1999. Biodiversity Survey of the Libau Marsh.

- Manitoba Natural Resources. Winnipeg.
- Schwinghamer, T.D. and R.C. Van Acker. 2008. Emergence timing and persistence of *Kochia* (*Kochia Scoparia*). *Weed Sci.* 56:37-41.
- Shamsi, S.R.A. and F.H. Whitehead. 1974a. Comparative eco-physiology of *Epilobium hirsutum* L. and *Lythrum salicaria* L. I. General biology, distribution and germination. *J. Ecol.* 62:279-290.
- Shamsi, S.R.A. and F.H. Whitehead. 1974b. Comparative eco-physiology of *Epilobium Hirsutum* L. and *Lythrum salicaria* L. II. Growth and development in relation to light. *J. Ecology* 19:631-645.
- Shigesada, N., K. Kawasaki and Y. Takeda. 1995. Modeling stratified diffusion in biological invasions. *The American Naturalist* 146:229-251.
- Shrestha, A., B. D. Hanson, W. Fidelibus and M. Alcorta. 2010. Growth, phenology, and Intraspecific competition between glyphosate-resistant and glyphosate-susceptible horseweeds (*Conyza Canadensis*) in the San Joaquin Valley of California. *Weed Sci.* 58:147-153.
- Spencer, D.F., G.G. Ksander, J.D. Madsen and C.S. Owens. 2000. Emergence of vegetative propagules of *Potamogeton nodosus*, *Potamogeton pectinatus*, *Vallisneria Americana*, and *Hydrilla verticillata* based on accumulated degree days. *Aquatic Botany* 57:237-249.
- Sutherst, R.W., F. Constable, K. Finlay, R. Harrington, J. Luck and M.P. Zalucki. 2011. Adapting to crop pest and pathogen risks under a changing climate. *Climate Change* 2:220-237.
- Thompson, D.Q., R.L. Stuckey and E.B. Thompson. 1987. Spread, Impact, and

- Control of Purple Loosestrife (*Lythrum salicaria*) in North American Wetlands. U.S. Fish and Wildlife Service. 55 pp.
- Ture, C., N.A. Bingol and B.A. Middleton. 2004. Characterization of the habitat of *Lythrum salicaria* L. in floodplain forests in western Turkey – effects on stem height and seed production. *Wetlands* 24:711-716.
- Van der Valk, A.G. and C.B. Davis. 1978. The role of seed banks in the vegetation dynamics of prairie glacial marshes. *Ecology* 59:322-335.
- Verbiwski, B.N. 1986. *Netley-Libau Marshes Resource Development and Management Proposal*. Manitoba Natural Resources. Winnipeg. 190 pp.
- Weiner, J. 2004. Allocation, plasticity and allometry in plants. *Perspectives in Plant Ecology, Evolution and Systematics* 6:207-215
- Woodward, F.I. 1987. *Climate and Plant Distribution*. Cambridge University Press, Cambridge.
- Wu, L. 2010. Development of a best management plan for spreading dogbane (*Apocynum androsaemifolium* L.) in wild blueberry fields. MSc. Thesis, Truro, NS, Nova Scotia Agricultural College, 86 p.
- Yang, G., A. Gemperli, P. Vounatsou, M. Tanner, X. Zhou and J. Utzinger. 2006. A growing degree-days based time-series analysis for prediction of *Schistosoma japonicum* transmission in Jiangsu Province, China. *Am. J. Trop. Med. Hyg.* 75:549-555.
- Yemshanov, D., F.H. Koch, D.W. McKenney, M.C. Downing and F. Sapio. 2009. Mapping invasive species risks with stochastic models: a cross-border United States-Canada application for *Sirex noctilio* Fabricius. *Risk Analysis* 29:868-884.

CHAPTER 6 - PREDICTING THE SPATIAL RISK OF PURPLE LOOSESTRIFE (*Lythrum salicaria*) TO PRAIRIE CANADA: EXTENDING THE APPLICATION OF ECOLOGICAL NICHE MODELLING TO BIOSECURITY RISK ANALYSIS

ABSTRACT. Purple Loosestrife (*Lythrum salicaria*) is an invasive plant introduced into North America in the early 1800s. It has since spread into the prairie provinces of Canada (Manitoba, Saskatchewan, and Alberta). It invades wetland habitats, marshes, riparian areas, and natural areas, and it outcompetes native wetland vegetation. In this chapter I modelled the potential distribution of Purple Loosestrife in the Prairies, explored which suites of predictive variables produced the best ecological niche models, and explored two different approaches to the partitioning of data in evaluating models. A number of performance measures and expert evaluation were used to select a best model. The best model was developed using a suite of climate variables and growing degree-days as the predictive variables and by partitioning testing and training data using stratified random sampling. The model indicated that Purple Loosestrife has not yet reached its full potential distribution in the Prairies. The modelling techniques presented in this paper may be used to predict the potential distribution of other emerging invasive plants, and the results can be used to optimize early detection and surveillance strategies for Purple Loosestrife in areas of the Prairies. A triage approach is recommended in selecting the best model using (1) predictive accuracy, (2) performance measures and (3) expert evaluation. The techniques used in this study need to be incorporated into biosecurity risk analysis frameworks modernizing regulatory frameworks for invasive plants. The results and techniques also support biosecurity agencies in directing limited resources towards risk-based early detection and surveillance strategies.

6.1 Introduction

Invasive plants threaten our economy, environment, and health. They threaten managed and unmanaged systems worldwide (Bradley et al. 2009). In Canada, there are an estimated 486 invasive alien plant species that have arrived through both intentional and unintentional pathways (CFIA 2008). The majority of these have arrived through intentional introductions from other countries through horticultural trade in the form of ornamental plants in the plants for planting pathway (CFIA 2008). In the United States (US), a similar invasion has taken place where over 5,000 invasive alien plants have established and displaced native plants (Pimental et al. 2005). Globalization is exacerbating the invasion as the number of new plant incursions and their impacts have increased rapidly over the past 30 years due to exponential (1) increases in air travel, (2) increases in the speed at which commodities and people traverse the globe, (3) increases in the numbers of ports of entry, (4) expanded exports and imports into new international markets, (5) increased interest in the use of exotic plants in gardening and water gardening, and (6) increased access to foreign ecosystems (Brasier 2008, Mullin et al. 2000). For a more detailed discussion, please see Chapter 2 of this Thesis.

Purple Loosestrife in the Prairie Canada

Purple loosestrife (*Lythrum salicaria*) is an alien invasive plant introduced into North America in the early 1800s that has since spread across Canada (Thompson et al. 1987, Lindgren 2003). It invades wetlands, marshes, riparian areas, and natural areas (White et al. 1993, Mal et al. 1997, Mullin 1998, Anderson et al. 2006). It has the ability to out compete and replace native vegetation and once established it becomes difficult

and costly to eradicate, in some cases, eradication is not achievable (Gaudet and Keddy 1988, Johansson and Keddy 1991, Gaudet and Keddy 1995, Mal et al. 1997). It is found in all three Canadian Prairie Provinces.

The current distribution of purple loosestrife in Prairie Canada can be described as follows. The first documented report of purple loosestrife in Manitoba was from the Neepawa area in 1896 (Fletcher 1900). The next collection was not until 1944 from the Lockport area on the Red River, and by the end of the 1950's purple loosestrife had colonized the Delta Marsh, Otterburne, Fannystelle, and the Cypress River (Ottenbreit 1991). By the mid-1980's purple loosestrife had formed contiguous populations along the Red River and Assiniboine Rivers (Ottenbreit 1994). By the mid-1990's purple loosestrife had established in every major river system in southern Manitoba. By 2001, there were 492 known purple loosestrife infestations in Manitoba with an estimated 5,500 ha of purple loosestrife (Lindgren 2003). In Saskatchewan, purple loosestrife is mostly found growing in urban settings around Saskatoon, Moose Jaw, Regina, Swift Current, and Yorkton (Lindgren et al. 2001). The first official report of purple loosestrife in Alberta was recorded in 1990 at Medicine Hat and it is believed that most incursions in Alberta are the result of garden escapes (Government of Alberta 2009). In Alberta, regions with large populations of purple loosestrife include the urban areas of Edmonton, Calgary, Lethbridge and Medicine Hat (Government of Alberta 2009). In 1994, there were more than 315,000 plants in as many as 185 wetlands in Alberta (Ali and Verbeek 1999). Purple loosestrife is of economic and environmental concern to regional, provincial, and federal agencies with biosecurity mandates.

Biosecurity Decision Making

Biosecurity decision makers are continually concerned with which invasive plant might intentionally or unintentionally be introduced and establish, and which of those plants might affect economic or environmental damage. In many cases, biosecurity agencies base policy decisions on spatial information describing where a pest can establish, and what its probability of spread is after establishment. Unfortunately, there is no crystal ball to predict the next new or emerging pest. Hence, there is a need to incorporate spatial predictive tools into risk analysis frameworks. Tools that might predict the potential distribution of an emerging pest such as purple loosestrife and support the biosecurity decision-making process are required (Lindgren 2011).

Biosecurity agencies currently use screening tools which are comprised of a series of questions to assess which invasive plants might become problematic (Pheloung et al. 1999, Daehler and Carino 2000, Gordon et al. 2008, McClay et al. 2010). However, the use of tools that spatially predict invasions are generally lacking in such assessments. Specifically, biosecurity agencies need to be able to spatially predict areas that are at risk from a new or emerging pest. Spatial information provides opportunities to successfully apply phytosanitary measures. The environmental and economic costs associated with the introductions of new invasive plants, combined with exponential increases in the international trade of ornamental plants, exacerbates the need for biosecurity agencies to incorporate spatial predictive tools into the risk analysis tool box (Pheloung et al. 1999, Zalba et al. 2000, Brasier 2008, Dehnen-Schmutz et al. 2010, Lindgren 2011).

Ecological Niche Modelling

Spatially predicting the potential geographic distribution of a pest is commonly referred to as ecological niche modelling (Peterson and Cohoon 1999). Ecological niche modelling generally uses the abiotic conditions (e.g., climatic conditions) associated with a known location of a species in one area to predict the potential distribution of that species. There are a variety of modelling approaches that have been used to estimate the ecological niche, including BIOCLIM (Busby 1986), CLIMEX (Sutherst and Maywald 1985; Sutherst et al. 2000), and the Genetic Algorithm for Rule-set Prediction (GARP) (Stockwell and Noble 1992, Stockwell 1997, Stockwell and Peters 1999), see Chapter 4 for a review of these modelling approaches. An objective of this chapter is to evaluate how GARP can be used by biosecurity agencies to predict the potential distribution of a pest, in this case purple loosestrife.

The Genetic Algorithm for Rule-set Production (GARP)

The GARP algorithm is a spatial predictive tool that has been used to model pest distributions (see below). A literature search found no studies examining how GARP might be used in biosecurity decision making. The algorithm has several advantages over other approaches in that it (1) iteratively evaluates and improves on prediction rules used to generate a predictive risk map (Stockwell and Peters 1999); (2) is data-driven, producing informative models that allow parameters to be optimized using errors of omission and commission (Peterson and Cohoon 1999, Stockwell and Peterson 2002); (3) has been used by a wide variety of practitioners across a number of disciplines (see examples below); (4) is predictive in that it anticipates a pest's distribution in geographic

areas where distribution information is lacking (Peterson 2001); (5) is a superset of other modelling approaches, providing greater predictive ability than any one individual approach (Peterson 2001); and (6) is freely available. Free access is critical, as it allows practitioners to conduct modelling exercises that support biosecurity decisions without the prohibitive costs associated with similar approaches. In addition, access allows others to critically scrutinize risk maps produced by others rather than just being presented with results that they cannot replicate (Kriticos and Randall 2001). Free access is particularly important, for example, for countries that are signatory to the International Plant Pest Convention (IPPC) and have obligations to conduct science-based risk assessments. However, there may be countries that do not have the resources to purchase and update expensive modelling software. The primary advantage of GARP over other spatial modelling approaches is that it is superset of other modelling approaches that provides greater predictive ability than any one individual approach (Peterson 2001).

The algorithm has been used across a wide range of disciplines to successfully spatially predict species distributions (Madsen 1999, Daehler and Carino 2000, Peterson 2001, Anderson et al. 2002, Welk et al. 2002, Ganeshaih et al. 2003, Peterson and Robins 2003, Oberhauser and Peterson 2003, Peterson et al. 2003, Levine et al. 2004, Welk 2004, Adjemian et al. 2006, Tadesse et al. 2006, Kerns et al. 2009). It has been used to predict spatial distributions of invasive plants such as garlic mustard (*Alliaria petiolata*), Russian olive (*Elaeagnus angustifolia*), hydrilla (*Hydrilla verticillata*) and sericea lespedeza (*Lespedeza cuneata*) (Welk et al. 2002, Peterson et al. 2003). Despite its successful use and proven ability to produce useful spatial predictive models across a

number of pest taxa, surprisingly GARP has not been used by biosecurity agencies in their risk analysis frameworks (Lindgren 2011).

Selecting Predictive Variables

In developing an ecological niche model, the choice of predictive variables affects the final risk model and how robust it will be. When models perform well, it is generally because predictor variables that are associated with habitat suitability have been selected. When models do not perform well, it suggests that meaningful predictor variables were not selected (Evangelista et al. 2008). It would be of value to know which predictor variables determine a species' distribution; however, such knowledge is generally lacking (Jimenez-Valverde et al. 2011). Hence, an objective of this chapter is to determine which of suites of predictive variables produced the most realistic ecological niche models for purple loosestrife.

There are many variables that determine a species geographic distribution, but it is likely that climate, topography, and growing degree-days are the primary variables constraining the distribution of purple loosestrife in the Prairie Canada. In this chapter, climate (i.e., temperature and precipitation) was explored as a predictive variable as it is known to be principal variable in determining species distribution (Andrewartha and Birch 1954, Peterson and Cohoon 1999, Welk et al. 2002, Pearson and Dawson 2003, Welk 2004, Helaouet and Beaugrand 2009, Kearney and Porter 2009). Climate variables were also explored as they have been found to be a determining factor in the distribution of invasive plants including kudzu (*Pueraria lobata*) (Follak 2011) and purple loosestrife (Bella 2009).

In addition to climatic variables, growing degree-days (a thermal measure associated with air temperature) (GDD's) was explored as a predictive variable. It is considered a spatially dynamic variable (Hassan et al. 2000; Jodoin et al. 2008; Hassan and Bourque 2009) that is known to constrain the distribution of purple loosestrife (Lindgren and Walker 2012) and is a driver of species' distributions (Austin et al. 2006). In Chapter 5, I created a new GDD's raster layer specific to purple loosestrife. In this chapter, I used this new raster layer as a GARP input in developing a spatial predictive model.

I also explored the influence of topographic variables as they have been reported to be important variables constraining species distributions (Kearney and Porter 2009) as well as being correlated with distributions of wetland plants (Welk 2004). Climate, topography, and GDD's are also landscape-scale variables which are meaningful in assessing distributions at large spatial scales (Peterson et al. 2011), such as the Prairie Canada.

Geographic Partitioning of Data

Evaluating the performance of ecological niche models also involves partitioning spatial data into either testing or training datasets. The partitioning of occurrence points has important modelling implications and should be dependent on the application (Fielding and Bell 1997). Hence, the way in which the data are partitioned needs to be carefully considered (Fielding and Bell 1997, Peterson and Shaw 2003). Models developed using all available occurrence data will perform better than those based upon a smaller subset of the available data, however, measures of predictive accuracy require an independent testing dataset that is withheld entirely from model training (Fielding and

Bell 1997). In developing an independent testing dataset, data can be partitioned in a variety of ways including dividing the study area into different geographic regions where data from one region is used to test models from another region (Osborne and Suarez-Seoane 2002, Peterson and Shaw 2003, Heikkinen et al. 2007, Peterson et al. 2007, Syartinilia and Tsuyuki 2008, Peterson et al. 2008). Partitioning data geographically challenges the accuracy of a model to predict areas outside the training dataset range (Osborne and Suarez-Seoane 2002, Peterson and Shaw 2003). Data can be partitioning in a variety of ways including at large country level scales by random sampling (Osborne and Suarez-Seoane 2002), by stratified random sampling (Hirzel and Guisan 2002), or by administrative boundaries (Kapetsky et al. 1988). How to partition data to optimize modelling results is a challenge facing modelling practitioners.

In this chapter, I explored the use of two approaches to data partitioning in testing the predictive power of our GARP models: (1) stratified random sampling, in which the data were partitioned by province; and (2) a quintile approach, in which the data were partitioned into five regions of equal size. Partitioning data using these approaches forces the model to predict into broad, unsampled areas from which no input occurrence points are available (Peterson and Shaw 2003, Peterson et al. 2007). Partitioning the testing and training data using a stratified random sampling approach simulated a scenario whereby sampling effort might be planned through provincial survey efforts, with specific administrative boundaries. Both partitioning methods allowed for realistic model evaluation, as the majority of the evaluation area is limited to areas into which purple loosestrife might disperse and hence should reduce overall errors of commission in the model (Peterson et al. 2011).

Objectives

The objectives of this chapter are (1) to determine if GARP can be successfully extended and used as a biosecurity risk analysis tool, in this case, to spatially predict the potential distribution of purple loosestrife; (2) to determine which suites of predictive variables (i.e., climatic, topography, GDD's, or combinations of these) produced the best predictive model based on performance measures and expert knowledge; (3) to determine which geographic sub-setting method (i.e., quintile or stratified random sampling) was most useful in producing risk models; and (4) to determine how the information can be applied in biosecurity decision making.

6.2 Materials and Methods

Study Area

The study area covers an area of 360,000 km² and includes the Canadian provinces of Manitoba, Saskatchewan and Alberta; it will hereafter be referred to as Prairie Canada. It is approximately 600 km in length and 1,200 km in width and extends from the Rocky Mountains of western Alberta to the Canadian Shield in eastern Manitoba, and its southern border is the United States. The study area is largely comprised of three terrestrial ecozones, the Prairie, Boreal Plains and Boreal Shield.

The study area, or spatial extent, was selected as it has both biological and regulatory relevance. Biologically, purple loosestrife should be able to disperse into most areas of the study area, the spatial extent of the study area represents accessible area, an important consideration often overlooked in modelling studies (Anderson and Raza 2010, Barve et al. 2011, Peterson 2011). Additionally, all occurrence point data are

known to be accurate, which is not common in spatial modelling studies. The study area reflects geographic space whereby purple loosestrife has established and biologically may extend its range based upon abiotic, biotic, and accessibility factors (see Peterson 2011). From a regulatory perspective, the study area allows for the regional application of international biosecurity concepts.

Field Data

One of the challenges of spatial predictive modelling is obtaining accurate data as the quality and quantity of occurrence point data directly influences the reliability of predictive distributional modeling efforts (Welk 2004, Elith et al. 2006, Yemshanov et al. 2010). Occurrence point data for invasive species are rarely available resulting in risk maps that are built on imprecise data or ill-defined model assumptions leading to general misconceptions on risk levels (Elith et al. 2006, Yemshanov et al. 2010). In this study, I used field collected data that were part of a long-term monitoring study. The availability of a long-term database containing validated spatial data that characterizes the biogeography of any invasive is uncommon. I obtained 631 geo-referenced occurrence points for the study area. Manitoba occurrence data (i.e., site records) were collected between 1992 and 2004 (Lindgren 2003), and the remaining validated data were collected by the Saskatchewan Purple Loosestrife Eradication Project (Sumners 2005) and the Alberta Purple Loosestrife program (Ali and Verbeek 1999, Cole et al. 2007). Models were developed using presence only data (GARP generates pseudo-absence points in model development), and no occurrence data from garden plantings, herbaria,

or museums were included in the dataset. No occurrence data from garden plantings were included in this study.

Model Building

The GARP algorithm was used to model the potential distribution of purple loosestrife across Prairie Canada. Occurrence points were divided 50% into training data and 50% testing datasets by GARP. In producing each GARP model, optimization parameters were set to 100 runs (i.e., each run produced a unique model) or a convergence limit 0.01 with the number of maximum iterations set to 1000.

For each task, atomic, range, negated range, and logistic regression rule sets were selected. The algorithm selects a rule-set method and applies it to the training data to develop a rule. Rules then evolve through an iterative process to maximize predictivity where each change in predictive accuracy from one iteration to the next is used to determine if the specific rule should be incorporated (Peterson et al. 2007). Predictive accuracy is evaluated based upon 1,250 points resampled from the test data and 1,250 pseudo-absence points from the Prairies (Peterson and Shaw 2003). Each rule-set represents a different method of characterising the ecological niche. GARP creates pseudo-absence points by resampling from points within Prairie Canada where the species where there are no known occurrence points.

As each the 100 optimal models produce were unique and varied in quality, a best subset of 10 models was selected and summed to create a final composite model using procedures developed by Anderson et al. (2003). The best subset approach forces GARP to be more general and minimize over fitting (Peterson et al. 2008). Errors of

omission (i.e., model does not predict known occurrence points or leaves out true potential distributional areas) and commission (i.e., model includes areas not potentially suitable) (Peterson et al. 2007) were used in the selection of final models. The best subset was then selected from the zero omission models using a commission index (i.e., which was the pixels predicted present/all pixels). The best subset procedure prioritizes omission error over commission error as the latter can represent true overprediction. Extrinsic omission threshold was set at 10% so that models with greater than 10% of testing points omitted by the models were excluded from the final model. Using extrinsic training data, the median commission index across models with the lowest omission errors was calculated, and the models with indices closest to the commission median were chosen as the best subset. Commission threshold was set at 50%. Risk models were classified into six categories of probable risk 0, < 25%, 26-50%, 51-75%, 76-99% and 100% (i.e., all 10 models agreed).

Predictive Variables

In this study growing degree-days, a suite of climatic variables (mean daily temperature, mean annual diurnal temperature, mean annual precipitation, and mean annual number of wet days), and a suite of topographic variables (elevation, slope, and aspect) as the predictive variables. To explore the influence of the predictive variables on predictive accuracy, I ran GARP models with each variable alone (i.e., first order models) as well as with all possible combinations of the variables (i.e., second and third order models).

I was unable to find growing degree-days data that were specific to purple loosestrife, so I created a new predictive layer using a T_{base} of 8°C , which is a threshold temperature specific to purple loosestrife growth (Shamsi and Whitehead 1974). To calculate growing degree-days (GDD's), the following equations were used: $\text{GDD}_{\text{daily}} = (T_{\text{max}} + T_{\text{min}}) / 2 - T_{\text{base}}$, and cumulative GDD's = $\sum \text{GDD}_{\text{daily}}$, where T_{max} is the maximum daily temperature, T_{min} is the minimum daily temperature, and T_{base} is the base temperature where growth and development are not deemed to occur (McMaster and Wilhelm 1997, Miller et al. 2001, Lawson et al. 2006, Shrestha et al. 2010). Cumulative growing degree-days were calculated by summing those daily growing degree-days that were above 0°C . Temperature data from 48 weather stations that covered the geographic extent of the Prairies were used to interpolate a GDD's surface. Data were imported into an Excel spreadsheet to process cumulative growing degree-days. Methods used to interpolate the GDD's surface are found in Chapter 6.

Digital raster GIS datasets for climate and topography predictor variables were obtained from the Intergovernmental Panel on Climate Change (Intergovernmental Panel on Climate Change 2001). Data were sampled at a pixel resolution of $0.2^{\circ} \times 0.2^{\circ}$ or about 20×20 km grid. A study area mask of the Prairies was created to prevent GARP from selecting pseudo-absence data from areas where purple loosestrife was absent for possible abiotic or dispersal reasons. The mask forced models to be trained in the geographic area of interest (see Barve et al. 2011 and Peterson et al. 2011 for a discussion). In addition, it prevents GARP from selecting pseudoabsence data from areas from which the purple loosestrife is absent for biotic or dispersal reasons (Peterson et al. 2011).

Selecting Predictor Variables

An objective of this study was to determine which predictive layer (e.g., topography, climate, GDD's or combinations of these) produced the best spatial risk model. Digital raster GIS datasets were used to describe topography, climate and as well as a kriged GDD's surface. Raster grids for climate and topography predictor variables were obtained from the Intergovernmental Panel on Climate Change (IPCC 2001) (Table 6.1). Climate layers included mean annual diurnal temperature range, mean annual precipitation, and mean annual number of wet days while topography layers included elevation, slope and aspect. Data were sampled at a pixel resolution of $0.2^0 \times 0.2^0$ or about 20 x 20 km grid, and a study area mask was created as required to develop ecological niche models (Figure 6.1). The spatial extent of the study region and selected level of resolution, are consistent with biosecurity decision making in that it is generally made at coarse scales, and it allows for testing which associated coarse scale predictive variables are important in developing risk models.

Table 6.1 Summary of predictor variables used to develop spatial predictive models. Predictor variables were obtained from the Intergovernmental Panel on Climate Change (IPCC, 2001).

Predictor Dataset	Variable	Source
Topography	Elevation	1961-1990 annual average, IPCC
	Slope	1961-1990 annual average, IPCC
	Aspect	1961-1990 annual average, IPCC
Climate	Precipitation	1961-1990 annual average, IPCC
	Mean Temperature	1961-1990 annual average, IPCC
	Diurnal Temperature	1961-1990 annual average, IPCC
Growing degree-days	Number of Wet Days	1961-1990 annual average, IPCC
	Growing degree-days	Lindgren and Walker (2011)

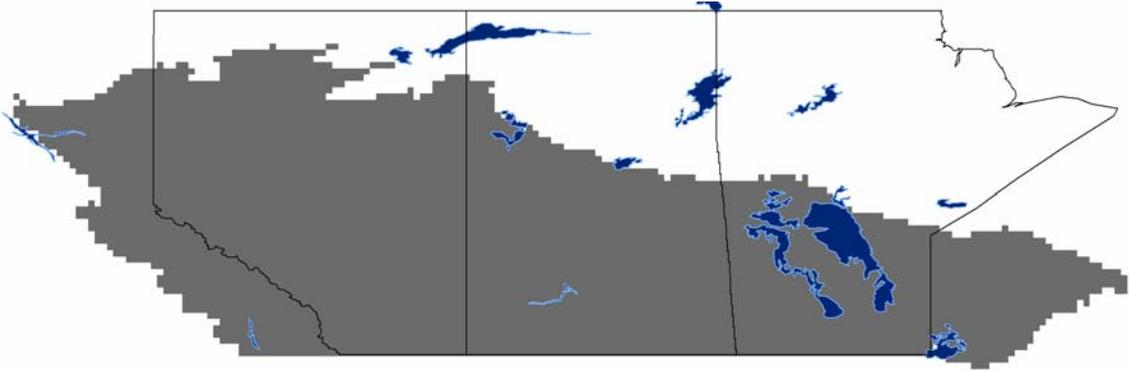


Figure 6.1 A study area project mask was used to develop the ecological niche models. It prevented the algorithm from selecting pseudoabsence data from areas from which the purple loosestrife is absent for biotic or dispersal reasons.

Evaluating Model Performance

Model evaluation is used to identify models that predict into either excessively small or excessively large areas (Raxworthy et al. 2007). As there is no accepted single way to measure model performance (Fielding and Bell 1997, Peterson et al. 2011, Tarkesh and Jetschke 2012) a number of measures as well as expert evaluation was used to evaluate model performance (Table 6.3).

The GARP algorithm produces binary models that allow performance measures to be calculated from elements of a 2×2 confusion matrix (Fielding and Bell 1997, Welk 2004) (Table 6.2). In the confusion matrix “*a*” represented known species localities that are correctly predicted as present by model (i.e., true positive, the model predicts a point as present and it in reality is present); “*b*” represented known absence localities predicted incorrectly as present (i.e., false positive or commission error, the model predicts a point as present and it in reality is absent); “*c*” represented known

species locations that are incorrectly identified as absent by model (i.e., omission error, the model predicts a point as absent when in reality it is present, real modelling error); and “*d*” represented known absence localities that are correctly identified as absent by model (i.e., true negative, model predicts a point as present when in reality it is actually absent).

Table 6.2 Confusion matrix used to measure the accuracy of GARP models.

Purple loosestrife Predicted Occurrence		
	Present	Absent
Actual Present	<i>a</i> True Positive	<i>b</i> False Positive
Actual Absent	<i>c</i> False Negative	<i>d</i> True Negative

Extrinsic accuracy, testing accuracy, sensitivity, specificity, omission error rate, and commission index were used to measure the performance of the models. Sensitivity is the proportion of observed true positives, correctly indicating how good the model is at detecting a pest or an occurrence point (Fielding and Bell 1997). Specificity is the proportion of observed true negatives or absences that are predicted as absent, indicating how good the model is at detecting absences or predicting no presence (Fielding and Bell 1997). The intrinsic omission error is the proportion of known localities that fall outside

the predicted area (i.e., the false negative rate), and the intrinsic commission index (i.e., the false positive rate) is the proportion of pixels predicted as present by the model (Anderson et al. 2003). In general, models with zero or low errors of omission that are sensitive are desired (Peterson et al. 2011). I also measured model accuracy by using independently withheld testing data to calculate the percentage of the number of known occurrence points predicted correctly.

While it is important that practitioners quantitatively evaluate models, the importance of expert evaluation in evaluating models cannot be overlooked (Anderson et al. 2003), and expert evaluation should be incorporated into final model selection methodology (Thuiller 2003). Expert evaluation is required to determine whether the ecological niche model is geospatially realistic and make senses both intuitively and biologically. Expert evaluation has been found to be very informative, for example, in risk analysis frameworks (Pheloung et al. 1999, Therriault and Herborg 2008). In this study, an expert was someone who has both extensive biological knowledge of Purple Loosestrife (i.e., the species) and knowledge of the biogeography of the Prairies (i.e., the study area). This definition of an expert is similar to that of Anderson et al. (2003). Composite models were evaluated as either good or poor. A good model (in this chapter I refer to a good model also as a realistic model) excluded unsuitable areas where Purple Loosestrife could not exist (i.e., high elevations of the Rocky Mountains in Alberta or areas of the Boreal Plains ecozone (Ecological Stratification Working Group 1996) where Purple Loosestrife cannot become established) or disperse (i.e., areas where there would be no known pathways for possible introduction). A poor model was one that included large unsuitable areas (i.e., areas where Purple Loosestrife could not disperse or

become established due to biotic or abiotic events). For example, a good model accurately delimited the current distribution as well as predicting potential distribution into novel areas where expert opinion determined there were suitable abiotic conditions as well as a potential to disperse into these areas.

I also employed an error cost criterion, where errors of omission (i.e., false negatives) were considered to be more costly than errors of commission (i.e., false positives); an error of omission is more serious than an error of commission, as it indicates a model has failed to predict known occurrence points (Raxworthy et al. 2003, Chen et al. 2007, Peterson et al. 2008).

The Kappa statistic (K) is a measure of model accuracy in that it corrects for the overall accuracy of the model predictions by the accuracy expected to occur by chance, it also accounts for both commission and omission errors in one parameter (Liu et al. 2005, Allouche et al. 2006, Zhu et al. 2007). Kappa is calculated from elements of the confusion matrix (Table 6.2) and ranges from +1 which indicates perfect agreement to values less than zero to -1, that indicate performance is no better than random (Fielding and Bell 1997, Allouche et al. 2006). In analyzing performance, a Kappa statistic of $K < 0.4$ indicates poor performance, $0.4 < K < 0.75$ good performance, and $K > 0.75$ excellent performance (Landis and Koch 1977). It has been suggested that Kappa statistic be used with caution as it weights omission and commission errors equally and hence may not be a good measure of model performance for invasive species models where omission errors are considered more serious than commission errors (Guisan and Thuiller 2005, Peterson et al. 2011).

Table 6.3 Measures used to evaluate performance and accuracy of best subset composite models.

Measure	Calculation
Intrinsic Omission error (Performance)	$c / (a + c)$
Intrinsic Commission index (Performance)	$b / (b + d)$
Sensitivity (Performance)	$a / (a + c)$
Specificity (Performance)	$d / (d + b)$
Kappa (Accuracy)	$\frac{(a+d)-((a+c)(a+b)+(b+d)(c+d))/N}{N - ((a+c)(a+b)+(b+d)(c+d))/N}$
Testing Accuracy	$(a + b) / (a + b + c + d)$
Extrinsic Accuracy	$\text{outside model}_{\text{test points}} / N_{\text{test points}}$

Geographic Information Processing

In this study, ArcMap 9.3 (Environmental Systems Research Institute, Redlands, CA, USA) was used to process and analyze the ecological niche models. The 10 best models were imported into ArcMap and converted from ASCII files to raster grid files, and projected onto a map of contiguous prairie Canada. For each of the risk models, GARP predicts purple loosestrife as either present (1) or absent (0). The ArcMap Spatial Analyst tool (i.e., local cell statistics) was used to sum all 10 best subset models together

to create a final composite risk model. Projection of the rule set composite model onto a map of prairie Canada provided a final invasive risk map.

Geographic Partitioning of Data

Two geographic partitioning methods were used to test the predictive power of the ecological niche model using (1) a quintile approach, and (2) a stratified random sample approach (i.e., provincial approach). Both test the models ability to predict into unknown geographic areas based upon data partitioning (Figure 6.2). In the quintile approach, the study area was partitioned into quintiles for model testing and training. Longitude was used to partition the known occurrence data into quintiles of about 4⁰ longitude each. To test the accuracy of the model in predicting across unsampled areas of the study area, we used quintiles A, C, and E to independently test models (number of occurrence points) ($N = 609$) and we used quintiles B and D to train ($N = 22$) GARP models. The quintile test is a rigorous test of the model predictivity, as it forces the model to predict into broad areas from which no input occurrence points are available (Peterson and Shaw 2003, Peterson et al. 2007). In the stratified random sampling approach, occurrence data were first partitioned among the three provincial boundaries, and then about 30% of the data from each province were randomly selected for model testing ($N = 441$ for model training and $N = 190$ for model testing). This partitioning approach simulated a scenario whereby survey data might have been collected provincially through for example a provincially based program with provincial administrative boundaries and survey requirements. Occurrence data are often collected through provincial survey efforts with specific administrative boundaries forming the

bases for regional policy decisions. Both partitioning methods allow for realistic model evaluation as the majority of the evaluation area is limited to areas where purple loosestrife might disperse, and hence should reduce overall model commission errors (Peterson et al. 2011).

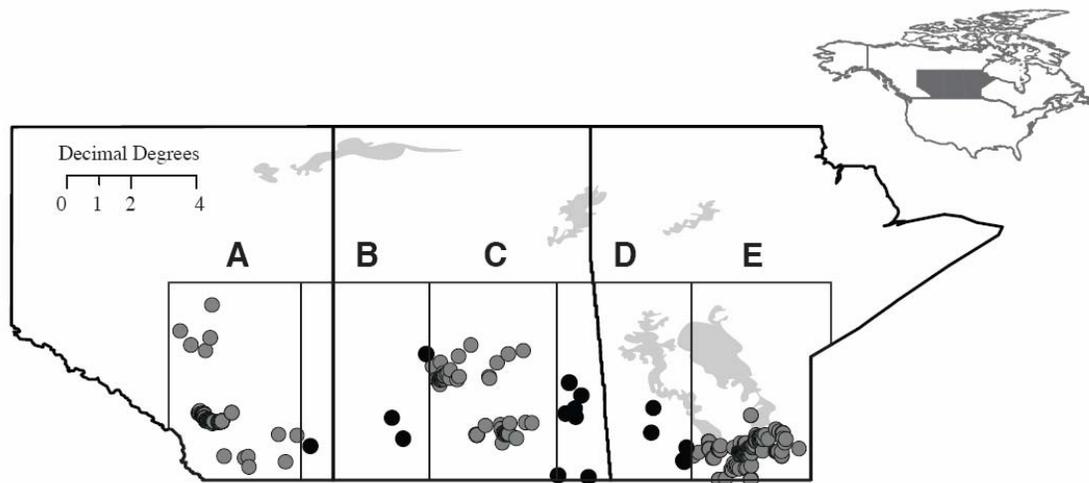


Figure 6.2 Illustration of geographic partitioning used to evaluate model predictivity. The quintile approach is illustrated where inside middle quintiles were used to train models using N=22 (dark circles) occurrence points, and the western, middle, and eastern quintiles were used to test the model N=609 (grey circles).

6.3 Results and Discussion

The results indicated that GARP is a robust tool that can be used by biosecurity agencies for modelling the ecological niche of an emerging pest, in this case purple loosestrife. Although purple loosestrife has been established in Prairie Canada for some time, the GARP models indicated that the risk of further spread in Prairie Canada is significant. Using expert evaluation as the final discriminatory measure, the best overall model used the suite of climate variables and growing degree days as the predictive

variables, and stratified random sampling to partition the data (Figure 6.8). This model had good performance measures, including low omission and commission error (Table 6.4). The potential distribution of purple loosestrife generally followed the extent of the Prairies ecozone. For example, the potential distribution is constrained by the Rocky Mountains in western Alberta, and by the Boreal Plains ecozone in all three provinces. Areas predicted as 100% probable for invasion (e.g., all 10 models agree) follow the 49th parallel across the prairie provinces, then in a pattern north to Strathmore (Alberta), Prince Albert (Saskatchewan), and Yorkton (Saskatchewan), and then east to the south eastern part of Manitoba. The model indicates that there are considerable areas suitable in Prairies Canada for purple loosestrife to continue to expand its distribution.

6.3.1 Geographic partitioning of data

The way in which data was partitioned into training and testing subsets influenced the modelling results. A discussion follows.

Quintile Data Partitioning

Evaluation data for the models developed using the quintile data partitioning approach are found in Table 6.4. Using the performance measures and expert evaluation to assess the quintile models, we determined that the single variable climate model (Figure 6.7) was the best model. The next best model was the three variable model (Figure 6.6), which had good performance and accuracy measures but suffered from errors of omission (i.e., the model failed to predict as suitable areas of central Alberta where there are known established populations). Using the adopted error cost criteria,

whereby omission error was considered to be more serious than commission error (Wiley et al. 2003), the three variable model was also evaluated as poor. The remaining models also had errors of omission (e.g. Figures 6.3, 6.8, and 6.9), errors of commission (e.g., Figures 6.4 and 6.5), and in some cases both (e.g., Figures 6.3, 6.4, 6.5, 6.9), and were hence all evaluated as poor. For example, the topography models and the topography and climate models (Figures 6.4 and 6.5) both predicted potential distributions into northern areas where purple loosestrife would not be expected to establish or disperse.

Stratified Random Sampling Partitioning

Evaluation data for composite models developed using the stratified random sampling partitioning approach are found in Table 6.5. Using the performance measures and expert evaluation, the climate and growing degree-day's model was selected as the best model (Figure 6.8). This model had a low intrinsic commission index, as well as high values for testing accuracy and sensitivity. Expert evaluation determined it was the most realistic model in predicting the potential distribution.

The next best model was determined to be the single variable climate model (Figure 6.7), which had a low commission index and high values for sensitivity and testing accuracy. Expert evaluation determined it to be a good model, but, when it was compared with the climate and growing degree-days model, it overpredicted into areas of north western Alberta where climate conditions as well land use (i.e., boreal forest) would most likely prevent purple loosestrife from becoming established.

The remaining models were evaluated as poor, as they suffered from errors of omission (e.g., 6.3, 6.4, 6.9), errors of commission (e.g., Figure 6.3, 6.4, 6.5, 6.6, 6.9), or

both (e.g., Figure 6.3, 6.4, 6.9). Overall, I concluded that the most realistic models were produced when data were partitioned using a stratified random sampling approach (see expert evaluation discussion below). This approach provided more model training data distributed across the broad Prairie landscape resulting in more realistic models.

6.3.2 Expert evaluation

Expert evaluation was found to be a useful discriminatory measure in selecting the best or most realistic models. Overall, expert evaluation determined that 78% of the models were poor and 22% were good. If the best models were selected using performance measures alone, a different suite of best models would have been selected. Our results demonstrated that a model could have high values for performance measures but could conversely be evaluated by an expert as poor or unrealistic (e.g., Figures 6.5 and 6.7). Modelling practitioners need to incorporate expert evaluation into their evaluation process. In some experiments it may be the case that the modeller has never seen the invasive plant and has no knowledge of the geographic study area, leading to incorrect assumptions and modelling results. Based on the results of this study, a triage approach is recommended to select the best ecological niche model using (1) measures of predictive accuracy, (2) performance measures, and (3) expert evaluation as the final discriminatory measure.

Expert evaluation was also found to be important in evaluating the results of different data partitioning approaches. Both approaches had errors of commission in that they overpredicted into areas of north western Alberta or northern Saskatchewan where purple loosestrife would not be expected to become established or disperse. In this study,

expert evaluation concluded that using stratified random sampling to partition the testing and training data produced more realistic models than the quintile data partitioning approach. This was also supported by performance measures when the independently withheld dataset was used (see Tables 6.4 and 6.5) and the overall mean independent tests of accuracy for the quintile and stratified random sampling approach were 80% and 99%, respectively. The GARP algorithm has been reported to generally have commission errors or to overpredict (Peterson et al. 2007), however, the choice of predictive variables and data partitioning methods will influence the degree of overprediction.

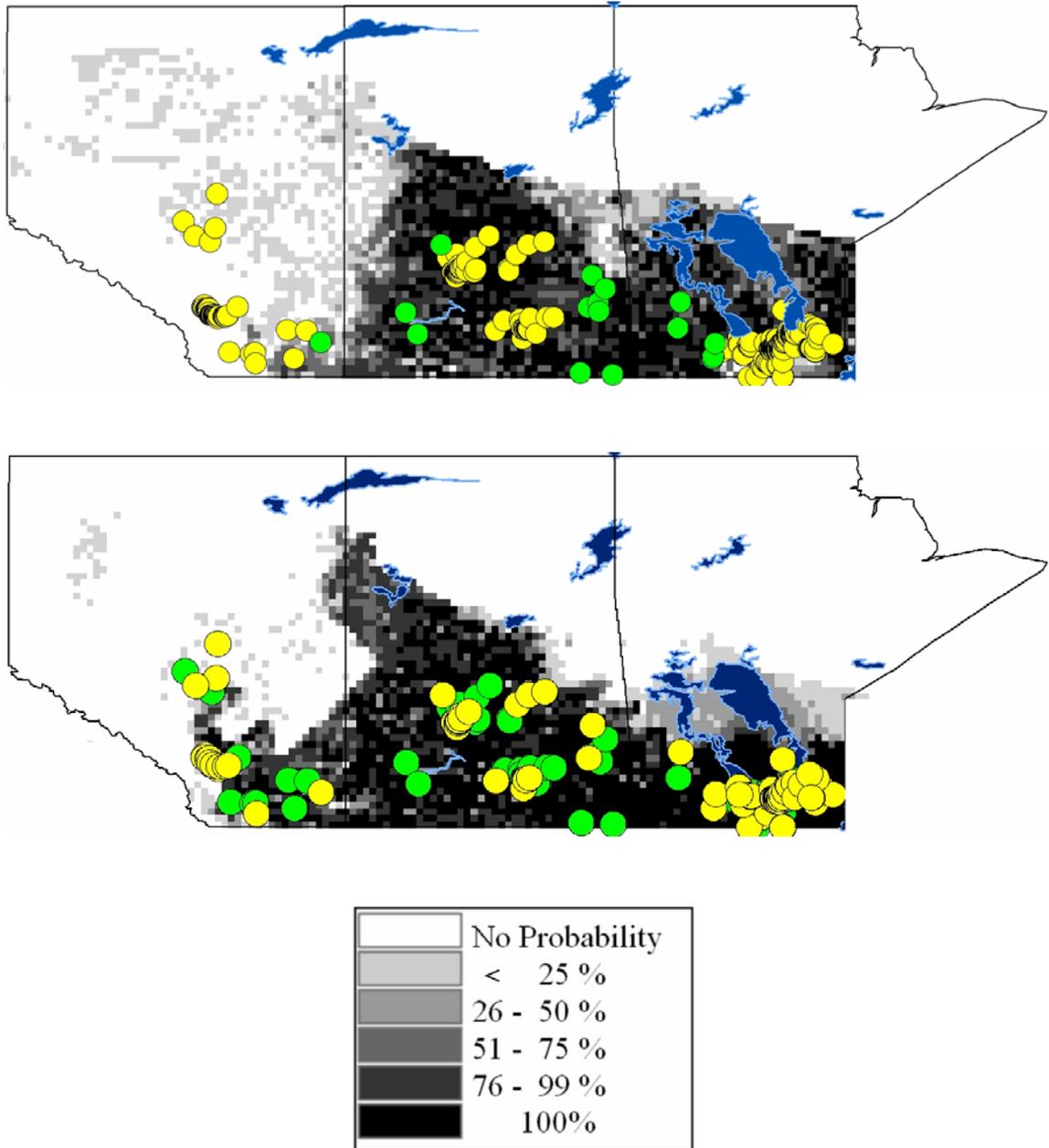


Figure 6.3 Comparing risk maps created using the quintile (above) and provincial (below) approach. Topography and growing degree days were used as the predictive variables. Green circles are occurrence data used to test the model while yellow circles were used to train the model. Major lakes are provided for context in blue.

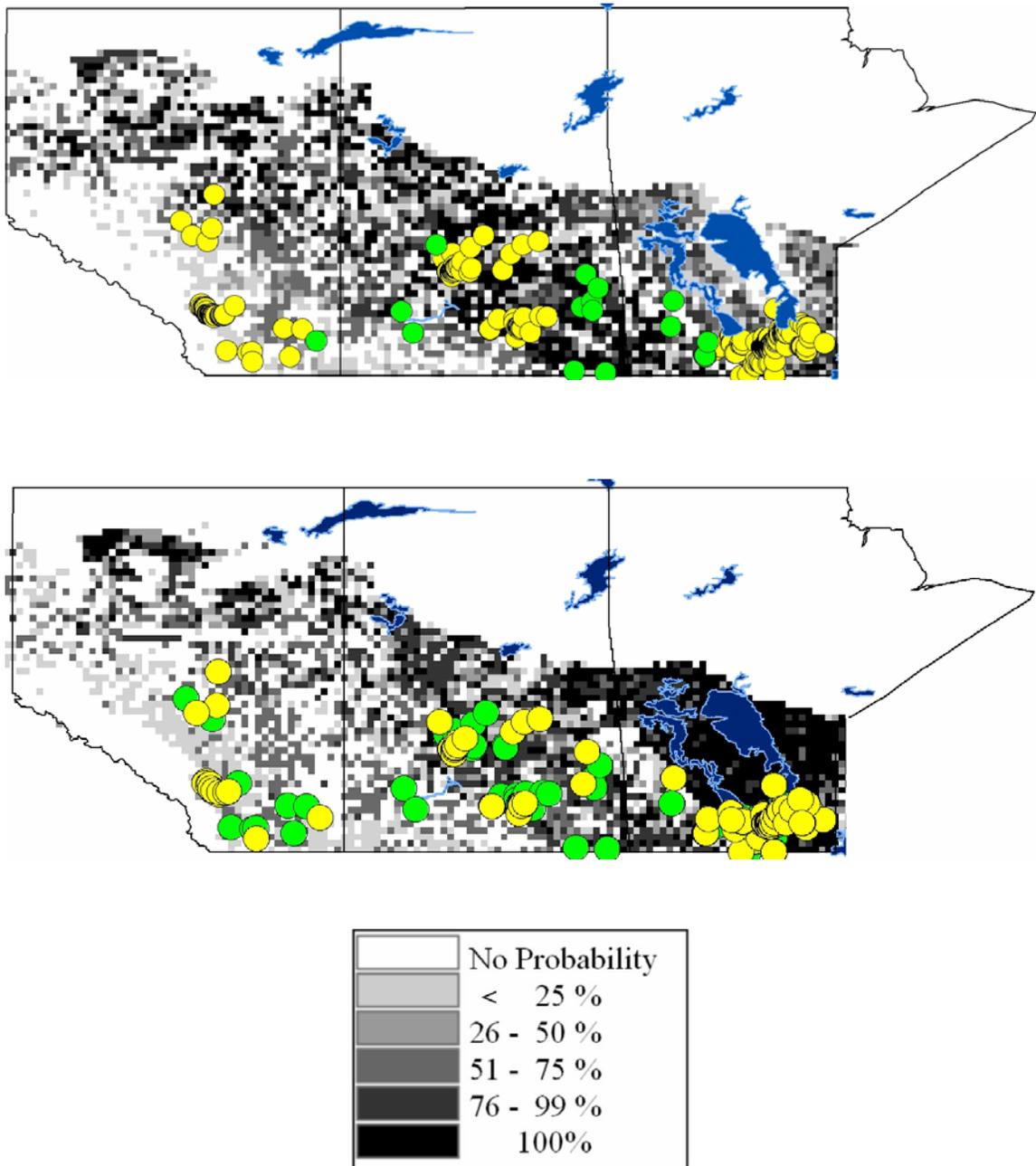


Figure 6.4 Comparing risk maps created using the quintile (above) and provincial (below) approach. Topography was used as the predictive variable. Green circles are occurrence data used to test the model while yellow circles were used to train the model. Major lakes are provided for context in blue.

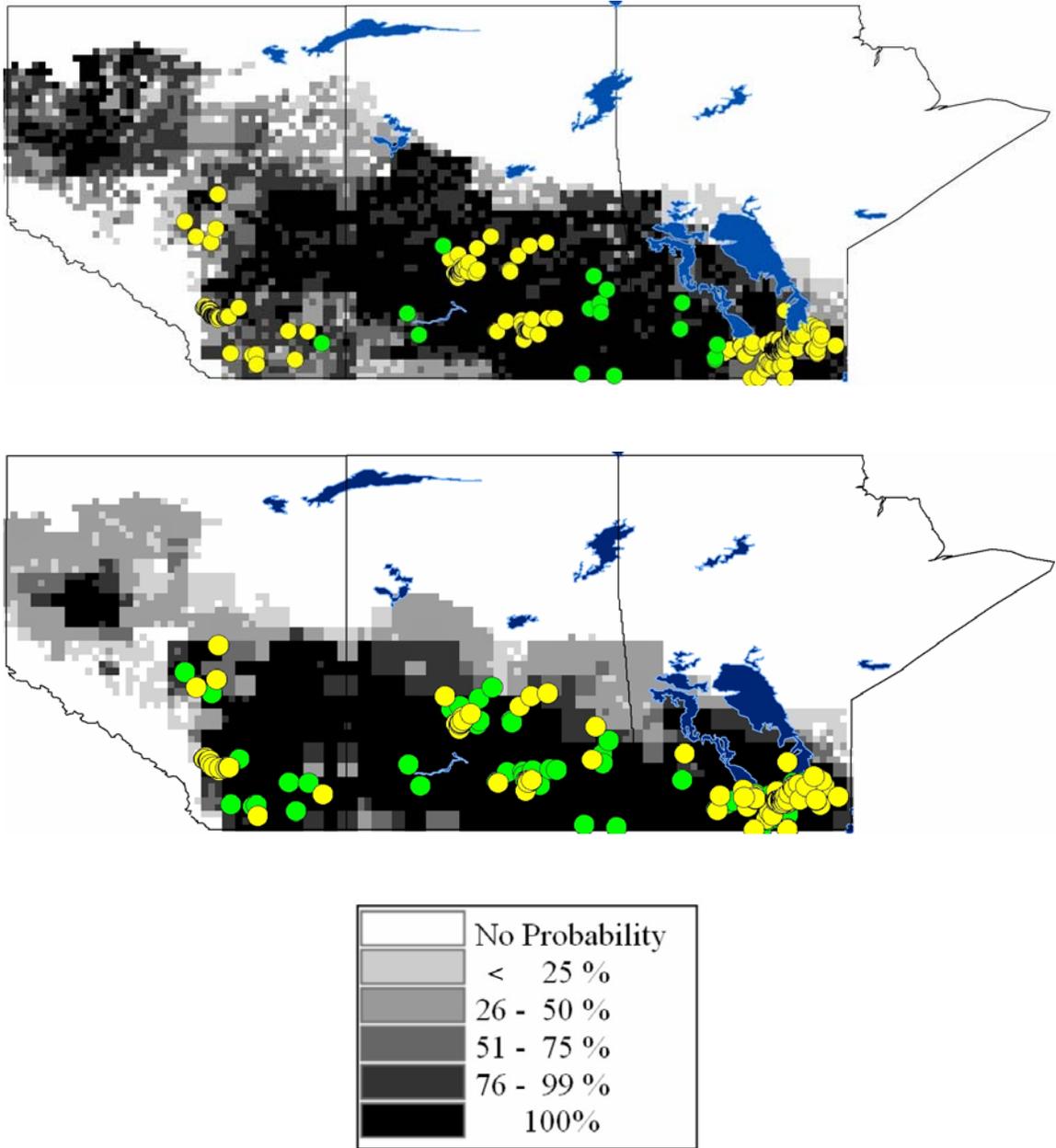


Figure 6.5 Comparing risk maps created using the quintile (above) and provincial (below) approach. Topography and climate were used as the predictive variables. Green circles are occurrence data used to test the model while yellow circles were used to train the model. Major lakes are provided for context in blue.

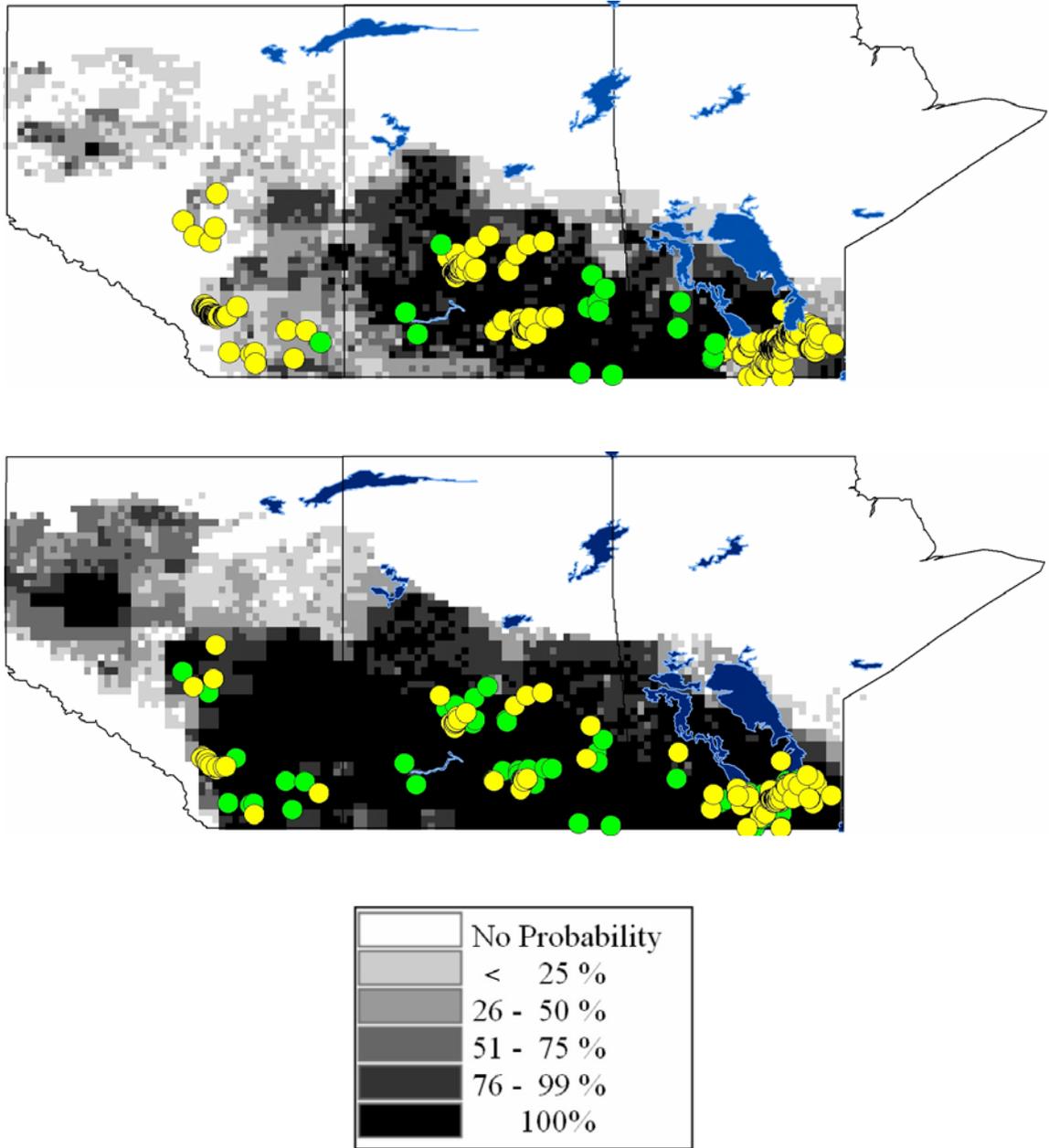


Figure 6.6 Comparing risk maps created using the quintile (above) and provincial (below) approach. Topography, climate and growing degree-day's were used as the predictive variables. Green circles are occurrence data used to test the model while yellow circles were used to train the model. Major lakes are provided for context in blue.

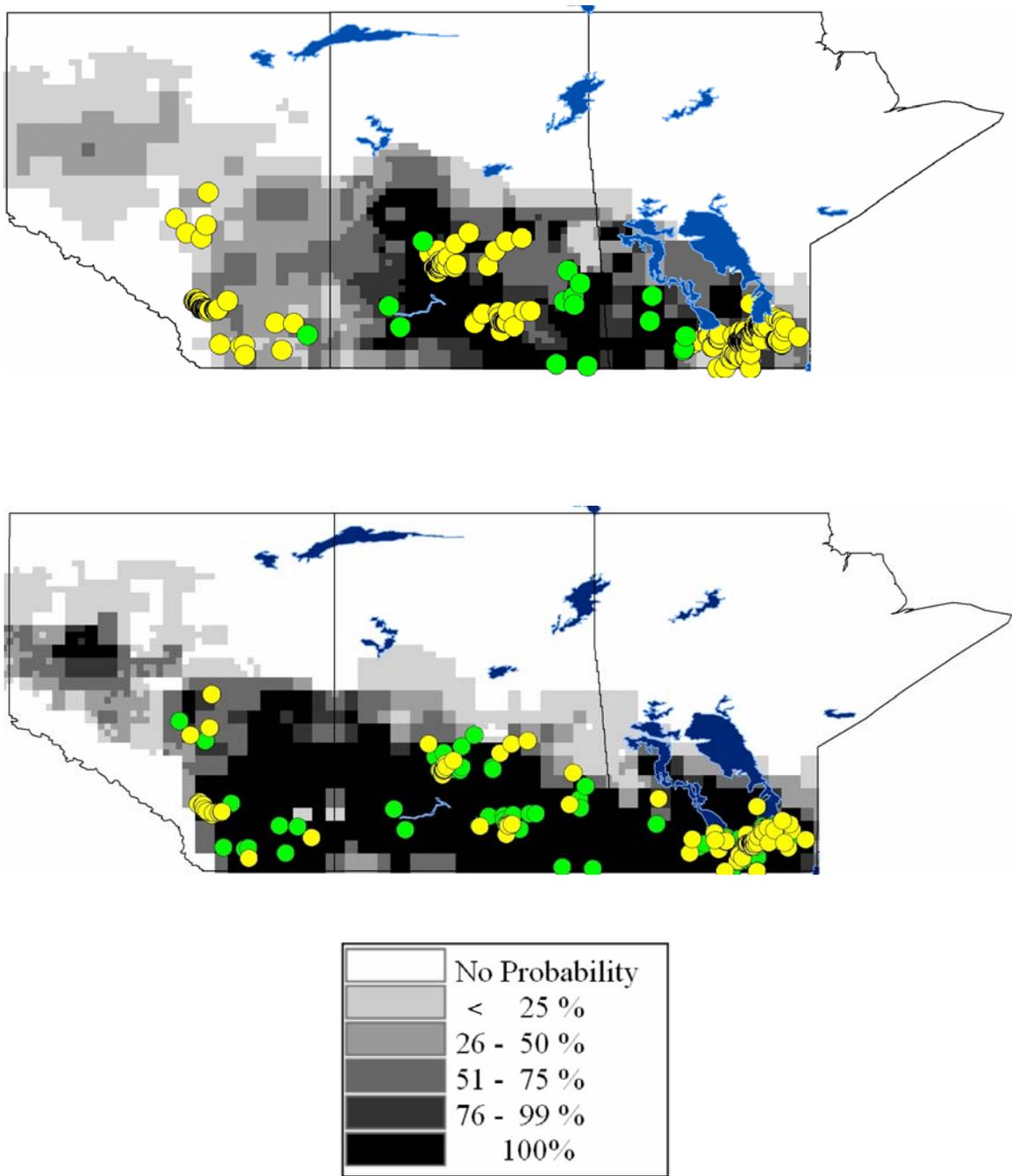


Figure 6.7 Comparing risk maps created using the quintile (above) and provincial (below) approach. Climate was used as the predictive variable. Green circles are occurrence data used to test the model while yellow circles were used to train the model. Major lakes are provided for context in blue.

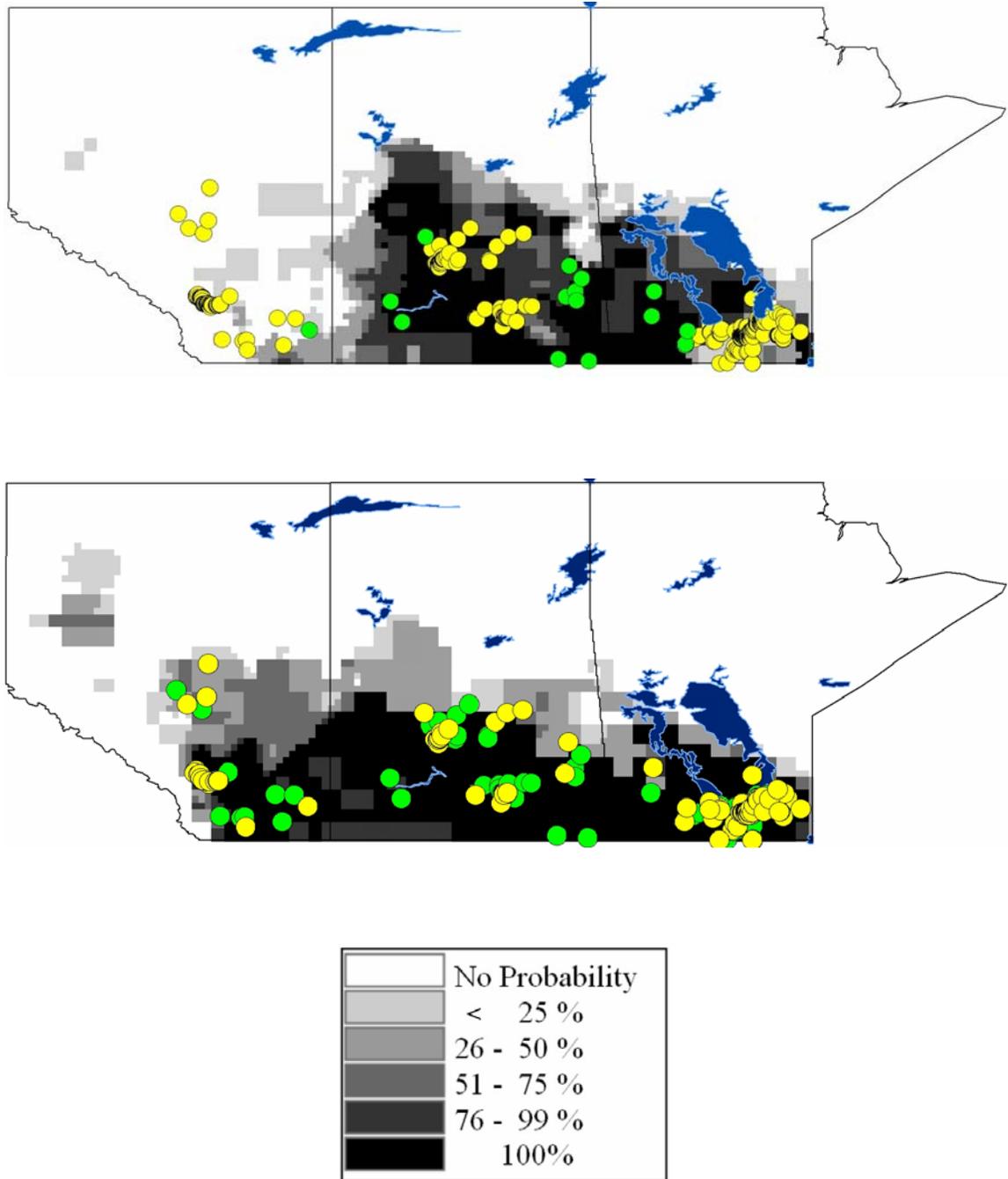


Figure 6.8 Comparing risk maps created using the quintile (above) and provincial (below) approach. Climate and growing degree-day's were used as the predictive variables. Green circles are occurrence data used to test the model while yellow circles were used to train the model. Major lakes are provided for context in blue.

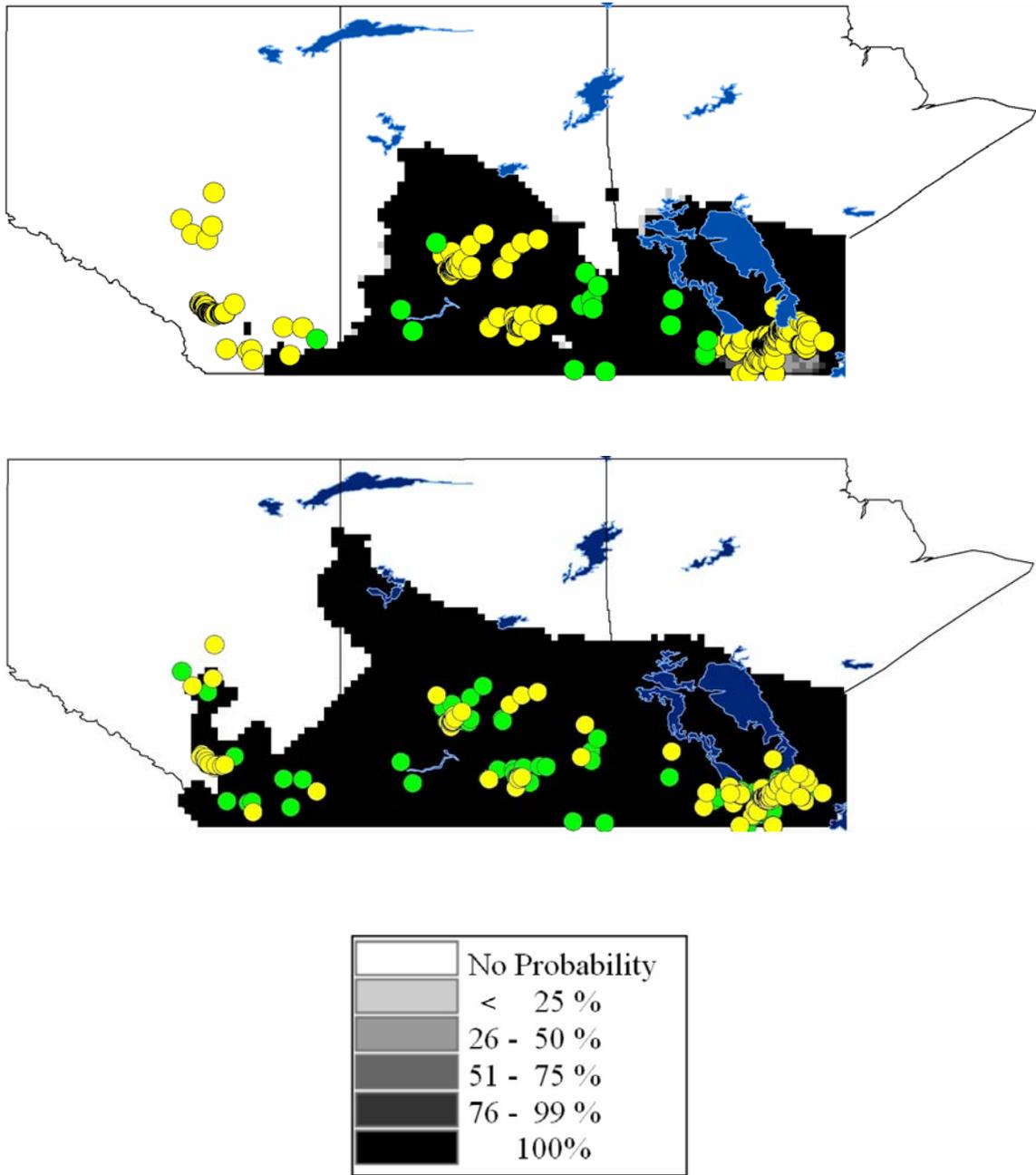


Figure 6.9 Comparing risk maps created using the quintile (above) and provincial (below) approach. Growing degree-day's was used as the predictive variable. Green circles are occurrence data used to test the model while yellow circles were used to train the model. Major lakes are provided for context in blue.

Table 6.4 Measuring model performance using the quintile approach with N=22 model training points. Measures represent mean value for the best subset composite model.

Predictor Dataset	Model Evaluation					Model Error		
	Specificity	Sensitivity	Test Acc	Kappa	ROC Ex_{Eval}	Commission	Omission	
<i>Third Order Model</i>								
Climate+Topo+GDD	69%	97%	59%	0.98	0.66	poor	35%	0%
<i>Second Order Models</i>								
Climate + GDD	25%	90%	73%	0.98	0.57	good	25%	0%
Topo + GDD	34%	78%	71%	0.99	0.67	poor	34%	0%
Topo + Climate	65%	95%	61%	0.98	0.76	good	54%	0%
<i>First Order Models</i>								
Climate	33%	75%	70%	0.85	0.61	good	34%	0%
Topography	35%	70%	67%	0.99	0.55	poor	34%	2%
GDD	44%	100%	77%	0.98	0.71	poor	43%	0%

Table 6.5 Measuring model performance using stratified random sampling (i.e., provincial approach) with N=441 training points. Measures represent mean value for the best subset composite model.

Predictor Dataset	Model Evaluation					Model Error		
	Specificity	Sensitivity	Test Acc	Kappa	ROC Ex_{Eval}	Commission	Omission	
<i>Third Order Model</i>								
Climate+Topo+GDD	56%	96%	69%	0.77	0.57	good	50%	1.7%
<i>Second Order Models</i>								
Climate + GDD	31%	94%	82%	0.83	0.59	good	32%	1.5%
Topo + GDD	42%	92%	74%	0.82	0.61	poor	42%	9.0%
Topo + Climate	32%	92%	73%	0.83	0.61	poor	32%	3.4%
<i>First Order Models</i>								
Climate	25%	89%	79%	0.76	0.59	good	25%	7.0%
Topography	59%	84%	63%	0.79	0.70	poor	58%	10.0%
GDD	58%	99%	70%	0.77	0.80	poor	59%	0.8%

Table 6.6 Predictive accuracy of composite models based using independently withheld test occurrence points. In the provincial approach N=188 occurrence points were withheld, and in the quintile approach N=609 occurrence points were withheld. The number of known occurrence points found outside the risk model is followed by the model accuracy.

	Provincial Approach		Quintile Approach	
	Outside _{test pts}	Accuracy	Outside _{test pts}	Accuracy
<i>Third Order Model</i>				
Climate+Topo+GDD's	0	100%	114	82%
<i>Second Order Models</i>				
GDD's + Topography	1	99%	183	70%
Climate + GDD's	0	100%	185	70%
Topography + Climate	0	100%	0	100%
<i>First Order Models</i>				
GDD's	1	99%	189	69%
Topography	7	97%	188	70%
Climate	0	100%	0	100%

Table 6.7 The number of models and pixels predicted by each predictor variable's final best subset top 10 composite risk model. The "0" column represents the number of pixels predicted as not suitable for purple loosestrife in Prairie Canada.

Approach	Predictor	Number of Models										
		0	1	2	3	4	5	6	7	8	9	10
Provincial	Climate	2607	205	122	233	191	144	209	46	34	127	1312
	Topography	1976	475	214	230	48	86	200	319	211	432	1039
	All Layers	1203	196	288	212	160	167	196	171	234	331	2072
	GDD	2166	0	0	0	0	0	0	0	0	1	3113
	Climate + GDD	2607	205	122	233	191	144	209	46	34	127	1312
	Climate + Topo	1655	324	160	377	308	162	104	118	223	129	1670
	GDD + Topo	2236	301	132	158	88	87	101	138	158	366	1465
Quintile	Climate	1502	178	161	189	177	223	236	228	235	594	1507
	Topography	2101	369	478	256	186	114	203	209	260	401	653
	All Layers	2008	619	343	254	195	130	157	136	209	260	919
	GDD	2909	0	23	22	0	12	6	9	16	0	2233
	Climate + GDD	3012	356	120	87	127	80	66	157	125	412	688
	Climate + Topo	1502	178	161	189	177	223	236	228	235	594	1507
	GDD + Topo	2134	479	186	100	84	99	221	243	423	237	1024

For the best subset climate and GDD's risk model, an evaluation of the relationship between the intrinsic commission index and intrinsic omission error revealed a positive relationship ($R^2 = 0.43$) where omission error increased slightly with increases in commission error (Figure 6.10). The data cloud illustrates that the composite model was comprised of models that were clustered around very low levels of intrinsic omission error and intrinsic commission index.

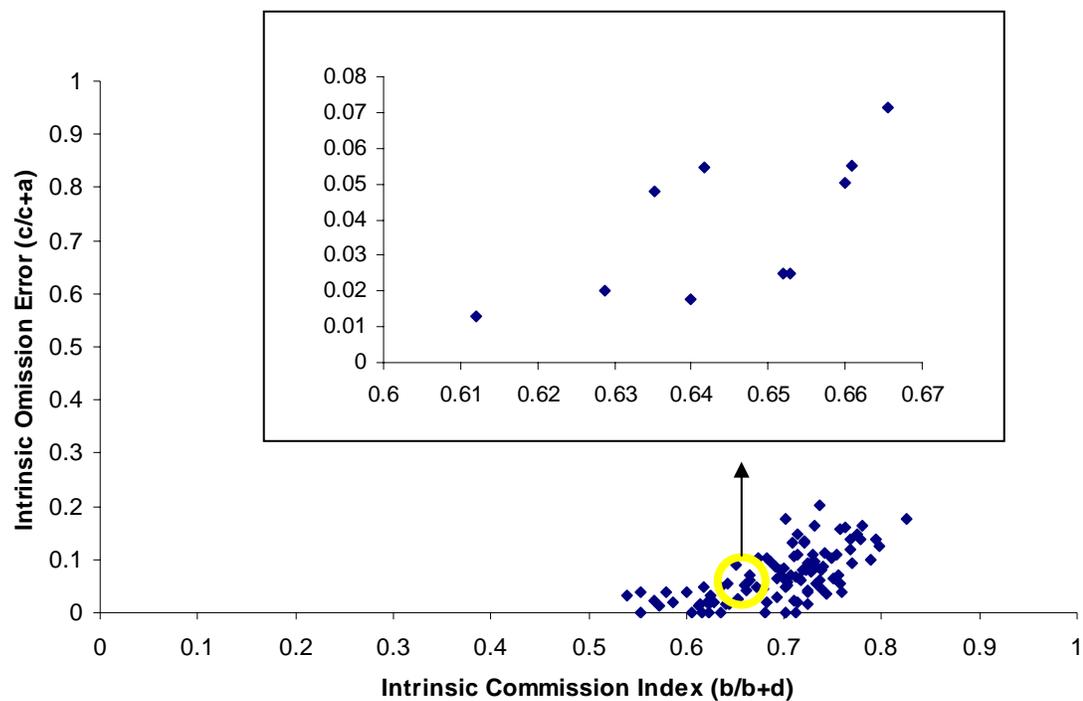


Figure 6.10 Cloud of all 100 climate and GDD's risk models developed using the provincial approach. Plot of the top 10 best model subset inserted. Plot indicates that models reduce omission error while still predicting a reasonable proportion of the study area.

The risk model predicted a geographically disjunct area near Grande Prairie, Alberta, as having suitable habitat for purple loosestrife (Figure 6.11). This area was also

predicted as suitable by models using topography and climate, all layers, and climate alone as predictive variables, and in many of these composite models all 10 models agreed. A kriged GDD's surface as presented in Chapter 5, also predicted the Grande Prairie region as having enough GDD's for purple loosestrife to establish (Lindgren and Walker 2011). This area is about 460 km northwest of Edmonton Alberta, and is surrounded by flat to gently rolling terrain and farmland. As Grande Prairie is a City with a population over 50,000 and most likely garden centers that retail ornamental plants (i.e., dispersal pathway). The long-distance dispersal of purple loosestrife this predicted area is anticipated. The area also has wetlands, reservoirs, and rivers that provide suitable aquatic habitat in the event an ornamental planting escapes. It is recommended that this area of Alberta implement an early detection rapid response (EDRR) program as well as a preventive strategy.

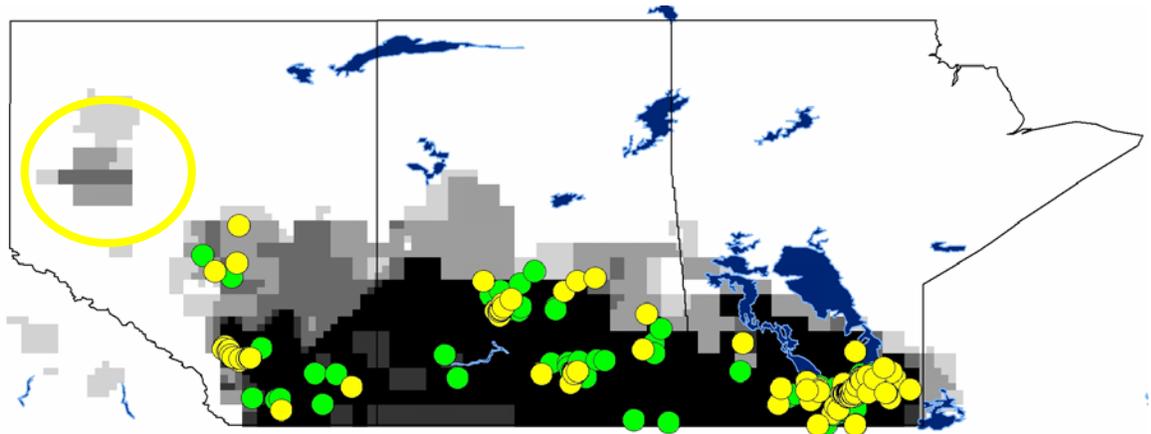


Figure 6.11 The model predicted a geographically disjunct area in north-western Alberta near Grande Prairie (as indicated by yellow circle) as having suitable habitat for invasion. This area was also predicted as suitable area by models using topography and climate, all layers, and climate alone as predictive variables, and in many of these models all 10 models agreed.

6.3.4 Areas at risk - wetlands

The risk model indicated that areas of Prairie Canada, that includes the prairie pothole region, as suitable for further purple loosestrife invasion. These areas are environmentally and economically important. It is recognized that invasive plants such as purple loosestrife have replaced the indigenous vegetation of a substantial portion of inland wetlands of North America (Galatowitsch et al. 1999) impacting nesting waterfowl (Balogh and Bookhout 1989) and waterfowl populations (Thompson et al. 1987). Further loss or degradation of wetland habitat by purple loosestrife, as predicted by the risk model developed in this study, would be detrimental to North America's waterfowl production and wetlands. Wetlands in Prairie Canada are part of the prairie pothole region and recognized as the most productive habitat for waterfowl in the world (Johnson et al. 2005). All the risk models produced in this study predicted the prairie pothole region as suitable area for further purple loosestrife invasions.

6.3.5 Implications for Biosecurity Risk Analyses and Policy

If biosecurity agencies adhere to the precautionary principle, spatial risk models that overpredict (i.e. commission error), rather than underpredict (i.e., omission error) should be preferred. Omission error should be a concern to practitioners as it indicates the model cannot predict known occurrence points (Chen et al. 2006). For example, regulatory decisions based upon models that underpredict potential spatial distributions might have dire economic consequences for biosecurity agencies. Commission error or overpredicting, could also arise from an invasive plant not yet dispersing into all suitable area (Peterson 2003, Jimenez-Valverde et al. 2011). For example, the results of this

study predicted suitable areas in the Grande Prairie region of Alberta where no purple loosestrife is known to occur, the question then becomes is this commission error or has purple loosestrife just not dispersed into this region?

Biosecurity policy depends upon accurate spatial and temporal characterizations of risk (Venette et al. 2010). Hence, it is recommended that GARP and the spatial predictive modelling techniques used in this study be incorporated into biosecurity risk analysis frameworks. Geographic information systems (Jarnevich et al. 2010) and predictive algorithms such as GARP, are tools need to embraced. Biosecurity agencies representing the interests of Governments must prioritize funds towards prevention, eradication or control (Waage and Mumford 2008). This finding indicates biosecurity agencies can use GARP to produce risk models when faced with limited resources and budget, however, the limitations need to be recognized.

Based upon the results of this study, what might be the biosecurity policy decision? A country might restrict or prohibit the import of purple loosestrife if it meets the definition of a quarantine pest. The International Plant Pest Convention (IPPC) defines a quarantine pest as a pest of potential economic importance to the area endangered thereby and not yet present there, or present but not widely distributed and being officially controlled (IPPC 2008). Since purple loosestrife is present in the area (e.g., Canada), a biosecurity agency would then need to determine if purple loosestrife is widely distributed and/or being officially controlled. A pest is considered widely distributed when it is present in an area and has reached the limits of its ecological range (FAO 2005). The risk models developed in this study indicated that purple loosestrife has not reached the limits of its ecological range in prairie Canada, and hence

phytosanitary measures to prevent its spread may be justified. It may also be argued that it is under official control as a classical biological control program has been implemented across prairie Canada. Realistically, biosecurity agencies most likely would not regulate an established plant such as purple loosestrife as it would be considered too widely distributed and generally limited biosecurity resources and priorities are strategically directed towards new pests (i.e., a pest not yet in the country).

Risk models can also be used by biosecurity agencies to develop strategies to avoid introductions of new pests (Peterson and Vieglais 2001). The identification of areas suitable for invasion can guide biosecurity surveillance efforts by geographically directing early detection and rapid response (EDRR) resources (Figure 7.12). Spatial predictive models can be used to direct survey efforts into high risk target areas resulting in savings to limited biosecurity surveillance budgets. The best risk model selected in this study indicates that EDRR efforts should be concentrated in (1) predicted suitable areas in southern Manitoba, Saskatchewan and Alberta along the Canada U.S. border, and (2) in the predicted suitable area near Grande Prairie in Alberta. Biosecurity agencies, provincial governments, weed supervisors, rural municipalities, cities, and conservation districts would be well advised to prepare EDRR programs to prevent further establishment of purple loosestrife into these regions.

6.3.6 Practical applications of the model

Spatial and temporal characterizations of risk or models of potential distribution are required in order to develop strategies to respond to an invasive plant (Venette et al. 2010). Models of potential distribution are very useful in preparing response strategies

for invasive plants, as limited resources can then be prioritized for prevention, eradication, or control strategies (Waage and Mumford 2008). Prevention is the preferred strategy, and predictive models provide the spatial information required to develop response strategies. Therefore, based on the predictive map developed in this study, we make the following recommendations: (1) to prevent Purple Loosestrife from becoming established in areas of the Prairies predicted by the model, authorities should develop regulations to prohibit horticultural sales of Purple Loosestrife (to prevent human-mediated dispersal); (2) provinces should develop regional programs that target either the eradication or the containment of localized populations; and (3) provinces should focus early detection programs on areas predicted as suitable by the model into which Purple Loosestrife has not yet dispersed or where Purple Loosestrife has not yet become established.

The spatial predictive model can be used to optimize early detection programs by identifying high-risk areas for surveillance, leading to efficient allocation of survey resources. For example, the model suggests that early detection efforts should be directed to areas near Grande Prairie, Alberta (i.e., an area predicted by the model as having suitable habitat for Purple Loosestrife but where Purple Loosestrife has not yet become established). A city about 460 km northwest of Edmonton, Grande Prairie has a population of over 50 000, and garden centres there may retail ornamental plants that could provide dispersal pathways. The area also has wetlands, reservoirs, and rivers that would provide suitable aquatic habitat if an ornamental planting of Purple Loosestrife escaped. Early detection strategies should also consider using field naturalists in their survey efforts.

6.3.7 Future research

Biosecurity and quarantine agencies are continually interested in methods that help determine optimal management and regulatory strategies for a pest, and more importantly the transition points between these policy decisions (e.g., when to change from an eradication strategy to a slow the spread strategy). Future research should investigate how to extend the application of GARP as a decision support tool by considering both local and long distance dispersal. Consider the following case. Invasive plants generally disperse through stratified diffusion where the pest spreads through both local growth of the main infestation (i.e., neighbourhood diffusion from a founder population) and growth and dispersal of new infestations ahead of the main infestation successively created by long-distance migrants (Hengeveld 1989, Andow et al. 1993, Bogich and Shea 2008). Bogich and Shea (2008) referred to this type of invasion as a mainland-island metapopulation consisting of a moving mainland population (i.e., the main infestation) and smaller dispersed island populations ahead of the mainland population. Purple loosestrife is spreading across Prairie Canada in an invasion pattern that is consistent with stratified diffusion spreading locally by neighbourhood diffusion well as by human mediated intentional introductions that allow for long-distance dispersal into new areas where it would not disperse by neighbourhood diffusion. It is suggested that future research attempt to model potential spatial distribution by including both local and long-distance dispersal inputs. Long distance dispersal may be predicted on the assumption that garden centers in large urban centers import and sell ornamental purple loosestrife, which will in turn escape from gardens and form new foci

populations. The use of GARP and GIS tools should be further extended to predict spatial distribution based on short and long-distance dispersal events.

6.4 Conclusions

Based on the results of the chapter, it is concluded that GARP is a useful tool that can be successfully used by biosecurity agencies to model the potential distribution of an emerging or invasive pest. The models indicate that although purple loosestrife has been established in the Prairie Canada for some time, there is considerable potential for further invasion. In predicting the potential distribution of an invasive plant, it may be wise to err on the side of caution and accept some reasonable amount of commission error, which may represent geographic space where a purple loosestrife simply has not yet dispersed (Jimenez-Valverde et al. 2011). The general modelling approach employed in this study is illustrated in Figure 6.12. In the next chapter, I will determine if GARP can be extended to model the potential distribution of an invasive plant that has only recently established in Prairie Canada.

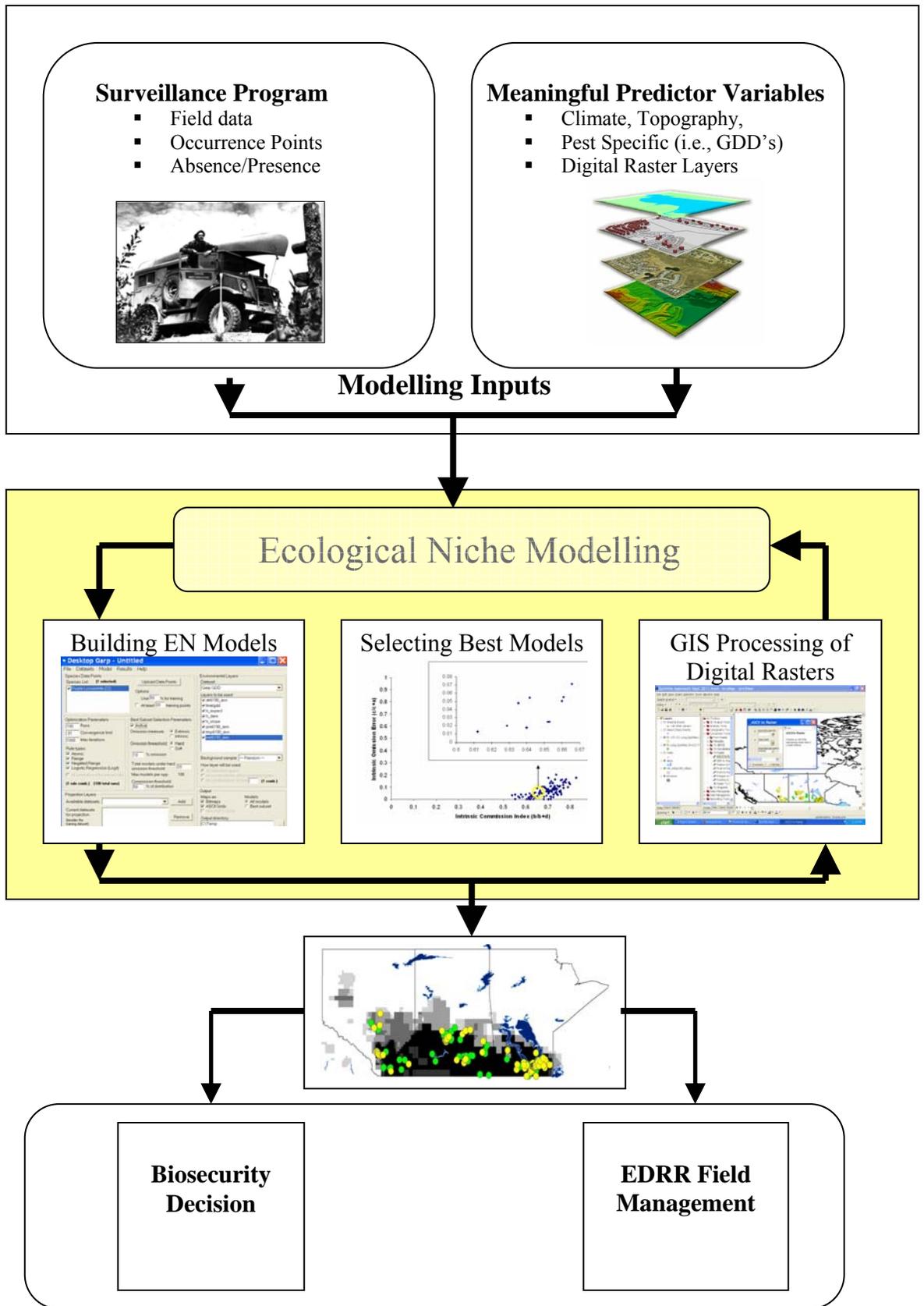


Figure 6.12 Illustration of spatial predictive modelling architecture used in this study.

6.5 References

- Adjemian, J.C., E.H. Girvetz, L. Beckett and J.E. Foley. 2006. Analysis of genetic algorithm for rule-set production (GARP) modeling approach for predicting distributions of fleas implicated as vectors of plague, *Yersinia pestis*, in California. *J. of Medical Entomology* 43:93-103.
- Andrewarth, H.G. and L.E. Birch. 1954. *The Distribution and Abundance of Animals*. University of Chicago Press, Chicago, 782 pp.
- Ali, S. and C. Verbeek. 1999. *The Alberta Purple Loosestrife Eradication Program 1999 Status Report*. Alberta Agriculture, Food and Rural Development, Edmonton, Alberta.
- Allouche, O., A. Tsor and R. Kadmon. 2006. Assessing the accuracy of species distribution models: prevalence, kappa and the true sill statistic (TSS). *Journal of Applied Ecology* 43:1223-1232.
- Anderson, R.P., A.T. Peterson and S.L. Egbert. 2006. Vegetation-index models predict areas vulnerable to purple loosestrife (*Lythrum salicaria*) invasion in Kansas. *The Southwestern Naturalist* 51:471-480.
- Anderson, R.P., M. Gomez-Laverde and A.T. Peterson. 2002. Geographical distributions of spiny pocket mice in South America: insights from predictive models. *Global Ecology and Biogeography* 11:131-141.
- Anderson, R.P., D. Lew and A.T. Peterson, A.T. 2003. Evaluating predictive models of species' distributions: criteria for selecting optimal models. *Ecol. Model.* 162:211-232.

- ArcGIS 9.3. Environmental Systems Research Institute, Inc., Redlands, CA.
- Austin, M.P., L. Belbin, J.A. Meyers, M.D. Doherty and M. Luoto. Evaluation of statistical models for predicting plant species distributions: Role of artificial data and theory. *Ecological Modelling* 199:197-216.
- Barve, N., V. Barve, A. Jimenez-Valverde, A. Lira-Noriega, S.P. Maher, A.T. Peterson, J. Soberon and F. Villalobos. 2011. The crucial role of the accessible area in ecological niche modeling and species distribution modeling. *Ecological Modelling* 222:1810-1819.
- Balogh, G.R. and T.A. Bookhout. 1989. Purple loosestrife (*Lythrum salicaria*) in Ohio's Lake Erie Marshes. *Ohio J. Science* 89:62-64.
- Bean, W.T., R. Stafford and J.S. Brashers. 2011. The effects of small sample size and sample data bias on threshold selection and accuracy assessment of species distribution models. *Ecography* 34:1-9.
- Bradley, B.A., Oppenheimer, M. and S.A. Wilcove. 2009. Climate change and plant invasions: restoration opportunities ahead? *Global Change Biology* 15:1511-1521.
- Brasier, C.M. 2008. The biosecurity threat to the UK and global environment from international trade in plants. *Plant Pathology* 57:792-808.
- CFIA (Canadian Food Inspection Agency). 2008. Invasive Alien Plants in Canada Summary Report. Canadian Food Inspection Agency, Ottawa, ON.
- Chen, P., E.O. Wiley, and K.M. Mcnysset. 2007. Ecological niche modeling as a predictive tool: silver and bighead carps in North America. *Biological Invasions* 9:43-51.
- Chen, X. and Y. Lei. 2012. Effects of sample size on accuracy and stability of species

- distribution models: a comparison of GARP and Maxent. *Lecture Notes in Electrical Engineering* 125:601-609.
- Cousins, R.D., R.W. Brown, A.B. McBratney, B. Whelan and M. Moerkerk. 2002. Sampling strategy is important for producing weeds maps: a case study using kriging. *Weed Science* 50:542-546.
- Daehler, C.C. and D.A. Carino. 2000. Predicting invasive plants: prospects for a general screening system based on current regional models. *Biological Invasions* 2:93-102.
- Dehnen-Schmutz, K., O. Holdenrieder, M.J. Jegar and M. Pautasso. 2010. Structural change in the international horticultural industry: some implications for plant health. *Scientia Horticulturae* 125:1-15.
- Elith, J. and C.H. Graham. 2009. Do they? How do they? WHY do they differ? On finding reasons for differing performances of species distribution models. *Ecography* 32:66-77.
- Elith, J., Graham, C., Anderson, R., Dudik, M., Ferrier, S., Guisan, A., Hijmans, R., Huettmann, F., Leathwick, R., Lehmann, A., Lucia, J., Lohman, G., Loiselle, B., Manion, G., Moritz, C., Nakamura, M., Nakazawa, Y., Overton, J., Townsend Peterson, A., Phillops, S., Richardson, K., Scachetti-Pereira, R., Schapire, E., Soberon, J., Williams, S., M. Wisz and N.E. Zimmerman. 2006. Novel methods improve prediction of species distributions from occurrence data. *Ecography* 29:129-151.
- Evangelista, P.H., S. Kumar, T.J. Stohlgren, C.S. Jarvevich, A.W. Crall, J.B. Norman III, and D.T. Barnett. 2008. Modelling invasion for a habitat generalist and a specialist plant species. *Diversity and Distributions* 14:808-817.

- Follak, S. 2011. Potential distribution and environmental threat of *Pueraria lobata*.
Central European Journal of Biology 6:457-469.
- Fielding, A.H. and J.F. Bell. 1997. A review of methods for the assessment of prediction errors in conservation presence/absence models. Environmental Conservation 24:38-49.
- Gaudet, C.L. and P.A. Keddy. 1988. A comparative approach to predicting competitive ability from plant traits. Nature 334:242-243.
- Gaudet, C.L. and P.A. Keddy. 1995. Competitive performance and species distribution in shoreline plant communities: a comparative approach. Ecology 76:280-291.
- Galatowitsch, S.M., Anderson, N.O. and Ascher, P.D. 1999. Invasiveness in wetland plants in temperate North America. Wetlands 19:733-755.
- Ganeshiah, K.N, N. Barve, N. Nath, K. Chandrashekara, M. Swamy and R. Shaanker. 2003. Predicting the potential geographic distribution of the sugarcane woolly aphid using GARP and DIVA-GIS. Current Science 85:1526-1528.
- Gordon, D.R., D.A. Onderdonk, A.M. Fox, R.K. Stocker and C. Gantz. Predicting invasive plants in Florida using the Australian weed risk assessment. Invasive Plant Science and Management 1:178-195.
- Government of Alberta. 2009. Control of Purple Loosestrife in Alberta. Viewed August 7 2009. Agriculture and Rural Development.
- Guisan, A. and W. Thuiller. 2005. Predicting species distributions: offering more than simple habitat models. Ecological Letters 8:993-1009.
- Hassan, Q., C. Bourque, F. Meng and W. Richards. 2007. Spatial mapping of growing degree days: an application of MODIS-based surface temperatures and enhanced

- vegetation index. *Journal of Applied Remote Sensing* 1:1-12.
- Hassan, Q. and C. Bourque. 2009. Potential species distribution of Balsam Fir based on the integration of biophysical variables derived with remote sensing and process-based methods. *Remote Sensing* 1:393-407.
- Helaouet, P. and G. Beaugrand. 2009. Physiology, ecological niches and species distributions. *Ecosystems* 8:1235-1245.
- Herborg, L.M, C.L. Jerde, D.M. Lodge, G.M. Ruiz and H.J. MacIsaac. 2007. Predicting invasion risk using measures of introduction effort and environmental niche models. *Ecological Applications* 17:663-674.
- Hernandez, P.A., C.H. Graham, L.L. Master and D.L. Albert. 2006. The effect of sample size and species characteristics on performance of different species distribution modeling methods. *Ecography* 29:773-785.
- Heikkinen, R.K., M. Luoto, R. Virkkala, R.G. Pearson and J.H. Korber. 2007. Biotic interactions improve prediction of boreal bird distributions at macro-scales. *Global Ecology and Biogeography* 16:754-763.
- Hijmans, R., S.E. Cameron, J.L. Parra, P.G. Jones and A. Jarvis. 2005. Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology* 25:1965-1978.
- Hirzel, A. and A. Guisan. 2002. Which is the optimal sampling strategy for habitat suitability modelling? *Ecological Modelling* 157:331-341.
- IPPC. 2001. Climate data archive. Geneva, Switzerland. Available from <http://www.ipcc.ch/> (accessed May 2010).
- IPPC. 2008. International Standards for Phytosanitary Measures ISPM No. 5 Glossary of

- Phytosanitary Terms. Secretariat of the International Plant Protection Convention.
FAO, Rome.
- Jacobs, M.J. and H.J. Macissac. 2009. Modelling spread of the invasive macrophyte *Cabomba Carolina*. *Freshwater Biology* 54:269-305.
- Javis, C.H. and N. Stuart. 2001. A comparison among strategies for interpolating maximum and minimum daily air temperatures. Part II: the interaction between number of guiding variables and the type of interpolation method. *American Meteorological Society* 40:1075-1084.
- Jimenez-Valverde, A.T. Peterson, J. Soberon, J.M. Overton, P. Aragon and J.M. Lobo. 2011. Use of niche models in invasive species risk assessments. *Biological Invasions*:13:2785-2797.
- Jodoin, Y., C. Lavoie, P. Villeneuve, M. Theriault, J. Beaulieu, and F. Belzile. 2008. Highways as corridors and habitat for the invasive common reed *Phragmites australis* in Quebec, Canada. *Journal of Applied Ecology* 45:459-466.
- Johansson, M.E. and P.A. Keddy. 1991. Intensity and asymmetry of competition between plant pairs of different degrees of similarity: an experimental study on two guilds of wetland plants. *Oikos* 60:27-34.
- Johnson, W.C., B.V. Millett, T. Gilmanov, R.A. Voldseth, G.R. Gunterspergen and N.E. Naugle. 2005. Vulnerability of Northern Prairie Wetlands to Climate Change. *BioScience* 55:863-872.
- Kerns, B.K., B.J. Naylor, M. Buonopane, C.G. Parks and B. Rogers. 2009. Modeling *Tamarix (Tamarix spp.)* habitat and climate change effects in the northwestern United States. *Invasive Plant Science and Management* 2:200-215.

- Kapetsky, J.M., J.M. Hill and L.D. Worthy. 1988. A geographic information system for catfish farming development. *Aquaculture* 68:311-320.
- Kearney, M. and W. Porter. 2009. Mechanistic niche modelling: combining physiological and spatial data to predict species' ranges. *Ecology Letters* 12:334-350.
- Kleijnen, J.P.C. 2009. Kriging metamodeling in simulation: a review. *European Journal of Operational Research* 192:707-716.
- Landis, J.R. and G.C. Koch. 1977. The measure of observer agreement for categorical data. *Biometrics* 33:159-174.
- Larson, S.R., J.P. DeGroot, L.C. Bartholomay and R. Sugumaran. 2009. Ecological niche modeling of potential West Nile virus vector mosquito species in Iowa. *Journal of Insect Science* 10:1-17.
- Levine, R.S., A.T. Peterson and M.Q. Benedict. 2004. Geographic and ecological distributions of the *Anopheles gambiae* complex predicted using a genetic algorithm. *Am. J. Trop. Med. Hyg.* 70:105-109.
- Lindgren, C.J. 2003. A brief history of Purple Loosestrife, *Lythrum salicaria*, in Manitoba and its status in 2001. *Canadian Field-Naturalist* 117:100-109.
- Lindgren, C.J., J. Corrigan and R.A. DeClerk-Floate. 2001. *Lythrum salicaria* L., Purple Loosestrife (Lythraceae). p. 383-390 *In* G. Mason and J.T. Huber (eds.) *Biological Control Programmes in Canada, 1981-2000*. CABI Publishing, Wallingford, UK.
- Lindgren, C.J. 2008. Addressing the Threats of Invasive Plants Through Spatial Predictive Modeling and Early Detection and Rapid Response. p. 98-107 *In* S. Darbyshire and R. Prasad (eds.) *Proceedings of the Weeds Across Borders 2008*

- Conference.
- Lindgren, C.J. 2012. Biosecurity policy and the use of geospatial predictive tools to address invasive plants: updating the risk analysis toolbox. *Risk Analysis* 32:9-15.
- Lindgren, C. and D. Walker. 2012. Growth rate, seed production, and assessing the spatial risk of *Lythrum salicaria*) using growing degree days. *Wetlands* 32:885-893.
- Liu, C., P.M. Berry, T.P. Dawson and R.G. Pearson. 2005. Selecting thresholds of occurrence in the prediction of species distributions. *Ecography* 28:395-393.
- Mal, T.K., J. Lovett-Doust, L. Lovett-Doust and G.A. Mulligan. 1992. The biology of Canadian weeds. 100. *Lythrum salicaria*. *Canadian Journal of Plant Science* 72: 1305-1330.
- Mal, T.K., J. Lovett-Doust and L. Lovett-Doust. 1997. Time-dependent competitive displacement of *Typha angustifolia* by *Lythrum salicaria*. *OIKOS* 79:26-33.
- Mal, T.K. and J. Lobett-Doust. 2005. Phenotypic plasticity in vegetative and reproductive traits in an invasive weed, *Lythrum salicaria* (Lythraceae), in response to soil moisture. *American Journal of Botany* 92:819-825.
- Madsen, J.D. 1999. Predicting the invasion of Eurasian watermilfoil into Northern Lakes. US Army Corps of Engineers Waterways Experiment Station. Technical Report A-99-2, February 1999.
- McClay, A., A. Sissons, C. Wilson and S. Davis. 2010 Evaluation of the Australian weed risk assessment system for the prediction of plant invasions in Canada. *Biological Invasions* 12:4085-4089.

- McNyset, K.M. 2005. Use of ecological niche modelling to predict distributions of freshwater fish species in Kansas. *Ecology of Freshwater Fish* 14:242-255.
- McPherson, J.M., W. Jetz and D.J. Rogers. 2004. The effects of species' range sizes on the accuracy of distribution models: ecological phenomenon or statistical artefact. *Journal of Applied Ecology* 41:811-823.
- Mullin, B.H. 1998. The biology and management of Purple Loosestrife (*Lythrum salicaria*). *Weed Technology* 12:397-401.
- Mullin, B., L. Anderson, J. DiTomaso, R. Eplee and K. Getsinger. 2000. Invasive Plant Species. Issue paper for the Council for Agricultural Science and Technology. Number 13. Ames, Iowa.
- Oberhauser, K. and A.T. Peterson. 2003. Modelling current and future potential wintering distributions of eastern North American monarch butterflies. *Proceedings of the National Academy of Sciences of the United States of America*. Published online 2003 November 11.
- Office of the Auditor General of Canada. 2002. Report of the Commissioner of the Environment and Sustainable Development to the House of Commons. Government of Canada. Minister of Public Works and Government Services Canada 2002.
- Osborne, P.E. and S. Suarez-Seoane. 2002. Should data be partitioned spatially before building large scale distribution models? *Ecological modelling* 157:249-259.
- Ottenbreit, K. 1991. The distribution, reproductive biology, and morphology of *Lythrum* species, hybrids and cultivars in Manitoba. M.S. thesis, University of Manitoba, Winnipeg, Manitoba.
- Ottenbreit, K. and R.J. Staniforth. 1994. Crossability of naturalized and cultivated

- Lythrum* taxa. Can. J. Bot. 72:337-341.
- Pearson, R.G. and T.P. Dawson. 2003. Predicting the impacts of climate change on the distribution of species: are bioclimate envelope models useful? Global Ecology & Biogeography 12:361-371.
- Peterson, A.T. and K.P. Cohoon, 1999. Sensitivity of distributional prediction algorithms to geographic data completeness. Ecological Modelling 117:159-164.
- Peterson, A.T. and D.A. Vieglais. 2001. Prediction species invasions using ecological niche modeling: new approaches from bioinformatics attach a pressing problem. BioScience 51:363-371.
- Peterson, A.T. 2001. Predicting species' geographic distributions based on ecological niche modeling. The Condor 103:599-605.
- Peterson, A.T. and J. Shaw. 2003. *Lutzomyia* vectors for cutaneous leishmaniasis in Southern Brazil: ecological niche models, predicted geographic distributions, and climate change effects. International Journal for Parasitology 33:919-931.
- Peterson, A.T. and C.R. Robins. 2003. Using ecological-niche modeling to predict barred owl invasions with implications for spotted owl conservation. Conservation Biology 17:1161-1165.
- Peterson, A.T., M. Papes and D.A. Kluza. 2003. Predicting the potential invasive distributions of four alien plant species in North America. Weed Science 51: 863-868.
- Peterson, A.T. and R. Scachetti-Pereira. 2004. Potential geographic distribution of *Anoplophora glabripennis* (Coleoptera: Cerambycidae) in North America. American Midland Naturalist 151:170-178.

- Peterson, A.T., R. Williams, and G. Chen. 2007. Modeled global invasive potential of Asian gypsy moths, *Lymantria dispar*. *Entomologia Experimentalis et Applicata* 125:39-44.
- Peterson, A.T. 2011, Ecological niche conservatism: a time-structured review of evidence. *Journal of Biogeography* 38:817-827.
- Peterson, A.T., J. Soberon, R.G. Pearson, P. Anderson, E. Martinez-Meyer, M. Nakamura, and M. Bastos Araujo. 2011. *Ecological Niches and Geographic Distributions*. Princeton University Press, Princeton, New Jersey. 316 pp.
- Pimentel, D., Zuniga, R. and D. Morrison. 2005. Update on the environmental and economic costs associated with alien-invasive species in the United States. *Ecological Economics* 52:273-288.
- Pheloung, P.C., P.A. Williams, and S.R. Halloy. 1999. A weed risk assessment model for use as a biosecurity tool evaluating plant introductions. *J. of Environmental Management* 57:239-251.
- Stockwell, D.R.B. and A.T. Peterson. 2002. Effects of sample size on accuracy of species distribution models. *Ecological Modelling* 148:1-13.
- Stockwell, D.R.B. 1997. Generic predictive systems: An empirical evaluation using the learning base system (LBS). *Expert Systems With Applications* 12:301-310.
- Stockwell, D. and D. Peters. 1999. The GARP modelling system: problems and solutions to automated spatial prediction. *International Journal of Geographical Information Science* 13:143-158.
- Syartinilia, and S. Tsuyuki. 2008. GIS-based modeling of the Javan Hawk-Eagle distribution using logistic and autologistic regression models. *Biological Conservation*

- 141:756-769.
- Therriault, T.W. and L. Herborg. 2008. A qualitative biological risk assessment for vase tunicate *Ciona intestinalis* in Canadian waters: using expert knowledge. ICES Journal of Marine Science 65:781-787.
- Thompson, D.Q., R.L. Stuckey, and E. Thompson, 1987. Spread, Impact and Control of Purple Loosestrife (*Lythrum salicaria*) in North American Wetlands. U.S. Fish and Wildlife Service, Fish and Wildlife Research 2, 55.
- Thuiller, W. 2003. BIOMOD – optimizing predictions of species distributions and projecting potential future shifts under global change. Global Change Biology 9:1353-1362.
- Venette, R., D. Kriticos, D. Magarey, F. Koch, R. Baker, S. Worner, N. Raboteau, D. McKenny, E. Dobesberger, D. Yemshanov, P. De Barro, W. Hutchison, G. Fowler, T. Kalaris, and J. Pedlar. 2010. Pest risk maps for invasive alien species: a roadmap for improvement. BioScience 60:349-362.
- Welk, E., K. Schubert and M.H. Hoffmann. 2002. Present and potential distribution of invasive garlic mustard (*Alliaria petiolata*) in North America. Diversity and Distributions 8:219-233.
- Welk, E. 2004. Constraints in range predictions of invasive plant species due to non-equilibrium distribution patterns: Purple loosestrife (*Lythrum salicaria*) in North America. Ecological Modelling 19:551-567.
- White, D.J., E. Haber and C. Keddy. 1993. Invasive Plants of Natural Habitats in Canada: An integrated Review of Wetland and Upland Species and Legislation Governing their Control. Report prepared for the Canadian Wildlife Service,

- Environment Canada, Ontario Canada.
- Wiley, E.O., K.M. McNyset, A.T. Peterson, C.R. Robins, and A.M. Stewart. 2003. Niche modeling and geographic range predictions in the marine environment using a machine-learning algorithm. *Oceanography* 16:120-127.
- Wisz, M.S., R.J. Hijmans, J. Li, A.T. Peterson, C.H. Graham, A. Guisan and NCEAS Predicting Species Distributions Working Group. Effects of sample size on the performance of species distribution models. *Diversity and Distributions* 14:763-773.
- Yemshanov, D., F.H. Koch, Y. Ben-Haim, and W.D. Smith. 2010. Robustness of risk maps and survey networks to knowledge gaps about a new invasive pest. *Risk Analysis* 30:261-276.
- Zalba, S.M., M.I. Sonaglioni, C.A. Compagnoni and C.J. Belenguer. 2000. Using a habitat model to assess the risk of invasion by an exotic plant. *Biological Conservation* 93:203-208.
- Zhu, L., O. Sun, W. Sang, L. Zhenyu and K. Ma. 2007. Predicting the spatial distribution of an invasive plant species (*Eupatorium adenophorum*) in China. *Landscape Ecology* 22:1143-1154.

CHAPTER 7 – *TAMARIX RAMOSISSIMA LEDEB.*, *T. CHINENSIS LOUR.* AND HYBRIDS A NEW INVASIVE PLANT TO CANADA; EXTENDING THE APPLICATION OF ECOLOGICAL NICHE MODELLING TO BIOSECURITY RISK ANALYSIS

ABSTRACT. This Chapter provides a comprehensive biological, ecological, and geographic review for *Tamarix spp.* from a Canadian perspective, which was found to be lacking in the literature. Saltcedar is a deciduous, long-lived invasive plant that is described as a shrub or small tree. It has become invasive in the western United States and only recently naturalized in Prairie Canada. In this study the use of ecological niche modelling to predict the potential distribution of saltcedar in Prairie Canada was explored by (1) creating a new ecological niche model for saltcedar in Prairie Canada, (2) determining which suites of predictive variables influenced were useful in model development, (3) evaluating performance measures in selecting the most meaningful predictive variables, (4) interpreting how the results can be applied to prevent further incursions, (5) determining how the spatial information can be used by biosecurity agencies. In developing models, training and testing data was partitioned into quadrants where data from one quadrant was used to validate a model created from the other. The odds-ratio was found to be a useful performance measure in selecting which predictive variables to retain in model building. The results indicated that the GARP algorithm was successful in predicting the potential distribution of saltcedar in Prairie Canada. The final composite model indicated that saltcedar has not yet reached the limits of its potential distribution Prairie Canada. The results of this chapter further demonstrate that ecological modelling can be successfully used by biosecurity agencies to predict potential distributions of emerging pests. The spatial information can also be used by

provincial governments, weed supervisors, rural municipalities, and invasive species councils to design early detection programs to prevent the further establishment of saltcedar in Prairie Canada. Hybridization, multiple intentional introductions through garden plantings, natural dispersal from populations in the northern United States, and climate warming will increase the risk and promote the spread of saltcedar in Canada.

Key words. Saltcedar, *Tamarix ramosissima*, *Tamarix chinensis*, invasive alien plant, weed biology, invasion biology, ecological niche modeling

7.1 Introduction

Species Name and Taxonomic Relationships

I. *Tamarix ramosissima* Ledeb. — Synonym: *T. odessana* Steven ex Bunge; *T. pentandra* Pall. -- saltcedar, five-stamen tamarisk; tamaris, tamaris à cinq étamines. European and Mediterranean Plant Protection Organization (Bayer code): TAAPE.

II. *Tamarix chinensis* Lour. — Synonym: *T. japonica* Dippel -- saltcedar, tamarisk, Chinese tamarisk, Chinese saltcedar; tamaris chinois. European and Mediterranean Plant Protection Organization (Bayer code): TAACH.

These two species are difficult to distinguish and hybridize freely. The name saltcedar is used in this account to refer to both these species and their hybrids collectively. Other species are involved in hybrid complexes in North America to

varying degrees (Gaskin and Schaal 2003). Saltcedar refers to the plants' fine cedar-like foliage, its ability to excrete salt, and its tolerance of saline or alkaline soils (Carpenter 1998). Both species and their hybrids are members of the Tamarix family, Tamaricaceae, Tamaricacées.

The Tamaricaceae consist of five genera and about 54 species found in warmer parts of Europe, Africa and Asia (Baum 1978; Crins 1989). *Tamarix* L. is the largest genus and the only one to occur in North America, although not naturally. Gaskin and Schaal (2003) noted that at least 12 taxa have been associated with naturalized saltcedar in the United States (U.S.): *T. africana* Poir., *T. aralensis* Bunge, *T. aphylla* (L.) Karst., *T. canariensis* Willd., *T. chinensis* Lour., *T. gallica* L., *T. juniperina* Bunge, *T. parviflora* DC., *T. pentandra*, *T. ramosissima* Ledeb., *T. tetrandra* Pall. ex M.Bieb. emend Willd., and *T. tetragyna* Ehrenb. *Tamarix pentandra* was considered a synonym of *T. ramosissima* and the name *T. tetrandra* to be misapplied to *T. parviflora* specimens in North America (Baum 1967). Both Baum (1967) and Crins (1989) noted that *T. aralensis* is rarely cultivated and not known to be naturalized in North America. Gaskin and Schall (2002) identified *T. ramosissima*, *T. chinensis*, and their hybrids as the most widespread and invasive forms, hence these will be referred to as the invasive alien plant “saltcedar” within this paper.

7.2 Description and Account of Variation

(a) *Species Description* - Saltcedar is a facultative phreatophyte (i.e., a long-rooted plant which has adapted to desert or arid environments by developing a deep root system that

absorbs water from the water table) (Carpenter 1998). It is described either as a tree or shrub growing between 8 and 10 m (DiTomaso 1998).

Saltcedars are often multi-stemmed and young branches are usually flexible and willowy. The bark of young branches varies from reddish-brown, to brown, blackish-brown, dark purple, grey or black, and is glabrous (Baum 1978). The older trees or shrubs develop grey or brownish bark, often shredded. The stems commonly reach 10-15 cm in diameter, although trees with single trunks to 30 cm diameter are not uncommon in old stands along rivers in the southwestern U.S. and the northern Great Plains. Crins (1989) described the leaves as herbaceous, scale-like, entire, alternate, exstipulate, glabrous or papillose, sessile and punctuated with salt-secreting glands. The scale-like leaves cause the foliage to resemble that of *Juniperus*. The inflorescence is racemose, often paniculately branched. Species can have both vernal and aestival (i.e., continuous) anthesis (Crins 1989). Flowers are borne on slender racemes 2-5 cm long; 5-merous (5 petals, 5 stamens, 5 (rarely 3 styles); petals are white, pink or red, ovate or elliptic to obovate and contorted in bud (Crins 1989). The ovaries usually consist of three, sometimes four, and rarely five, carpels and stigmas, the number varying in a single raceme. The fruit is a small, three-valved, lanceolate-ovoid capsule, 3-4 mm long. Seeds are about 0.45 mm long, and have an apical coma of fine hairs (Merkel and Hopkins 1957; Carpenter 1998).

Both *T. ramosissima* and *T. chinensis* are diploid with $2n = 24$ chromosomes (Baum 1978, Zhai and Li 1986). Crins (1989) reported a base chromosome number of 12 for Tamaricaceae in the southwestern United States.

(b) *Distinguishing Features*. There are no other North American plants with which mature *Tamarix* may be confused. In the field, young *Tamarix* may appear similar, at first glance, to *Equisetum arvense* L. and *E. fluviatile* L. *Tamarix ramosissima*, *T. chinensis*, and their hybrids cannot be easily distinguished in the vegetative state (Crins 1989).

The North American *Tamarix* species are 5-merous (i.e. have five stamens and five petals), except for *T. parviflora* which has four of each. Halvorson and Guertin (2003) characterized *T. chinensis*, with persistent petals which are oblong-ovate and narrowed distally, entire sepals, and stamens that alternate with the disk lobes. In contrast, *T. ramosissima* has obovate persistent petals, erose and denticulate sepals, with bracts longer than the pedicels, and stamens which alternate with the disk lobes. Baum (1967) had also indicated that *T. chinensis* flowers occasionally have more than 5 stamens, and that, flowers of racemes which occur on green branches may have only 1-2 of the filaments inserted between the lobes of the disk. *Tamarix ramosissima* is similar but sepals are denticulate, petals are obovate, with all filaments of all flowers inserted below the disk near the margins. Gaskin and Schaal (2003) reported that *T. ramosissima* can be distinguished from *T. chinensis* by its erose-denticulate vs. entire sepals, obovate vs. elliptic-ovate petals, halophilous vs. non-halophilous soil preference, 3–4 mm vs. 5–77 mm raceme width, and hypodiscal vs. hypo-peridiscal filament insertion, respectively.

(c) *Intraspecific variation* - Both wild and commercially cultivated *T. ramosissima* can differ in flower color, density of inflorescences, and foliage color (Gaskin and Kazmer 2006). Sexton et al. (2002) collected seed from Montana and Arizona and found

ecotypic differentiation within *T. ramosissima* growth traits as a function of temperature. Baum (1967) reported the bark of *T. chinensis* can be brown to black-purple.

(d) *Illustrations* - Figure 7.1 provides an illustration of a saltcedar seedling. Colour photographs and illustrations can also be found on the United States Department of Agriculture's PLANTS data base (<http://plants.usda.gov/index.html>) and on the Government of British Columbia's Pest Management website (<http://www.agf.gov.bc.ca/cropprot/saltcedar.htm>).



Figure 7.1 A *Tamarix* seedling. Photo taken in 2005 at Lake Sakakawea, North Dakota. Lake Sakakawea is on the Missouri River where unvegetated sand bars are becoming colonized by saltcedar.

7.3 Economic Importance and Environmental Impact

(a) *Detrimental* – Economic and environmental impacts are a result of saltcedar’s ability to invade and dominate an area, out-competing native plants for resources (Hart et al. 2005). The invasion by saltcedar is reported to be one of the worst ecological disasters impacting riparian ecosystems in the United States, replacing native plants, degrading wildlife habitat and biological diversity, increasing fire frequency, as well as being associated with the decline of threatened and endangered species (DiTomaso 1998, DeLoach et al. 2000, Kauffman 2005). Invasions have led to dramatic declines in native woody and herbaceous plant composition and abundance on some US sites (Hughes 1993).

The most detrimental environmental impact of saltcedars is on hydrological regimes which include reducing water flow and lowering water tables (DeLoach et al. 2000; Hart 2005). Changes in water flow can also result in increases in salinity that further encourages the establishment of saltcedar (DiTomaso 1998). Reports on saltcedar water usage are variable. A single large plant has been reported to absorb up to 757 L (200 gallons) of water a day (Holdenbach 1987). While Owens and Moore (2007) examined sap flux rates and sap wood area with potential evaporation rates, estimating the daily water usage for *Tamarix* in the southwestern U.S. to be 122 L (32.2 gallons). Saltcedar invasions dry up springs, wetlands, small streams, widen floodplains, clog drainage channels, and increase sediment deposition (Carpenter 1998).

Salt-secreting glands on the leaves excrete numerous salts and minerals, increasing soil salinity (Berry 1970) and killing salt-intolerant plants (DeLoach et al. 2000). These salts inhibit germination of native plant species (Elgan et al. 1993) making

it difficult or even impossible for these species to colonize after a saltcedar invasion (Carpenter 1998).

Saltcedar invasions detrimentally impact bird communities. Saltcedars have been reported to be responsible for riparian bird population declines in the Rio Grande valley (Young and Finch 1997) and to replace plant communities that provide required food for migratory birds (Hunter et al. 1988). Brookman (2004) noted that there is great concern from waterfowl managers over possible invasion of saltcedar into the prairie pothole region of North America, which produces a significant portion of North America's waterfowl. Saltcedar has detrimental impacts on threatened and endangered bird species by altering essential habitats, required for example by the least tern (*Sterna antillarum* Lesson), Yuma clapper rail (*Rallus longirostris yumanensis* Dickey), bald eagle (*Haliaeetus leucocephalus* L.), and whooping crane (*Grus americana* L.) (Kauffman 2005). In areas such as Lake Sakakawea on the Missouri River, unvegetated sand bars are becoming colonized by saltcedar, resulting in habitat loss for piping plovers (*Charadrius melodus* Ord.) (Pearce and Smith, unpublished data).

Economic damage results from water losses from irrigation and municipal water systems, flooding of impeded water channels, reduction in hydropower capacity, costs associated with the loss of wildlife habitat, and interference with recreational activities on rivers. It is estimated that the presence of saltcedar in the western United States alone will cost between \$7 and \$16 U.S. billion in lost ecosystem functions over the next 55 years (Zavaleta 2000). Economic costs to society also include costs of herbicide control programs that are shared by taxpayers. In Big Horn County, Wyoming, herbicide control of saltcedar was estimated at \$1,000 U.S. per acre with a total cost of \$22.5 million

(Kauffman 2005), while along the Pecos River in Texas 5189-ha of saltcedar was treated at a cost of U.S. \$2.5 million (Carruthers et al. 2008).

(b) Beneficial – Saltcedar has been widely cultivated as an ornamental plant.

Ornamental cultivars of *T. ramosissima* include 'Pink Cascade', 'Rosea,' 'Rubra,' and 'Summer Glow' (Gaskin and Kazmer 2006) and assumptions of their sterility need to be considered (Lindgren and Clay 1993). Saltcedar is also beneficial as a source of firewood, shade for domestic animals, ground cover for some wildlife, a pollen source for honeybees, and as a control for stream bank erosion (Kauffman 2005). Saltcedar is also used as an ornamental to create windbreaks (Neill 1985, DiTomaso 1998), a source of tannins, and the wood serves as a source for fuel, charcoal, and construction material (Crins 1989). Some species are excellent dune binders (Baum 1978, Zhang et al. 2003).

Saltcedar is beneficial for some wildlife. The southwestern subspecies of the willow flycatcher (*Empidonax traillii extimus* Phillips), listed federally in the United States as endangered, now nests extensively in saltcedar which has replaced the native nesting trees (Owen and Sogge 2002, Kauffman 2005). Saltcedar provides habitat and food for some mammals including woodrats (*Neotoma* spp.) and the desert cottontail (*Sylvilagus audubonii*); however mammal numbers are generally lower in saltcedar than in other vegetation types (Engel-Wilson and Ohmart 1978). Sogge et al. (2008) reported that as many as 49 bird species use saltcedar for breeding habitat in North America. Brown and Trosset (1989) reported that the black chinned hummingbird (*Archilochus alexandri* Bourcier and Mulsant) nested only in saltcedar in the Grand Canyon, Colorado, because its native habitats were no longer present. However, birds in general

are reported to prefer native vegetation to saltcedar (e.g., Engel-Wilson and Ohmart 1978).

(c) **Legislation** – In Canada, saltcedar is not presently regulated federally as a quarantine pest either under the *Seeds Act and Regulations* or the *Plant Protection Act and Regulations*. Saltcedar is not listed as an invasive or noxious weed by any Canadian province or territory. In the United States, saltcedar is listed as a state noxious weed in California, Colorado, Montana, Nebraska, Nevada, New Mexico, North Dakota, Oregon, South Dakota, Texas, Washington, and Wyoming; however, it is not regulated federally (USDA-NRCS 2008). Other legislation in the United States includes the *Salt Cedar and Russian Olive Control Demonstration Act* signed in 2006, Assembly Bill 984, which authorized the federal government to cooperate with Colorado River basin states for the purpose of preparing a plan to control or eradicate saltcedar plants in the Colorado River watershed, and Colorado's Executive Order D-002-03, passed in 2003, directs state agencies to coordinate efforts to eradicate *Tamarix* on public lands.

7.4 Geographical Distribution

In Canada, the geographical distribution of naturalized saltcedar is restricted to populations of *T. ramosissima* found in 2007 in ditches near Penticton and on the shore of Osoyoos Lake, British Columbia (Catling and Lomer 2007) and in Saskatchewan. Saltcedar is also found in Canada in ornamental plantings. Baum (1967) reported that herbarium specimens of *T. chinensis* from ornamental plantings have been collected in British Columbia, Manitoba, Ontario, and Quebec; specimens of *T. parviflora* were

collected from ornamental plantings in British Columbia, Ontario and Nova Scotia; and specimens of *T. ramosissima* were collected from ornamental plantings in Manitoba. Pearce and Smith (2003) reported that purportedly sterile cuttings have been distributed by nurseries in Saskatchewan, Alberta, and British Columbia for many years. Of specific concern to western Canada is that saltcedar is extending its range northward and has naturalized as far north as 48°N latitude in North Dakota (Gaskin and Shafroth 2005) and at Havre, Montana on the Milk River.

Saltcedar is now common as naturalized plants in Arizona, California, Colorado, Montana, Nevada, New Mexico, North Dakota, Oklahoma, South Dakota, Texas, Utah and Wyoming (Carpenter 1998; DiTomaso 1998). In Montana, it has been found on the Milk River as far north as Havre and on the Marias River west of the Tiber Dam, rivers that are close to or downriver of the Canadian border. Sexton et al. (2006) found that saltcedar is increasing in central eastern Montana and is now found in most major riparian corridors. In eastern Montana, saltcedar establishes and persists where woody natives are not abundant, and once established it is unlikely that a shift back to native vegetation will occur within the observed age span for saltcedar estimated at 35 years (Sexton et al. 2006).

Pearce and Smith (2003) described the establishment of more than 10,000 plants at a delta where the Musselshell River enters the Fort Peck Reservoir in Montana and that this infestation may be the largest in the northern Great Plains. They reported that there may be as many as 1 million saltcedar plants on the mudflats around Fort Peck Reservoir. It is found in every North Dakota county along the Little Missouri, Yellowstone and Missouri Rivers and at Lake Sakakawea, as well as in wildlife

management areas in the southeastern and southwestern regions where it is spreading rapidly (Pearce and Smith 2003, Kauffman 2005). Saltcedar was found in Minnesota in 2003 near Hibbing (Exotic Species Program 2004).

Baum (1978) noted that saltcedar is found as far north as 52°N latitude in Asia and that most saltcedar species introduced into the United States originated from southern Eurasia. The native area of the genus extends from China and Mongolia through central and southern Asia to southern Europe, the Mediterranean countries, the Middle East, and North Africa. Others report that the native range of *T. ramosissima* and *T. chinensis* extends from eastern Turkey to Korea, central Asia, the Middle East, northern Africa, the Mediterranean region of Europe, Mongolia, Tibet, central China and North Korea (Crins 1989, Carpenter 1998, Gaskin and Schaal 2002). Baum (1978) reported *T. ramosissima* is native to temperate Asia while *T. chinensis* is native to China, Korea, and Japan. Saltcedar is also occurs in South Africa (DiTomaso 1998).

7.5 Habitat

(a) Climatic Requirements – Saltcedar should be expected to survive in the Canadian Prairies as both *T. ramosissima* and *T. chinensis* originated from cold, dry deserts from eastern Turkey to northern China and Korea, where winters are severe and frost-free seasons range from only 60 to 120 days (Baum 1978). Hybrids may be even more cold-hardy than the parent species (Sexton et al. 2002, Gaskin and Schaal 2003). Saltcedar has established in Montana and Wyoming along the Bighorn, Powder and Yellowstone Rivers in semi-arid and continental climates which include mean January temperatures of -15 °C and maximum July temperatures of 32 °C (Lesica and Miles 2001), with frost-

free periods ranging from 112 to 179 days (Pearce and Smith 2003). Hence, the northward spread of saltcedar into Canada may not be prevented by cold temperatures and an abbreviated growing season (Pearce and Smith 2003, 2007). Climate change may also promote further range expansion.

(b) *Substratum* – Saltcedar can grow on many different substrates from below sea level to about 2100 m elevation (Carpenter 1998). These include sand, sandy loam, loam, and clay soils, as well as saline and alkaline substrates (Kauffman 2005). DiTomaso (1998) reported that saltcedar invasions typically occur on bare, moist, exposed substrates. Saltcedar can tolerate substratum with high concentrations of soluble salts in soil, ranging from 650 to 36,000 ppm, which provides a competitive advantage over native riparian species (DiTomaso 1998, Glenn and Nagler 2005). Saltcedar also influences substratum conditions by taking in salt from saline habitats through the roots and exuding concentrated salts through its glands in the stems and leaves (Carpenter 1998).

(c) *Communities in which the species occurs* - Saltcedar has become established over as much as a million hectares of floodplains, wetlands, lake margins, lake shores, irrigation ditches, wet pastures, sub-irrigated pastures in the western United States (Carpenter 1998). In the northern Great Plains, saltcedar has primarily established in riparian and other wet environments (Pearce and Smith 2007). Saltcedar can establish in deserts and along mountain streams (Crins, 1989) and has been found growing in stock watering dug-outs, railway rights-of-way, and parks. Saltcedar commonly occurs in numerous ecosystems including the oak and hickory, elm-ash-cottonwood, ponderosa pine,

sagebrush, desert shrub, chaparral-mountain shrub, mountain grasslands, plains grasslands, and prairie desert grassland (Kauffman 2005).

7.6 History

Naturalized saltcedar was first reported in Canada near Penticton and at Osoyoos Lake in British Columbia (Catling and Lomer 2007) and later in Saskatchewan. These remain the only Canadian accounts of naturalized saltcedar. Baum (1967) reported herbarium specimens of *T. chinensis* collected from British Columbia, Ontario and Quebec, and a single herbarium record of *T. ramosissima* collected from Manitoba, however no collection dates or specific location data were provided and it is difficult to determine if these collections included naturalized specimens. Saltcedar has been imported and sold in Canada as an ornamental plant for many years.

The history of saltcedar in North America has been reviewed by numerous authors (Horton 1964, Crins 1989, Brock 1994, DiTomaso 1998, Lesica and Miles 2001, Pearce and Smith 2003, 2007). Lesica and Miles (2001) reported that saltcedar was first introduced into North America in the early 1800s as an ornamental plant and was recognized as an invasive species as early as the 1920s in the southwestern United States. DiTomaso (1998) reported that as early as 1868, the U.S. Department of Agriculture grew six different species of saltcedar in its arboretum. Horton (1964) reported that saltcedar had naturalized along the Gulf Coast of Texas as early as 1877 and in North Carolina by 1897, and was first recorded in Arizona in 1901. By 1890 saltcedar had infested many river systems in the southwestern United States, and by the 1950s it had established in most western riparian systems from the central Great Plains to

the Pacific and from northern Mexico to southern Montana (Kauffman 2005). Saltcedar was offered for sale to the public in California beginning in the 1850s, collections of saltcedar started to appear in herbaria by 1877, and naturalized plants became a concern in the 1920s (Robinson 1965).

In the Pecos River valley in New Mexico, the first records of saltcedar date from 1912, but by 1915, 240 ha (600 acres) were covered (Ladyman 2003). Saltcedar increased in abundance from the 1930s through the 1950s, by which time it had occupied most available sites in Arizona, New Mexico, and western Texas (Christensen 1962, Horton 1977). Robinson (1965) reported that from the 1920s to the 1960s saltcedar spread from an estimated 4000 ha (10,000 acres) in 1920 to over 500,000 ha (1.2 million acres) in the mid-1960s. The construction of large dams and subsequent changes in hydrological regimes accelerated range expansion (Brock 1994). In communities adjacent to the Bighorn River in Wyoming, saltcedar was planted as part of urban beautification projects in 1936 and for erosion control in large irrigation projects in the 1940s and 1950s (Pearce and Smith 2007).

Lesica and Miles (2001) reported that saltcedar plants in southeast Montana were one to 40 years old indicating that initial incursions there began no later than 1960. There are large numbers of saltcedar adjacent to Fort Peck Reservoir in Montana (Pearce and Smith 2003) and Lake Sakakawea close to Garrison Dam in North Dakota (Brookman 2004). Large numbers of saltcedar on the Musselshell River (especially near Roundup and Melstone) in Montana likely originated from adjacent ornamental plantings, possibly from *T. ramosissima* “Pink Cascade” that has been sold in Montana for several years

(Gaskin and Schaal 2002). Between 1967 and the present, saltcedar has become common in Montana through seed dispersal on the Yellowstone and Missouri Rivers.

7.7 Growth and Development

Information on growth and development of saltcedar was taken from summaries provided by Brock (1994), Carpenter (1998), Stevens (1990), and Halvorson and Guertin (2003).

(a) Morphology – Saltcedar is a deciduous long-lived plant, characterized as a loosely branched shrub or small tree (Carpenter 1998). Saltcedar can grow rapidly with stem heights reaching 3-4 m within one growing season. One-year-old saltcedars can develop lateral roots up to 6 m, fibrous roots 30-50 cm, and primary roots 2.5 m long. Saltcedar is usually deep-rooted, with a tap root reaching to 30 m deep and lateral roots up to 50 m long. Merkel and Hopkins (1957) reported on a three-year-old plant with lateral roots extending as far as 6 m to the side. The tap roots grow down to the water table then spread laterally above the water table or above impenetrable layers (Gary 1963). Morphological data collected in Montana along the northern margin of its current naturalized range showed that saltcedars 30-40 years old had a mean number of 10 live stems and ranged from 1 to 70 stems; plants had a mean height of 2.1 m ranging from 0.5 to 4.0 m (Lesica and Miles 2001).

(b) Perennation – Saltcedar overwinters as a perennial shrub or tree. Saltcedar can resprout from its crown area, stems, and roots and can produce new plants from

adventitious roots or stem fragments. It will produce prolific numbers of new shoots from its crown and roots if top growth is damaged (DiTomaso 1998). Merkel and Hopkins (1957) reported one plant that had 28 adventitious roots noting that plants growing in this manner are effective in slowing down water flow.

(c) *Physiological data* – Saltcedar is an adaptable halophyte and xerophyte and is tolerant of heat, cold, drought, floods, and high concentrations of dissolved salts (Halvorson and Guertin 2003). Optimal temperature for photosynthesis ranges between 23-28 °C (Brock 1994). Saltcedars can live from 50 to 100 years but the upper limit is not known (Tesky 1992 in Halvorson and Guertin 2003). In eastern Montana the observed age span for saltcedar was estimated at 35 years (Sexton et al. 2006).

(d) *Phenology* – Seeds of saltcedar can germinate throughout the season (Merkel and Hopkins 1957). Many Tamarix species have both vernal and aestival anthesis (Baum 1967), although the species established in North America are all aestival. Plants flower between April and August in the southern United States, but have a shorter flowering and seed production season in the northern Great Plains. Flowering occurred from May to October in Kansas, with plants often having flower buds to mature seeds at one time (Merkel and Hopkins 1957). At the warmest locations saltcedar may flower at any time of the year (Carpenter 1998). Flowering usually occurs in the third year of growth or later; however, flowering can occur in the first year following establishment (Merkel and Hopkins 1957, Brock 1994, Sexton et al. 2002, Pearce and Smith 2003). Saltcedar foliage drops in October except in Arizona where plants stay evergreen (Brock 1994).

(e) *Mycorrhizae* – *Tamarix ramosissima* roots collected from the Mojave Desert in Nevada by Titus et al. (2002) were found to be non-mycorrhizal. Beauchamp et al. (2005) found field and greenhouse *Tamarix* roots collected from the southwestern United States also to be non-mycorrhizal.

7.8 Reproduction

(a) *Floral biology* – Reproductive strategies include both seeds and vegetative propagation (Merkel and Hopkins 1957, Crins 1989, Brock 1994). Flowers require insect pollination to set seed (Crins 1989, Carpenter 1998, Gaskin and Schall 2002); however, Brotherson and Field (1987) suggest pollination may also occur by wind. Saltcedar is normally outcrossing and is self-compatible when cross-pollination is unavailable (Brotherson and Field 1987).

(b) *Seed production and dispersal* – All saltcedar species produce seeds that are dispersed by wind, water, and birds (Brock 1994, DiTomaso 1998). Seed dispersal by wind is considered the primary dispersal vector, but dispersal by water is also important (Pearce and Smith 2003). Pearce and Smith (2003) estimated that saltcedar can disperse 2.5 km/year by wind and 11 km/year along rivers and other waterways. It has been estimated that a mature plant can produce as many as a half million seeds per season (DiTomaso 1998). In Arizona, The weight of a mature seed is 0.01 mg (Merkel and Hopkins 1957). Warren and Turner (1975) reported that saltcedar produces seed for about 5.5 months each year with peaks in late spring and early summer.

Pearce and Smith (2003) report that humans serve as the primary initial vectors of introduction and this includes plants that are dispersed away from naturalized infestations on reservoirs such as the Fort Peck Reservoir in northern Montana and other established populations for ornamental purposes. Vehicle travel, including recreational boaters from infested areas, also serves as a potential vector of introduction. Anglers participating in fishing tournaments, e.g., at Boysen Reservoir in Wyoming, Fort Peck Reservoir in Montana, and Lake Sakakawea in North Dakota, can transport seeds and plant material entangled on boats and trailers from infested locations to new sites (Pearce and Smith 2003). Saltcedar dispersal is also aided by flow regulation associated with the construction of reservoirs and dams, river diversions, and irrigation projects that all contribute to regulated water flows, allowing saltcedars to become established (DiTomaso 1998).

(c) *Seed banks, seed viability and germination* – Seed germination can occur in water and on bare moist substrates (Pearce and Smith 2007) and throughout the growing season where conditions are suitable (Merkel and Hopkins 1957). Seed likely will not remain viable over the winter in most areas (Wilgus and Hamilton 1962). Germination studies found that primary roots emerged from cotyledons after about 24 hrs, an average of 57% of the seeds germinated within the first 24 hrs, and seed viability decreased with increased age (Merkel and Hopkins 1957). Young et al. (2004) developed germination temperature profiles for seeds of saltcedar collected in western Nevada and reported germination percentages as high as 98% and 100% and germination over a wide range of constant or alternating temperatures ranging from 0°C to 40°C. Wilgus and Hamilton

(1962) reported saltcedar germination between 2°C and 56°C, with 90% germination percentages observed between 19°C and 33°C. Seeds have been reported to be viable from 45 days (Stevens 1990) to as long as 6 months (Wilgus and Hamilton 1962).

(d) Vegetative reproduction – Vegetative reproduction contributes to the spread of saltcedars with several species producing adventitious roots and new shoots from buried stem tissue (Crins 1989). Saltcedar can also regenerate vegetatively from root or crown sprouts following mechanical removal or burning of aerial portions of the plant (Brock 1994; Young et al. 2004).

7.9 Hybrids

Genetic analysis suggests that the US invasion may be composed of primarily novel genotypes and hybrids (Gaskin and Kazmer, *in press*), and these saltcedar hybrids can only be identified by examining nuclear genotypes (Gaskin and Schaal 2002, 2003, 2005). Gaskin and Schaal (2002) reported that hybridization is common between *T. ramosissima* and *T. chinensis*, and that hybrids are widespread in the United States. They also reported that less extensive hybridization exists among combinations of *T. ramosissima* and *T. chinensis* with *T. parviflora* and *T. gallica*. Gaskin and Shafroth (2005) also found hybrids between *T. ramosissima* or *T. chinensis* and *T. aphylla* in the southwestern United States but reported the hybrid is uncommon. A comparison of US genotypes by Gaskin and Schaal (2002) revealed that *T. ramosissima* was the dominant species in Montana, Wyoming, Nevada and southern California and at a few sites in Arizona, Oklahoma and Texas while *T. chinensis* was dominant in Texas and New

Mexico. The *T. ramosissima* x *T. chinensis* hybrid was the most common genotype in New Mexico, Oklahoma, Nevada, California and Montana. These species/hybrid complexes usually cannot be distinguished morphologically in the field.

7.10 Population Dynamics

Saltcedar populations have increased dramatically from about 4,000 ha in the 1920s (Neill 1985) to recent estimates of 600,000 ha (Brotherson and Field 1987) and 800,000 ha (Carruthers et al. 2008). In addition to characteristics that influence population dynamics discussed in previous sections, others include the ability to produce a continual supply of seeds during the growing season providing an ecological advantage over other woody riparian species (DiTomaso 1998) and the ability to recover faster after fires than native riparian species (Busch and Smith 1993), and the ability to produce allelopathic compounds such as flavenol bisulfates and bisulfate-glucuronides (Brock 1994). However population dynamics change at sites where water and soil conditions have not been disturbed by humans and saltcedar seedlings have not competed well against *Populus* seedlings (Sher and Marshall 2003) or against *Salix* species (Sher et al. 2002, Bay and Sher 2008).

7.11 Response to Herbicides and Other Chemicals

Numerous studies report that once saltcedar has established, it is almost impossible to eradicate (DiTomaso 1998, Pearce and Smith 2003). Pearce and Smith (2003) indicated that on the northern Great Plains herbicides may be the only solution; however,

they would be expensive and difficult to apply. In Canada, the use of herbicides is regulated both federally and provincially, and in most cases the use of herbicides in riparian zones, which are most susceptible to saltcedar invasion, is restricted if not prohibited.

Carpenter (1998) summarized herbicide control methods used for saltcedar in the United States including foliar application to intact plants (i.e., imazapyr and glyphosate were found to be effective), prescribed burning followed by foliar application (i.e., re-sprouting treated with triclopyr), cut-stump for areas 2 ha or smaller (i.e., cut stems of saltcedar within 5 cm of ground and treat with triclopyr), and basal bark treatment with herbicide (i.e., effective with a basal diameter of less than 10 cm). Kauffman (2005) reported that various herbicides (i.e., imazapyr, metsulfuron methyl, ammonium salt of fosamine, triclopyr, and glyphosate) have been used against saltcedar since the 1940s but that control is never complete and reinfestation may be rapid. In a restoration project in Texas, Hart et al. (2005) reported an average of 85-90% mortality of saltcedar two years after applications of ArsenalTM herbicide applied by helicopter with a specially designed boom. Herbicide control can be effective in the short-term (Figure 5.2); however, periodic retreatments are required with repeated costs and environmental damage (DeLoach et al. 2009).



Figure 7.2 A chemically treated *Tamarix* plant at Lake Sakakawea, a reservoir in the Missouri River in central North Dakota, photo taken in 2005. Once saltcedar has established it is almost impossible to eradicate.

7.12 Response to Other Human Manipulations

Most human manipulations promote further sprouting and flowering. Human manipulations have included mowing, ripping, bulldozing, cutting, burning, sawing, and hand removal, but these efforts have been largely unsuccessful (Pearce and Smith 2003, Kauffman 2005). Managed flooding may provide a means of saltcedar control but this has not yet been tested over large areas or in northern populations. Cutting and removal is effective only if all roots are removed or destroyed or saltcedar will produce new shoots (Ladyman 2003). Cutting followed by shading with dark plastic sheeting or by other vegetation has been effective (Ladyman 2003). However, this treatment would not be effective or practical for large populations. The integration of conventional control methods, such as fire followed by herbicides, or fire and/or herbicides followed by root-

ploughing and raking has provided increased control in some cases (Grubb et al. 2002, Hart 2003). However, these methods greatly increase costs and still do not eliminate the need for repeated application to control regrowth or re-invasion unless dense stands of native plants can be re-established to exclude or suppress the saltcedar.

A classical biological control program against saltcedar was initiated by the United States Department of Agriculture-Agricultural Research Service in the late 1960s which resulted in the release of Eurasian leaf beetles *Diorhabda elongata* (Brullé) sensu lato (Coleoptera: Chrysomelidae) using four ecotypes from Greece, Tunisia, Uzbekistan and China (Hudgeons et al. 2007, DeLoach et al. 2009). Beetles were first released into the field in the United States in 2001 (DeLoach et al. 2004). In Texas, releases of *D. elongata deserticola* have resulted in widespread defoliation (Hudgeons et al. 2007), three years after releases of *D. elongata* (Crete ecotype) in 2004, saltcedar biomass was reduced by 85-95% (DeLoach et al. 2009).

It is possible that river flow manipulation and adjustments to reservoir water levels could provide powerful, non-chemical alternatives to saltcedar control in North America. River floodplains are sensitive to invasion by introduced plants (Stohlgren et al. 1998, Stromberg et al. 2007). Floodplains provide bare moist germination and colonization sites, and river flows disperse seeds and other propagules downstream and to other connected water bodies. Rapid invasion of saltcedar in the southwestern United States between 1900 and 1940 has been associated with modifications to natural river flow following the construction of dams that favoured the establishment of saltcedar over native trees dominated by cottonwoods and willows (Brock 1994, DiTomaso 1998). Dam removal could return rivers to normal flow regimes to support colonization and

continued reproduction of native trees rather than saltcedar; however, decommissioning of dams is difficult, expensive, and controversial, and may not result in the restoration of native ecosystems (Shafroth et al. 2002, Rood et al. 2003). Instream flow regulation, such as increasing spring flows in some years during seed dispersal periods of the native trees followed by a slow decline in flows to allow seed germination and establishment, have been used by Rood et al. (2000, 2003) to restore degraded floodplains on the St. Mary's River in southwestern Alberta and the Truckee River in Nevada. Although saltcedar may dominate regulated riparian systems in the United States (Stromberg et al. 2007), instream flow regulation has not been used, as far as we know, to control it. Saltcedar seedlings appear to be less tolerant of flooding and flood-related disturbances than native riparian trees (Sher et al. 2000, 2002, 2003, Tallent-Halsell and Walker 2002), and thus they may not be able to compete with cottonwoods and willows when instream regulation promotes high spring flows.

Large reservoirs behind river dams also promote the rapid establishment of saltcedar on the unvegetated moist shore lands that surround the reservoir; once established on these sites, it is difficult to remove (Pearce and Smith 2003, 2007). Saltcedar may not be tolerant of continued flooding, particularly in fall (Gladwin and Roelle 1998, Sher et al. 2000, Sprenger et al. 2001, Pearce and Smith 2003). In years when precipitation and snow melt are sufficient to allow it, full reservoir levels could be maintained to drown established plants and inhibit colonization of new seedlings. However, this control method has not yet been tested in North America.

7.13 Response to Herbivory, Disease and Higher Plant Parasites

(a) *Herbivory*

(i) *Mammals*. DeLoach et al. (2000) noted that some wildlife use saltcedar for some needs, however wildlife tends to move out of saltcedar invaded areas.

(ii) *Birds*. Waterfowl, frugivores, and most insectivores generally avoid saltcedar (DiTomaso 1998). Saltcedar was negatively correlated with bird populations in Colorado (Anderson et al. 1977). Conversely, Ellis (1995) found that some insectivorous birds readily used saltcedar in the Middle Rio Grande Valley of New Mexico. Many bird species use salt cedar for breeding habitat in North America (reviewed in Section 3b). Birds have also been reported to feed on the leaf-beetle *Diorhabda elongata*, a biological control agent released in the United States against saltcedar (Dudley and DeLoach 2005).

(iii) *Insects*. Native insects feed occasionally on saltcedar but cause little damage (Liesner 1971). The nymphs of the Apache cicada (*Diceroprocta apache* Davis (Hemiptera: Cicadidae)) feed on saltcedar roots. Except for the Apache cicada, none of the native North American insect species caused more than sporadic and slight damage to saltcedar. Saltcedar flowers provide nectar and pollen for a large number of insects and generalist pollinators (DeLoach et al. 2000). Five natural insect enemies of saltcedar from the Old World have been unintentionally introduced in the United States. These are a small leafhopper [*Opsius stactogalus* (Hemiptera:Cicadellidae)], two scale insects (*Chionapsis etrusca* Leonardi and *C. gilli* Liu & Kosztarab) (Hemiptera: Geometroidea)

and two eriophyiid mites. The most commonly found is the introduced leafhopper (Liesner 1971).

(iv) *Nematodes*. No information found.

(b) *Diseases*. Beauchamp et al. (2005) found field and greenhouse *Tamarix* roots collected from the southwestern United States were colonized by dark septate endophytes, a fungal root associate.

7.14 Spatial Predictive Modelling of Saltcedar in Prairie Canada

Chapters 5 and 6 provide new data, methods, and techniques that extend the use of spatial predictive modelling for use by biosecurity agencies for assessing the spread of an established pest, purple loosestrife. In this chapter, those methods and techniques are further explored for assessing the potential distribution of a new emerging pest, saltcedar, which is not found in unmanaged areas of Prairie Canada.

7.14.1 Study Area

A description of the Prairie Canada study area is provided in Chapter 6 (see Section 6.2). The study area covers an area of 360,000 km² and includes the Canadian provinces of Manitoba, Saskatchewan and Alberta and will hereafter be referred to as Prairie Canada. The study area reflects geographic space whereby saltcedar has established and may extend its range based upon abiotic and dispersal factors. Because

of the broad scale of the study area biotic factors should not significantly influence the models and were hence not considered. The spatial extent of the study region and selected level of resolution are consistent with biosecurity decision making in that it is generally made at coarse scales.

7.14.2 Modelling Methods

Selecting Predictive Variables. The contribution of each predictive variable to the model was explored by evaluating changes in performance measures. An $N - 1$ jackknife procedure (i.e., leave one out) was employed where a model was built with suites of the predictive variables, and then one variable was removed building another model with $N - 1$ variables (Mac Nally 1996, Peterson and Cohoon 1999, Chen et al. 2007). This procedure is a time-efficient approach to identifying the most important predictive variables to be included in a model (Peterson and Cohoon 1999). Predictive accuracy (i.e., $PA = (a+b)/n$) (Stockwell and Noble 1992), extrinsic omission error (i.e., $EOE = (c/n) \times 100$) and the odds-ratio (i.e., $OR = (ad/cb)$) were used as performance measuring in selecting predictive layers.

Raster Layers. Digital raster GIS datasets for topographic and climatic variables were used as predictive datasets. Raster layers were obtained from the Intergovernmental Panel on Climate Change (IPCC 2001) (Table 7.1). The suite of climatic layers included mean annual diurnal temperature range, mean annual precipitation, and mean annual number of wet days. The suite of topographic layers included elevation, slope and aspect.

Data were sampled at a coarse pixel resolution of $0.2^0 \times 0.2^0$ or about a 20 x 20 km grid confined to 24.5988 -53.7988° N, 66.1417 -125.0217° W (e.g., North America).

Table 7.1 The interpolated predictive variables (i.e., independent variables) used in modeling the potential distribution of saltcedar in Prairie Canada. Climate variables represent annual average calculated from 1961 to 1990. Datasets are available from the Intergovernmental Panel on Climate Change world-wide Climate Data Distribution Centre (IPCC).

Predictive Variable	Description	Source
<i>Climate Variables</i>		
dtr6190_ann	Diurnal temperature range	IPCC
pre6190_ann	Precipitation	IPCC
tmp6190_ann	Mean Temperature	IPCC
<i>Topographic Variables</i>		
h_aspect	Aspect	IPCC
h_dem	Elevation	IPCC
h_slope	Slope	IPCC

Model Building. The GARP algorithm was used to model the potential distribution of saltcedar across Prairie Canada. To optimize performance parameters were set to produce 100 models with a convergence limit 0.01, while the number of maximum iterations was set to 1000, and all four rule-sets (i.e., atomic, range, negated range, and logistic regression) were employed. Occurrence points were divided 50% into training data and 50% testing datasets by the algorithm for intrinsic testing. Procedurally, GARP selects a rule-set and applies it to the training data to develop a rule, rules then evolve

through an iterative process that maximizes predictivity. The change in predictive accuracy from one iteration to the next was used to determine if a specific rule should be incorporated and each rule-set represents a different method of characterizing the ecological niche (Peterson and Shaw 2003, Peterson et al. 2007). Predictive accuracy was evaluated based upon 1,250 points resampled from the test data and 1,250 pseudoabsence points from prairie Canada (Peterson and Shaw 2003). For all models, a subset of data was withheld to allow for independent testing of the model.

Selecting Best Models. As each model is unique and varies in quality, a subset of ten best individual models was created and these were summed into one final composite model. This approach forced the algorithm to minimize over fitting as it prioritizes omission error over commission error, as the later represents true overprediction (Anderson et al. 2003, Peterson et al. 2008). An error cost criteria was employed where omission error (i.e., false negatives) were considered to be more costly than commission error (i.e., false positives). In selecting the best models, I employed a hard omission threshold of 10% (i.e., 10% of models with the lowest extrinsic omission error were selected for the final model) and a commission threshold of 50%. A low omission threshold was selected as models with low omission error are generally desired (Peterson et al. 2011).

Using Environmental Systems Research Institute's (Environmental Systems Research Institute, Redlands, California, USA ESRI) geographic information system software ArcGIS 9.3, the best models were summed into one composite model using the spatial analysis zonal statistics tool, and then projected onto a map of the Prairie Canada

to illustrate potential distribution. To further evaluate the potential distribution of saltcedar, the results were reclassified into six categories representing the probability of invasion: 0% (i.e., no models predict presence), < 25%, 26-50%, 51-75%- 76-99% and 100% (i.e., all 10 models predicted presence).

Occurrence Point Data. In building the ecological niche models 10,240 georeferenced point occurrences were used. Data were obtained from a number of sources which were determined to be accurate including Brookman (2004), the State of North Dakota (North Dakota Department of Agriculture), Fremont Country, Wyoming (Fremont County Weed and Pest), the Utah State College Herbarium, and the Missouri Botanical Gardens Tropicos database (i.e., data submitted by John Gaskin was selected). Saltcedar locations for Canada were obtained from Catling and Lomer (2007), the Saskatchewan Invasive Species Council, and the Swift Current Watershed Stewards.

Evaluating Model Performance. As GARP produces binary models, performance measures were calculated from the elements of a 2 X 2 confusion matrix (Fielding and Bell 1997, Pearce and Ferrier 2000). Equations used to calculate performance measures can be found in Table 6.3. In the confusion matrix, element *a* represents pixels where the species is known to occur and the model correctly predicts as present, *b* represents pixels where the species is not known to occur but are incorrectly predicted as present (i.e., commission error or false positive), *c* represents pixels of known distribution incorrectly predicted as absent by the model (i.e., omission error or false negative) and *d* represents pixels where the species has not been found and the model correctly predicts absent. As

there is no one single measure accepted for evaluating model performance (Fielding and Bell 1997, Welk 2004, Peterson et al. 2011, Tarkesh and Jetschke 2012) a number of performance measures were explored.

I used sensitivity and specificity, first described by Yerushalmy (1947), as one measure to assess performance. Sensitivity (i.e., $a/(a+c)$) is the capacity of the model to yield a positive result for areas where saltcedar occurs, where specificity (i.e., $d/(b+d)$) is the capacity to yield a negative result for an area without saltcedar, and both are theoretically independent of prevalence (Baldessarini et al. 1983). Baldessarini et al. (1983) suggested that models with high sensitivity scores are useful. Fielding and Bell (1997) suggested that sensitivity indicates how good a model is at detecting a pest, or is at predicting an occurrence point; and specificity indicates how good a model is at detecting absences, or how good a test is at predicting no presence (Pearce and Ferrier 2000). In measuring model performance, an error cost criteria approach was employed whereby sensitivity measures were more important than specificity measures (i.e., false positive errors were more costly than false negatives).

The correct classification rate (CCR) (i.e., $(a + d)/(a+b+c+d)$), also referred to an intrinsic measure of overall model performance, was also used to measure model performance. The CRR is based on how many test points are predicted present vs. not predicted present (Fielding and Bell 1997, Pearce and Ferrier 2000). The CCR ranges between 0 and 1, and includes contributions of both omission and commission error (Anderson et al. 2003). The value varies little between models with sample sizes of 20-50 (Stockwell and Peterson 2002, Anderson et al. 2003). The CCR, sensitivity, and

specificity are indices where values closer to 100% indicate better model performance (Pearce and Ferrier 2000).

The true skill statistic (TSS) (i.e., sensitivity + specificity - 1), also known as Youden's index, was also used as it characterized the ratio of the probability that an event of interest occurs to the probability that it does not and also takes into account both omission and commission errors (Youden 1950, Bland and Altman 2000). The TSS ranges from -1 (i.e., values of 0 or less indicated no better than random model performance) to +1 (i.e. perfect model performance) (Allouche et al. 2006). It is thought to be the best measure of model performance in medical diagnostic tests (Biggerstaff 2000) and it is not affected by prevalence, or the size of the validation subset and has all the advantages of the kappa statistic (Allouche et al. 2006).

The use of the odds ratio (OR) as a performance measure was explored. It is a cross product ratio used as a measure of association for binary predictions and it can be used to characterize the effect of explanatory variables on binary responses, as well as the size and direction of the effect (Stephenson 1999, Pepe et al. 2004, Rita and Komonen 2008). The OR has been reported to be a single measure of performance derived from sensitivity and specificity, and not prevalence dependent (Glas et al. 2003, Forbes 1995). The OR ranges from 0 to infinity with higher values indicating better discriminatory performance, and the ratio increases steeply when sensitivity or specificity becomes near perfect (Glas et al. 2003). The higher the ratio is above 1.0, the greater the effect the variable has in increasing the odds of presence, while an OR of 1.0 corresponds to a variable that does not affect the dependent variable (Si et al. 2010). The OR rises steeply when sensitivity and specificity become near perfect (Glas et al. 2003).

The OR has been used to evaluate the impact of predictive variables (Si et al. 2010, Costa et al. 2010), and as a measure of association for verifying binary predictions (Grimes and Schulz 2008). As an additional extrinsic measure of model performance, model accuracy was calculated as a percentage of the number of known occurrence points predicted correctly by the model using an independently withheld testing data.

Expert evaluation was used as a final discriminatory measure in selecting the best overall saltcedar model. Models need to be geographically realistic, and make sense intuitively, ecologically, and biologically which is often not captured by statistical evaluations (Pheloung et al. 1999, Therriault and Herborg 2008). While it is important that modelling practitioners attempt to quantitatively measure model performance, the importance of expert evaluation cannot be overlooked (Anderson et al. 2003, Johnson and Gillingham 2004, Kuhnert et al. 2010, Charney 2012) and should be incorporated into model selection methodology (Thuiller 2003). In this study, an expert was defined as someone who had both extensive biological knowledge of the species and knowledge of the geography of the Prairie Canada. This definition of an expert is similar to that of Anderson et al. (2003). Composite models were evaluated as either good or poor. A good model excluded unsuitable areas where saltcedar could not exist (i.e., high elevations of the Rocky Mountains in Alberta or areas of the Boreal Plains ecozone) where saltcedar cannot disperse (i.e., areas where there would be no known pathways for possible introduction). A poor model was one that included large unsuitable areas (i.e., areas where saltcedar could not disperse or become established due to biotic or abiotic events). For example, a good model is one that accurately delimits the current distribution as well

as predicting potential distribution into novel areas where expert opinion determined there were suitable abiotic conditions as well as a disperse pathways.

Geographic Partitioning of Data. Data can be partitioning in a variety of ways to validate model performance (Osborne and Suarez-Seoane 2002, Hirzel and Guisan 2002, Kapetsky et al. 1988). Data partitioning commonly involves partitioning data into testing and training subsets or learning and validation subsets, preferably using a testing subset that is entirely withheld from model training to test model robustness (Fielding and Bell 1997, Pearce and Ferrier 2000). In this study, data was spatially partitioned into quadrants to test model predictivity. As opposed to randomly subsetting testing data, partitioned by quadrants is a more rigorous test of the algorithm predictivity as it forces the model to predict into broad areas from which no input occurrence points are available (Peterson and Shaw 2003, Levine et al. 2007, Peterson et al. 2007). Data were spatially partitioned above and below median longitude and latitudes based on the saltcedar occurrence points resulting in four subsets of data in either the northwest, northeast, southwest or southeast quadrant (Figure 7.3). Models were trained using data from the northwest and southeast quadrants (i.e., NWSE, N=10,003 point occurrences), and then tested with data from the northeast and southwest quadrants (i.e., NESW, N=237 point occurrences), and then visa versa. This approach challenged the algorithm to predict into unsampled regions of the study area (Peterson and Shaw 2003, Peterson et al. 2007).

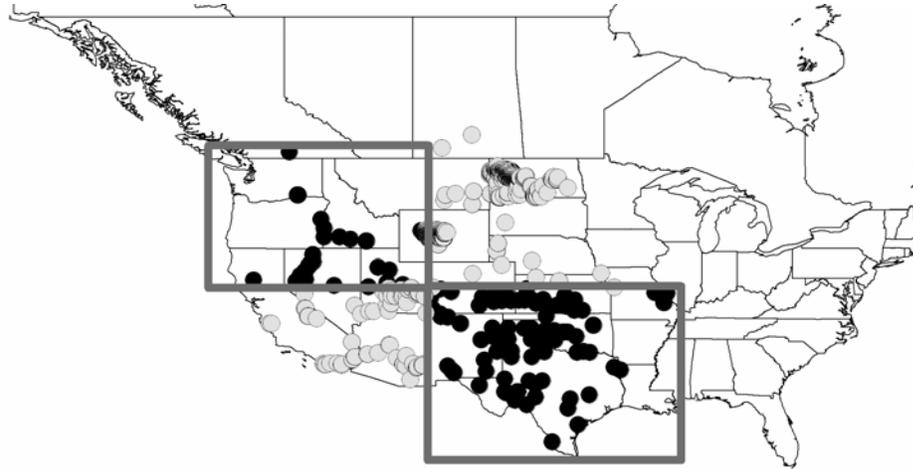


Figure 7.3 Data was partitioned into testing and training subsets using quadrants. In building ecological niche models, the northwest and southeast (NWSE) quadrants were used to train the model while the northeast and southwest (NESW) quadrants were used to test the model.

7.14.3 Results and Discussion

The results indicated that GARP is a spatial tool that can be used by biosecurity agencies to successfully model the ecological niche of a new emerging pest, in this case saltcedar. These results further support the conclusions of Chapter 6. The GARP model indicated that the risk of saltcedar establishing and spreading in Prairie Canada is high with potential distribution occurring in all three Prairie Provinces. A general spatial pattern emerged where models predicted suitable area (1) along the southern boundary of the study area from southwestern Manitoba to southwestern Alberta, (2) west of Calgary (Alberta) to Saskatoon (Saskatchewan), and then (3) areas in southeastern Manitoba approaching Lake Manitoba. The majority of the potential distribution occurs along the southern boundaries of each province becoming less suitable moving geographically into more northern areas of the Prairie Canada (Figure 7.4).

Jackknife Manipulations. The influence of each predictive variable was tested individually, and in combination, by assessing changes in PA, EOE, and OR (Table 7.2). In evaluating the suite of climate variables, the OR indicated that all three climate variables were important predictive variables. These results are similar to other studies that also found temperature, for example, to be strongly associated with saltcedar distribution (Friedman et al. 2005, Kerns et al. 2009). In evaluating the suite of topographic variables, the OR indicated that elevation was the most influential predictive variable. When compared to elevation, aspect and slope did not significantly contribute to model. Similar conclusions were reached when changes in PA and EOE were evaluated, however, the OR was found to be more useful in selecting which variables to be included in the models. In this study, the OR described a relationship where higher OR values indicated a predictive variable should not be included in the model development. Hence, slope and aspect were excluded as predictive variables in creating the saltcedar model, and all three climate layers were retained.

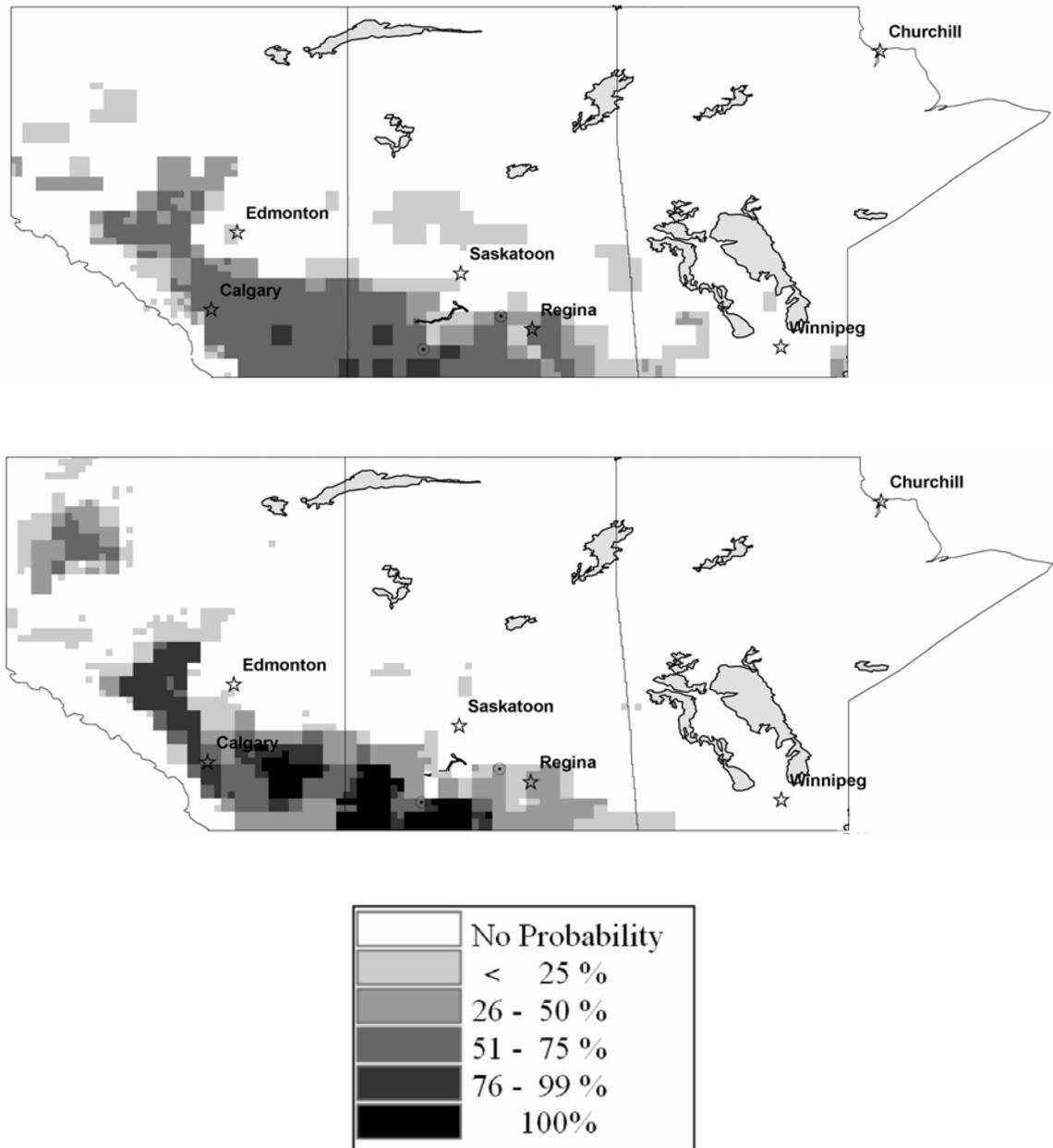


Figure 7.4 Predictive potential distribution of saltcedar in Prairie Canada using all three climate variables and elevation as predictive variables. The top model used the NWSE quadrant data to train the model while the bottom model used NESW quadrant data to train the model. Major lakes in the study area are outlined in black and shaded grey for reference.

Table 7.2 Hierarchical partitioning of predictive variables using an $N - 1$ jackknife procedure. Slope and aspect were excluded while elevation and all three climate variables were retained in final model building. Predictive accuracy (PA) $((a+b)/n)$, extrinsic omission error (EOE) $((c/n) \times 100)$ and the odds-ratio (OR) (ad/cb) was used to select predictive variables.

Predictive Variables	PA		EOE		OR	
	NESW	NWSE	NESW	NWSE	NESW	NWSE
Data Set:						
Topographic Variables						
Slope	57	56	42	43	565	1239
Elevation	77	80	16	20	8	4
Aspect	59	59	44	32	7945	9
Aspect and Elevation	80	79	17	17	7	10
Aspect and Slope	57	57	42	41	587	223
Slope and Elevation	80	80	15	16	4	6
Slope, Aspect and Elevation	82	79	17	12	8	3
Climate Variables						
Precipitation	75	56	21	38	12	62
Temperature	87	81	11	16	9	14
Diurnal Temperature	87	85	11	12	9	6
Precipitation and Temperature	88	88	8	8	3	2
Precipitation and Diurnal Temp	87	87	10	10	6	3
Temperature and Diurnal Temp	87	87	10	10	4	4
All Climatic Layers	88	88	8	8	4	3
Selected Variables Final Model						
All Climate and Elevation	88	83	8	13	3	5

Evaluating Model Performance. By geographically partitioning our data into quadrants (see Figure 7.1) two composite models were created each predicting the potential distribution of saltcedar in Prairie Canada. In validating our models with an independent testing data subset, both models performed very well (Table 7.3). Values for specificity, correct classification ratio, extrinsic omission and extrinsic commission suggested that the NWSE model performed slightly better than the NESW model. The model developed using NESW data to train the model had slightly higher values for predictive accuracy, however suffered from higher extrinsic commission error as it predicted potential distribution into more northern areas of Alberta. Both models predicted potential distributions that extended beyond the known distribution of saltcedar. Both models predicted large areas of the southern portions of Prairie Canada, primarily in Saskatchewan and Alberta, as potential distribution. In general, both models indicated a potential northern distribution that may extend as far north as high as 54°N latitude and as high as 58° N latitude in Alberta which is beyond the current occurrences in Saskatchewan which were at about 50 °N latitude (Figure 7.5). Both models predicted only small areas of south western Manitoba as having suitable conditions, however Manitoba should have abiotic, biotic and dispersal variables that would support establishment. Unexpectedly, the both models predicted large areas of northwestern Alberta as suitable for saltcedar with the NESW model predicting more than the NWSE model. Dispersal events (e.g. pathways for introductions are lacking hence no ability to access this area), general land use (e.g., it largely a forested area), and not enough growing degree-day's for development, would most likely not support establishment and spread into northwestern Alberta. However, phenotypic plasticity and evolution of

saltcedar hybrids may allow it to establish in areas where we would not expect it to occur in the future (Baum, 1978, Sexton et al. 2002, Gaskin and Kazmer 2009).

Table 7.3 Measuring the predictive accuracy of the saltcedar ecological niche models. Each model was created using a suite of three climate variables and elevation as predictive variables. Specificity (Sp), sensitivity (Sn), correct classification rate (CCR), predictive accuracy (PA), extrinsic omission error (ExOm), extrinsic commission error (ExCom), and the odds-ratio (OR) were used as performance measures.

Subsets		Performance Measures						
Training subset	Testing subset	Sp	Sn	CCR	PA	ExOm	ExCom	OR
NWSE	NESW	27%	77%	0.60	83%	4.1	27.4	5.3
NESW	NWSE	16%	84%	0.54	88%	8.4	46.4	2.6

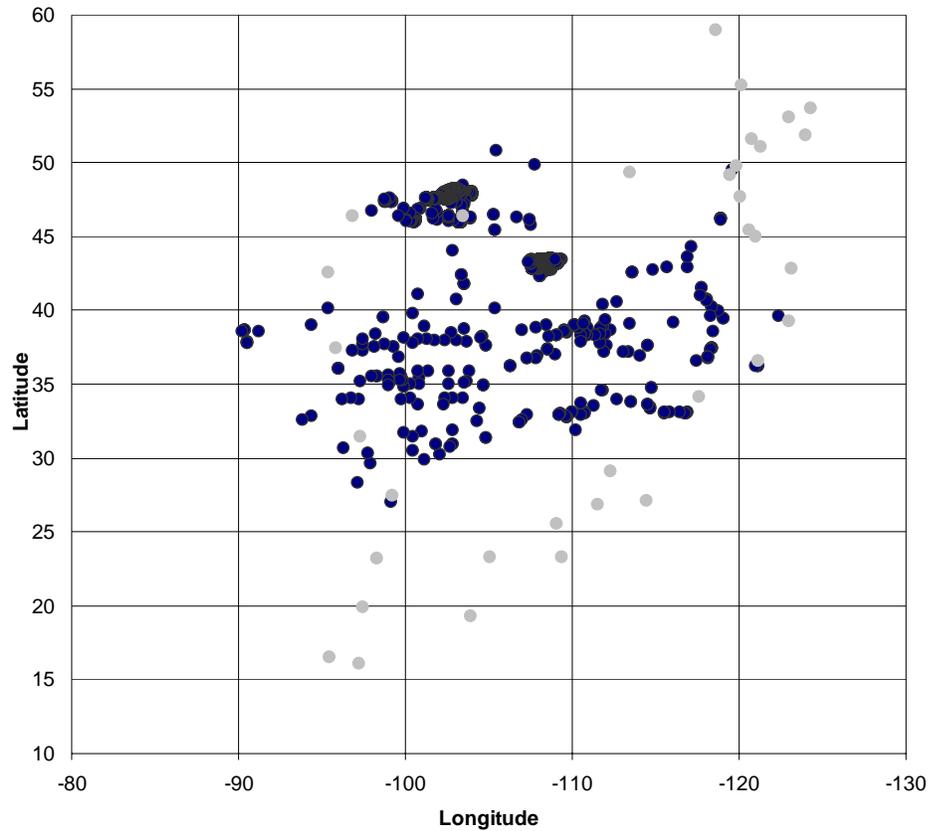


Figure 7.5 Comparing the current and potential distribution of saltcedar. Current distribution of saltcedar is represented by black dots. The grey dots represent the predicted potential distribution as predicted by using the NWSE data subset for training.

Expert Evaluation. Expert evaluation concluded that the NWSE model was a more realistic model of saltcedar's potential distribution in Prairie Canada. It is evident that variables associated with the Rocky Mountains in western Alberta constrained the western extent of the predicted potential distribution in Prairie Canada. In Utah, Brotherson and Winkel (1986) reported saltcedar is typically found at 1,386 m but has

been found as high as 1,800 m, and in Montana populations are found between 685 m and 677 m (Lehnhoff et al. 2011). Frasier and Johnsen (1991) reported saltcedar distribution in the southwestern US to be at elevations below 1,830 m. In China, saltcedar is reported to grow between -120 m to 2,500 m (Zhang et al. 2002). The results of this study indicated that the mountainous areas of western Alberta constrained the potential distribution in western Prairie Canada, similar to what Brotherson and Winkel (1986) reported.

In this study, expert evaluation was used as the final discriminatory measure in selecting the best model. Expert evaluation was found to be effective in determining, for example, where commission error was excessive (e.g., in the NESW model). Commission error, also referred to as overprediction has been identified by some as problematic in GARP models (Elith and Graham 2009, Sobek-Swant et al. 2012, Mateo et al. 2012). Conversely, the algorithm may just be identifying areas where saltcedar can establish but just has not dispersed into yet. Expert evaluation then becomes a critical discriminatory measure in assessing the true nature of the error. Expert evaluation needs to determine if the spatial model has over predicted into new areas where the pest cannot realistically access, or it has identified new area the pest may indeed invade and establish but just has not reached yet. In selecting final models, expert evaluation should be used as the final discriminatory measure.

In Chapter 6, I proposed a sequential triage approach be employed to select the best model using (1) measures of predictive accuracy, (2) performance measures and statistics, and finally (3) expert evaluation. The results of this study further validated the

recommended triage approach, whereby expert evaluation should be used as the final discriminatory measure in selecting the best model.

Based upon recent incursions in Saskatchewan and our models, it is predicted that saltcedar will further naturalize and become invasive in Prairie Canada in the near future. There are a number of potential pathways through which saltcedar may be introduced into Prairie Canada. Introductions may occur intentionally by humans through ornamental plantings (Pearce and Smith 2003), by natural spread (e.g., seed or stem fragments transported along riparian corridors), or unintentionally through the movement of contaminated materials. The plantings as ornamental trees or shrubs is a recognized threat, for example, saltcedar is still sold as an ornamental in the US and Canada, and there is evidence that these horticultural varieties are contributing to dispersal in the US as genetic material from *T. ramosissima* “Pink Cascade” has been found in specimens (Gaskin and Schaal 2002). Varieties of saltcedar have been available for sale in garden centers in Winnipeg, Manitoba, for several years (personal observation). Saltcedar may also spread naturally into Prairie Canada through riparian corridors connected to invaded areas of Montana or North Dakota. For example, a riparian pathway is provided by the Milk River which saltcedar has invaded in parts of central Montana and these incursions are about 60 km south of the Alberta border (i.e., the Milk River flows northeast into Alberta). The movement of contaminated materials such as gravel which may have resulted in incursions in Saskatchewan is an example of an unintentional pathway of introduction. Climate warming may also lead to saltcedar range extensions (Hamann and Wang 2006, Hellman et al. 2008).

Phenotypic plasticity, ecotypic differentiation, and high genetic variation increase the probabilities that saltcedar will establishment in the colder climates of Canada (Sexton et al. 2002). This is supported by detections of saltcedar in Saskatchewan in 2010 and near Penticton and Osoyoos in southern British Columbia (Catling and Lomer 2007). Prior to the detections of saltcedar in British Columbia and Saskatchewan in Canada, the northern distributional limits were found in Montana and Wyoming which have mean January temperatures of -15°C and maximum July temperatures of 32°C (Lesica and Miles 2001) and frost-free periods ranging from 112 to 179 days (Pearce and Smith 2003). Hence, the northward spread of saltcedar into Canada may not be prevented by cold temperatures and an abbreviated growing season (Pearce and Smith 2003, 2007). It is evident that saltcedar has not yet reached the limits of its potential northern distribution in Prairie Canada. Early detection, continuous monitoring, education, coordination and cooperation, and additional research are all required to prevent or delay the invasion of saltcedar into the Prairie Canada.

7.15 Conclusions

The results of this chapter support the conclusions of the preceding chapter further validating the use of GARP as a tool to be used in biosecurity risk analysis frameworks. The results of this chapter indicated that the algorithm can be used to successfully predict the potential distribution of an invasive plant, and hence it should be included as a tool in the biosecurity toolbox. Based upon the spatial information provided in this chapter, what might be the policy decision a biosecurity agency might arrive at? Under the IPPC framework, a country might restrict or prohibit the import of a

pest if it meets the definition of a quarantine pest (see Chapter 6 for a definition). Saltcedar has not naturalized in Prairie Canada hence it would meet the definition of a quarantine pest (i.e., it has been detected in Saskatchewan but eradicated). The models developed in this study indicate that saltcedar has not reached the full limits of its ecological range and that Prairie Canada provides suitable area for further invasion. Hence, applying phytosanitary measures to prevent its establishment and spread may be justified by a biosecurity agency. An example phytosanitary measure maybe to prohibit the import of saltcedar for ornamental planting into Canada a strategy that would avoid new introductions (Peterson and Vieglais 2001).

Areas identified by the model as potential distribution for saltcedar should be targeted for biosecurity surveillance efforts and early detection and rapid response (EDRR) programs. As indicated in Chapter 6, the spatial predictive models produced in this dissertation should be used to target survey efforts towards high risk areas. This would result in resource savings to limited biosecurity surveillance budgets. For example, the model indicates that EDRR efforts should be targeted towards areas in southern Saskatchewan and Alberta along the Canada - US border. The results of this Chapter provides new spatial information to assist biosecurity agencies, provincial governments, weed supervisors, rural municipalities, cities, and conservation districts in designing EDRR programs that would prevent further establishment of saltcedar loosestrife in Prairie Canada.

7.16 References

Allouche, O., A. Tsor and R. Kadmon. 2006. Assessing the accuracy of species

- distribution models: prevalence, kappa and the true skill statistic (TSS). *Journal of Applied Ecology* 43:1223-1232.
- Anderson, B. W., A. Higgins and R.D. Ohmart. 1977. Avian use of saltcedar communities in lower Colorado River Valley. Pages 128-136 *in* R.R. Johnson and D.Jones (Technical co-ordinators). Importance Preservation and Management of Riparian Habitat: A Symposium, 9 July 1977, Tuscon, AZ. USDA Forest Service, Rocky Mountain Forest Range Experiment Station, General Technical Report RM-43. Fort Collins, Colorado.
- Anderson, R.P., D. Lew and A.T. Peterson. 2003. Evaluating predictive models of species' distributions: criteria for selecting optimal models. *Ecol. Model.* 162:211-232.
- Baldessarini, R.J., S. Finklestein and G. Arana. 1983. The predictive power of diagnostic tests and the effect of prevalence of illness. *Arch. General Psychiatry* 40:569-573.
- Baum, B.R. 1967. Introduced and naturalized tamarisks in the United States and Canada (Tamaricaceae). *Baileya* 15:19-25.
- Baum, B.R. 1978. The Genus *Tamarix*. Jerusalem, Israel: Israel Academy of Sciences and Humanities. 209 pp.
- Bay, R. and A. Sher. 2008. Success of active revegetation after *Tamarix* removal in riparian ecosystems of the Southwestern United States: a quantitative assessment of past restoration projects. *Restoration Ecology* 16:113-128.
- Beauchamp, V. B., J.C. Stromberg and J.C. Stutz. 2005. Interactions between *Tamarix ramosissima* (saltcedar), *Populus fremontii* (cottonwood), and mycorrhizal fungi: Effects on seedling growth and plant species coexistence. *Plant Soil* 275:221-231.

- Berry, W.L. 1970. Characteristics of salts secreted by *Tamarix aphylla*. *Am. J. Bot.* 57: 1226-1230.
- Biggerstaff, B.J. 2000. Comparing diagnostic tests: a simple graphic using likelihood ratios. *Statistics in Medicine* 19:649-663.
- Bland, J. and D. Altman. 2000. The odds ratio. *BMJ* 320:1468.
- Bradley, B.A., M. Oppenheimer and D.S. Wilcove. 2009. Climate change and plant invasion: restoration opportunities ahead? *Global Change Biol.* 15:1511-1521.
- Brock, J.H. 1994. *Tamarix* spp. (Saltcedar), an Invasive Exotic Woody Plant in Arid and Semi-arid Riparian habitats of Western USA. Pages 27-44 in L.C. de Wall, L.S. Child, P.M Wade, and J.H. Brock, ed. *Ecology and Management of Invasive Riverside Plants*. John Wiley & Sons, Chichester. 217 pp.
- Brookman, D.A. 2004. Remote sensing and predictive modeling of saltcedar (*Tamarix*) in the Northern Great Plains. Master of Science Thesis, University of North Dakota, Grand Forks, North Dakota.
- Brotherson, J.D. and D. Field. 1987. Tamarix: impacts of a successful weed. *Rangelands* 9:110-112.
- Brotherson, J.D. and V. Winkel. 1986. Habitat relationships of saltcedar (*Tamarix ramosissima*) in central Utah. *Great Basin Naturalist* 46:535-541.
- Brown, B.T. and M.W. Trosset. 1989. Nesting-habitat relationships of riparian birds along the Colorado River in Grand Canyon, Arizona. *Southwestern Nat.* 34:260-270.
- Busch, D.E. and S.D. Smith. 1993. Effects of fire on water and salinity relationships of riparian woody taxa. *Oecologia* 94:186-0194.
- Catling, P.M. and F. Lomer. 2007. Canadian List of Naturalized Alien Trees and Shrubs

- some additions and recent information. *Botanical Electronic News* 382:3-5.
- Carpenter A.T. 1998. Element Stewardship Abstract for *Tamarix ramosissima* Ledebour, *Tamarix pentandra* Pallas, *Tamarix chinensis* Loureiro, *Tamarix parviflora* De Candolle, Saltcedar, Salt cedar, & Tamarisk. The Nature Conservancy, Wildland Weeds Management and Research, 124 Robbins Hall, University of California, Davis, CA. 30 pp.
- Carruthers, R.I., C.J. DeLoach, J.C. Herr, G.L. Anderson and A.E. Knutson. 2008. Salt Cedar areawide pest management in the western USA. Pages 271-299 in O. Koul, G. W. Cuperus, and N. Elliot, eds. *Areawide Pest Management Theory and Implementation*. CAB International, Wallingford, Oxfordshire, UK.
- Charney, N.D. 2012. Evaluating expert opinion and spatial scale in an amphibian model. *Ecological Modelling* 242: 37-45.
- Chen, P., E. Wiley and K.M. Mcnyset. 2007. Ecological niche modeling as a predictive tool: silver and bighead carp in North America. *Biological Invasions* 9:43-51.
- Cook, W.C. 1925. The distribution of the alfalfa weevil (*Phytonomus pesticus* Gyll.); a study in physical ecology. *Journal of Agricultural Research* 30: 479-491.
- Christensen, E.M. 1962. The rate of naturalization of *Tamarix* in Utah. *Am. Midl. Nat.* 68:51-57.
- Costa, G., C. Nogueira, R.B. Machado and G.R. Colli. 2010. Sampling bias and the use of the ecological niche modeling in conservation planning; a field evaluation in a biodiversity hotspot. *Biodivers. Conserv.* 19:883-899.
- Crins, W.J. 1989. The Tamaricaceae in the southeastern United States. *J. Arnold Arbor.* 70:403-425.

- DeLoach, C.J., R.I. Carruthers, J.E. Lovich, T.L. Dudley and S.D. Smith. 2000. Ecological interactions in the biological control of saltcedar (*Tamarix* spp.) in the United States: toward a new understanding. Pages 819-873 in N. R. Spencer, ed. Proceedings of the X International Symposium on Biological Control of Weeds, 4-14 July 1999, Montana State University, Bozeman, Montana, USA.
- DeLoach, C.J., P.A. Lewis, J.C. Herr, R.I. Carruthers, J.L. Tracy and J. Johnson. 2003. Host specificity of the leaf beetle, *Diorhabda elongata deserticola* (Coleoptera: Chrysomelidae) from Asia, a biological control agent for saltcedars (*Tamarix*: Tamaricaceae) in the Western United States. *Biol. Control* 27:117-147.
- DeLoach, C. J., R.I. Carruthers, T.L. Dudley, D. Eberts, D.J. Kazmer, A. Knutson, D.W. Bean, J. Knight, P.A. Lewis, L.R. Milbrath, J.L. Tracy, N. Tomic-Carruthers, J.C. Herr, G. Abbott, S. Prestwich, G. Harruff, J.H. Everitt, D.C. Thompson, I. Mityaev, R. Jashenko, B. Li, R. Sobhian, A. Kirk, T. Robbins and E.S. Delfosse. 2004. First results for control of saltcedar (*Tamarix* spp.) in the open field in the western United States. Pages 505-513 in Cullen, J. M., Briese, D. T., Kriticos, D. J., Lonsdale, W. M., Morin, L., and Scott, J. K. (eds.). Proceedings of the XI International Symposium on Biological Control of Weeds, 28 April-2 May 2003. Canberra, Australia: CSIRO Entomology.
- DeLoach, C.J., A.E. Knutson and P.J. Moran. 2009. Progress on Biological Control of Saltcedar in Texas 2004-2008. Report of Information for the Public, United States Department of Agriculture. Texas. 59 pp.
- DiTomaso, J. M. 1998. Impact, biology, and ecology of saltcedar (*Tamarix* spp.) in the Southwestern United States. *Weed Technol.* 12:326-336.

- Dudley, T. L. and C.J. DeLoach. 2005. Saltcedar (*Tamarix* spp.), endangered species and biological control – Can they mix? *Weed Technol.* 18:1542-1551.
- Elith, J. and C.H. Graham. 2009. Do they? How do they? Why do they? On finding reasons for differing performances of species distribution models. *Ecography* 32:66-77.
- Elgan, T. B., R.A. Chavez and B.R. West. 1993. Afton Canyon saltcedar removal first year status report. Page 18 *in* L. Smith, and J. Stephenson, eds. *Proceedings of the Symposium on Vegetation Management. Hot Desert Rangeland Ecosystems.* Phoenix, AZ.
- Ellis, L. M. 1995. Bird use of saltcedar and cottonwood vegetation in the Middle Rio Grande Vally of New Mexico, U.S.A. *J. Arid Environ.* 30:339-349.
- Engel-Wilson, R.W. and R.D. Ohmart. 1978. Assessment of vegetation and terrestrial vertebrates along the Rio Grande between Fort Quitman, TX and Haciendita, TX. International Boundary and Water Commission, El Paso, Texas. 88 pp.
- Exotic Species Program. 2004. Harmful Exotic Species of Aquatic Plants and Wild Animals in Minnesota. Annual Report for 2003. Minnesota Department of Natural Resources, St. Paul, MN.
- Fielding, A.H. and J.F. Bell. 1997. A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environmental Conservation* 24:38-49.
- Follack, S. 2011. Potential distribution and environmental threat of *Pueraria lobata*. *Central European Journal of Biology* 3:457-469.
- Forbes, A.D. 1995. Classification-algorithm evaluation: five performance measures based on confusion matrices. *Journal of Clinical Monitoring and Computing* 11:189-

206.

- Frasier, G.W. and T.N. Johnsen. 1991. Saltcedar (Tamarisk): classification, distribution, ecology and control. In Noxious Range Weeds. L. James, J. Evans, M. Ralphs and R. Child (Eds). Westview Press, San Francisco.
- Friedman, J.M., G.T. Auble, P.B. Shafroth, M.L. Scott, M.F. Merigliano, M.D. Freehling and E.R. Griffin. 2005. Dominance of non-native riparian trees in western USA. *Biological Invasions* 7:747-71.
- Friedman, J.M., J.E. Roelle, J.F. Gaskin, A.E. Pepper and J.R. Manhart. 2008. Latitudinal variation in cold hardiness in introduced *Tamarix* and native *Populus*. *Evolutionary Applications* 1:598-607.
- Gary, H.L. 1963. Root distribution of five-stamen tamarisk, seepwillow, and arrowweed. *For. Sci.* 9:311-314.
- Gaskin, J.F. and B.A. Schaal. 2002. Hybrid *Tamarix* widespread in U.S. invasion and undetected in native Asian range. *Proc. Natl. Acad. Sci. U.S.A.* 99:11256-11259.
- Gaskin, J.F. and B.A. Schaal. 2003. Molecular phylogenetic investigation of U.S. invasive *Tamarix*. *Syst. Bot.* 28:86-95.
- Gaskin, J.F. and P.B. Shafroth. 2005. Hybridization of *Tamarix ramosissima* and *T. chinensis* (Saltcedars) with *T. aphylla* (Athel) (Tamaricaceae) in the southwestern USA determined from DNA Sequence Data. *Madrono* 52:1-10.
- Gaskin, J.F. and D.J. Kazmer. 2009. Introgression between invasive saltcedars (*Tamarix chinensis* and *T. ramosissima*) in the USA. *Biol. Invasions* 11:1121-1130.
- Glas, A.S., J. Lijmer, M. Prins, G. Bonsel and P. Bossuyt. 2003. The diagnostic odds ratio: a single indicator of test performance. *Journal of Clinical Epidemiology* 56:1129-

1135.

- Glenn, E.P. and P.L. Nagler. 2005. Comparative ecophysiology of *Tamarix ramosissima* and native trees in western U.S. riparian zones. *J. Arid Environ.* 61:419-446.
- Grimes, D.A. and K.F. Schultz. 2008. Making sense of odds and odds ratios. *Obstetrics & Gynecology* 111:423-426.
- Grubb, R.T., R.L. Sheley and R.D. Carlstrom. 2002. Saltcedar (Tamarisk). Montana State University Extension Service. Bozeman, MT.
- Halvorson, W.L. and P. Guertin. 2003. Factsheet for *Tamarix L. spp.*. USGS Weeds in the West project: Status of Introduced Plants in Southern Arizona Parks. U.S. Geological Survey, National Park Service. Tucson, Arizona. 47 pp.
- Hart, C.R. 2003. Saltcedar biology and management. Publ. No. L-5540. Texas Cooperative Extension, Texas A&M University System, College Station, Texas, USA. Science Advice and Biohazard Control Division.
- Hart, C.R., L. White, A. McDonald and Z. Sheng. 2005. Saltcedar control and water salvage on the Pecos river, Texas, 1999-2003. *J. Environ. Manag.* 75:399-409.
- Hamann, A. and T. Wang. 2006. Potential effects of climate change on ecosystem and tree species distribution in British Columbia. *Ecology* 87:2773-2786.
- Hellman, J., J. Byers, B. Bierwagen and J. Dukes. 2008. Five potential consequences of climate change for invasive species. *Conserv. Biol.* 22:534-543.
- Hirzel, A. and A. Guisan. 2002. Which is the optimal sampling strategy for habitat suitability modelling? *Ecological Modelling* 157:331-341.
- Holdenbach, G. 1987. Tamarix control. Pages 116-123 in M.R. Kunzmann, R.R.

- Johnson, and P. Bennet, eds. Tamarix control in the United States. Tucson, AZ: University of Arizona.
- Horton, J.S. 1964. Notes on the introduction of deciduous Tamarix. Fort Collins, CO: U.S. Forest Service Research Note R-16.
- Horton, J.S. 1977. The development and perpetuation of the permanent tamarisk type in the phreatophyte zone of the Southwest. Pages 124-127 in R. R. Johnson and D. A. Jones, eds. Symposium on the Importance, Preservation, and Management of Riparian Habitat, 9 July 1977, Tucson, Arizona. Fort Collins, Colorado, USA: USDA Forest Service, General Technical Report RM-43.
- Hudgeons, J. L., A.E. Knutson, K.M. Heinz, C.J. DeLoach, T.L. Dudley, R.R. Pattison and J.R. Kiniry. 2007. Defoliation by introduced *Diorhabda elongate* leaf beetles (Coleoptera: Chrysomelidae) reduces carbohydrate reserves and regrowth of *Tamarix* (Tamaricaceae). Biol. Control 43:213-221.
- Hughes, L.E. 1993. 'The devil's own' - tamarisk. Rangelands 15:151-155.
- Hunter, W.C., R.D. Ohmart and B.W. Anderson. 1988. Use of exotic saltcedar (*Tamarix chinensis*) by birds in arid riparian systems. Condor 90:113-123.
- IPPC. 2001. Climate data archive. Geneva, Switzerland. Available online at <http://www.ipcc.ch/> (accessed May 2010).
- Johnson, C.J. and M.P. Gillingham. 2004. Mapping uncertainty: sensitivity of wildlife habitat ratings to expert opinion. Journal of Applied Ecology 41:1032-1041.
- Kauffman, W. 2005. Program for Biological Control of Saltcedar (*Tamarix spp.*) in Thirteen States. Environmental Assessment June 2005. U.S. Department of Agriculture, Western Region. Fort Collins, Colorado. 56 pp.

- Kapetsky, J.M., J.M. Hill and L.D. Worthy. 1988. A geographic information system for catfish farming development. *Aquaculture* 68:311-320.
- Kerns, B.K., B. Naylor, M. Buonopante, C.G. Parks and B. Rogers. 2009. Modeling Tamarisk (*Tamarix* spp.) habitat and climate change effects in the Northwestern United States. *Invasive Plant Science and Management* 2:200-215.
- Kriticos, D.J. and R.P. Randall. 2001. A comparison of systems to analyse potential weed distributions. In *Weed Risk Assessment*, eds. R.H. Groves, F.D. Panetta and J.G. Virtue, pp 61-79. CSIRO Publishing, Melbourne.
- Kuhnert, P. M., T. G. Martin and S.P. Griffiths. 2010. A guide to eliciting and using expert knowledge in Bayesian ecological models. *Ecology Letters* 13:900-914.
- Ladyman, J.A. 2003. *Tamarix chinensis* Lour. Pages 332-333 in J.K. Francis, ed. *Wildland Shrubs of the United States and its Territories: Thamnisc Descriptions*. General Technical Report IITF-WB-1. U.S. Department of Agriculture, Forest Service International Institute of Tropical Forestry and Shrub Sciences Laboratory. [Online] (Accessed March 2013) Available at: <http://www.fs.fed.us/global/iitf/pdf/shrubs/Tamarix%20chinensis.pdf>.
- Lehnhoff, E.A., F.D. Menalled, and L.J. Rew. 2011. Tamarisk (*Tamarix* spp.) establishment in its most northern range. *Invasive Plant Science and Management* 4:58-65.
- Lesica, P. and S. Miles. 2001. Tamarisk growth at the northern margin of its naturalized range in Montana, USA. *Wetlands* 21:240-246.
- Levine, R.S., A.T. Peterson, K.L. Yorita, D. Carroll, I.K. Damon and M.G. Reynolds. 2007. Ecological niche and geographic distribution of human monkeypox in Africa.

2007. PLoS ONE 2: e176.
- Liesner, D.R. 1971. Phytophagous insects of *Tamarix* spp. in New Mexico. M.S. Thesis, New Mexico State University, Las Cruces, New Mexico, USA.
- Lindgren, C.J. and R.T. Clay. 1993. Fertility of "Morden Pink" *Lythrum virgatum* L. transplanted into wild stands of *L. salicaria* in Manitoba. HortScience 28:954.
- Mac Nally, R. 1996. Hierarchical partitioning as an interpretative tool in multivariate inference. Australian Journal of Ecology 21:224-228.
- Mahoney, J.M. and S.B. Rood. 1998. Streamflow requirements for cottonwood seedling recruitment: an integrative model. Wetlands 18:634-645.
- Mateo, R., T.B. Croat, A.M. Felicisimo and J. Munoz. 2012. Profile or group discriminative techniques? Generating reliable species distribution models using pseudo-absences and target-group absences from natural history collection. Diversity and Distributions 16:84-94.
- McNyset, K.M. 2005. Use of ecological niche modelling to predict distributions of freshwater fish species in Kansas. Ecol. Freshw. Fish 14:242-255.
- Merkel, D.L. and H. Hopkins. 1957. Life history of saltcedar (*Tamarix gallica* L.). Trans. Kan. Acad. Sci. 60:360-369.
- Neill, W.M. 1985. Tamarisk. Fremontia 12:22-23.
- Nilsson, C. and K. Berggren. 2000. Alterations of riparian ecosystems caused by river regulation. BioScience 50:783-792.
- Oberhauser, K. and A.T. Peterson. 2003. Modelling current and future potential wintering distributions of eastern North American monarch butterflies. Proc. Nat. Acad. Sci. U.S.A. 100:14063-14068.

- Osborne, P.E. and S. Suarez-Seoane. 2002. Should data be partitioned spatially before building large scale distribution models? *Ecological modelling* 157:249-259.
- Owen, J.C. and M.K. Sogge. 2002. Physiological condition of southwestern willow flycatchers in native and saltcedar habitats. U.S. Geological Survey report to the Arizona Department of Transportation, Phoenix. 27 pp.
- Owens, M.K. and G.W. Moore. 2007. Saltcedar water use: Realistic and unrealistic expectations. *Rangeland Ecol. Manag.* 60:553-557.
- Pearce, C.M. and D.G. Smith. 2003. Saltcedar: distribution, abundance, and dispersal mechanisms, northern Montana, USA. *Wetlands* 23:215-228.
- Pearce, J. and S. Ferrier. 2000. Evaluating the predictive performance of habitat models developed using logistic regress. *Ecological Modelling* 133:225-245.
- Pearce, C.M. and Smith, D.G. 2007. Invasive saltcedar (*Tamarix*): its spread from the American Southwest to the Northern Great Plains. *Physical Geogr.* 28:1-14.
- Peterson, A. T. and K.P. Cohoon. 1999. Sensitivity of distributional prediction algorithms to geographic data completeness. *Ecological Modelling* 117:159–164.
- Peterson, A.T. and D.A. Vieglais. 2001. Predicting species invasions using ecological niche modeling: new approaches from bioinformatics attack a pressing problem. *Bioscience* 51:363-371.
- Peterson, A.T., M. Papes and D.A. Kluza. 2003. Predicting the potential invasive distributions of four alien plant species in North America. *Weed Sci.* 51:863-868.
- Peterson, A.T. and J. Shaw. 2003. *Lutzomyia* vectors for cutaneous leishmaniasis in Southern Brazil: ecological niche models, predicted geographic distributions, and climate change effects. *International Journal for Parasitology* 33:919-931.

- Peterson, A.T., R. Williams and G. Chen. 2007. Modeled global invasive potential of Asian gypsy moths, *Lymantria dispar*. *Entomologia Experimentalis et Applicata* 125:39-44.
- Peterson, A.T., M. Papes and J. Soberon. 2008. Rethinking receiver operating characteristic analysis applications in ecological niche modeling. *Ecological Modelling* 213:63-72.
- Peterson, A.T. 2011. Ecological niche conservatism: a time-structured review of evidence. *Journal of Biogeography* 38:817-827.
- Peterson, A.T., J. Soberon, R.G. Pearson, P. Anderson, E. Martinez-Meyer, M. Nakamura, and M. Bastos Araujo. 2011. *Ecological Niches and Geographic Distributions*. Princeton University Press, Princeton, New Jersey. 316 pp.
- Pepe, M. H. Janes, G. Longton, W. Leisenring and P. Newcomb. 2004. Limitations of the odds ratio in gauging the performance of a diagnostic, prognostic, or screening marker. *American Journal of Epidemiology* 159:882-890.
- Pheloung, P.C., P.A. Williams and S.R. Halloy. 1999. A weed risk assessment model for use as a biosecurity tool evaluating plant introductions. *J. of Environmental Management* 57:239-251.
- Rita, H. and A. Komonen. 2008. Odds ratio: an ecologically sound tool to compare proportions. *Ann. Zool. Fennici* 45:66-72.
- Robinson, T.W. 1965. Introduction, spread and aerial extent of saltcedar (*Tamarix*) in the Western States. U. S. Geological Survey Professional Paper 491-A. 12 pp.
- Rood, S. B. and J.M. Mahoney. 2000. Revised instream flow regulation enables cottonwood recruitment along the St. Mary River, Alberta, Canada. *Rivers* 7:109-

125.

- Rood, S. B., C.R. Gourley, E.M. Ammon, L.G. Heki, J.R. Klotz, M.L. Morrison, D. Mosley, G. Scoppettone, S. Swanson and P.L. Wagner. 2003. Flows for floodplain forests: a successful riparian restoration. *BioScience* 53:647-656.
- Sexton, J.P., J.K. McKay and A. Sala. 2002. Plasticity and genetic diversity may allow saltcedar to invade cold climates in North America. *Ecol. Appl.* 12: 1652-1660.
- Sexton, J. P., A. Sala and K. Murray. 2006. Occurrence, persistence, and expansion of saltcedar (*Tamarix* spp.) populations in the Great Plains of Montana. *West. N. Am. Nat.* 66:1-11.
- Shafroth, P. B., J.M. Friedman, G.T. Auble, M.L. Scott and J.H. Braatne. 2002. Potential responses of riparian vegetation to dam removal. *BioScience* 52:703-712.
- Sher, A. and D. Marshall. 2003. Seedling competition between native *Populus deltoides* (Salicaceae) and exotic *Tamarix ramosissima* (Tamaricaceae) across water regimes and substrate types. *Am. J. Bot.* 90:413-422.
- Sher, A.A., D.L. Marshall and S.A. Gilbert. 2000. Competition between native *Populus deltoides* and invasive *Tamarix ramosissima* and the implications for re-establishing flooding disturbance. *Conserv. Biol.* 13:1744-1754.
- Sher, A., D. Marshall and J. Taylor. 2002. Establishment patterns of native *Populus* and *Salix* in the presence of invasive non-native *Tamarix*. *Ecol. Appl.* 12:760-772.
- Si, Y., T. Wang, A.K. Skidmore, W. de Boer, L. Li and H. Prins 2010. Environmental factors influencing the spread of the highly pathogenic avian influenza H5N1 Virus in wild birds in Europe. *Ecology and Society* 15: 26. [online] URL: <http://www.ecologyandsociety.org/vol15/iss3/art26/>

- Stephenson, D.B. 1999. Use of the “Odds-Ratio” for diagnosing forecast skill. *Weather and Forecasting* 15:221-232.
- Sobek-Swant, S, D.A. Kluza, K. Cuddington and B. Lyons. 2012. Potential distribution of emerald ash borer: what can we learn from ecological niche models using Maxent and GARP? *Forest Ecology and Management* 281:23-31.
- Sogge, M. K., S.J. Sferra and E.H. Paxton. 2008. Tamarix as habitat for birds: Implications for riparian restoration in the Southwestern United States. *Restor. Ecol.* 16:146-154.
- Sprenger, M. D., L.M. Smith and J.P. Taylor. 2001. Testing control of saltcedar seedlings using fall flooding. *Wetlands* 21:437-444.
- Stevens, L.E. 1990. The status of ecological research on Tamarisk (Tamaricaceae: *Tamarix ramosissima*) in Arizona. Pages 99-105 in M.R. Kunzmann, R.R. Johnson, and P.S. Bennett, eds. Tamarisk control in southwestern United States. Proceedings of Tamarisk Conference, September 2-3, 1987, Tucson, Arizona, Special Report No. 9. University of Arizona, Tucson, Arizona. National Park Service, Cooperative National Park resources Studies Unit, School of Renewable Natural Resources, University of Arizona, Tucson, Arizona.
- Stockwell, D. R. B. and I. R. Noble. 1992. Induction of sets of rules from animal distribution data: A robust and informative method of data analysis. *Math and Computers in Simulation* 33:385–390.
- Stockwell, D.R. and A.T. Peterson. 2002. Effects of sample size on accuracy of species distribution models. *Ecological Modelling* 148:1-13.
- Stohlgren, T.J., K.A. Bull, Y. Otuski, C. Villa and M. Lee. 1998. Riparian zones as

- havens for exotic plant species. *Plant Ecol.* 138:113-125.
- Stromberg, J.C., S.J. Lite, R. Marler, C. Paradzick, P.B. Shafroth, D. Shorrocks, N.G. Tallent-Halsell and L.R. Walker. 2002. Responses of *Salix gooddingii* and *Tamarix ramosissima* to flooding. *Wetlands* 22:776-785.
- Sutherst, R.W. and G.F. Mayward. 1985. A computerized system for matching climates in ecology. *Agriculture, Ecosystems and Environment* 13:281-299.
- Sutherst, R.W., G.F. Maywald and B.L. Russell. 2000. Estimating vulnerability under global change: modular modelling of pests. *Agriculture, Ecosystems and Environment* 82:303-319.
- Tarkesh, M. and G. Jeschke. 2012. Comparison of six correlative models in predictive vegetation mapping on a local scale. *Environmental and Ecological Statistics* 19:437-457.
- Tesky, J.L. 1992. *Tamarix ramosissima*. In: The Fire Effects Information System [database]. U.S.D.A., Forest Service, Intermountain Research Station, Missoula, MT.
- Therriault, T.W. and L. Herborg. 2008. A qualitative biological risk assessment for vase tunicate *Ciona intestinalis* in Canadian waters: using expert knowledge. *ICES Journal of Marine Science* 65:781-787.
- Thuiller, W. 2003. BIOMOD – optimizing predictions of species distributions and projecting potential future shifts under global change? *Global Change Biology* 9:1353-1362.
- Titus, J. H., P.J. Titus, R.S. Nowak and S.D. Smith. 2002. Arbuscular mycorrhizae of Mojave Desert plants. *West. N. Am. Nat.* 62:327-334.
- USDA-NRCS. 2008. The PLANTS Database. Baton Rouge, USA: National Plant Data

- Center. [Online] (Accessed July 27 2009). Available at: <http://plants.usda.gov>.
- Warren, D. K. and R.M. Turner. 1975. Saltcedar (*Tamarix chinensis*) seed production, seedling establishment, and responses to inundation. *J. Arizona Acad. Sci.* 10:135–144.
- Welk, E., K. Schubert and M. Hoffmann. 2002. Present and potential distribution of invasive garlic mustard (*Alliaria petiolata*) in North America. *Diversity and Distributions* 8:219-233.
- White, J.M. and M.S. White. 2007. Altered stream-flow regimes and invasive plant species: the *Tamarix* case. *Global Ecol. Biogeogr.* 16:381-393.
- Wilgus, F. and K.C. Hamilton. 1962. Germination of salt cedar seed. *Weeds* 10:332-333.
- Yerushalmy, J. 1947. Statistical problems in assessing methods of medical diagnosis, with special reference to X-ray techniques. *Public Health Reports* 62:1432-1449.
- Young, W. and D.M. Finch. 1997. Population trends of migratory land birds along the middle Rio Grande. *Southwest. Nat.* 42:137-147.
- Young, J.A., C.D. Clements and D. Harmon. 2004. Germination of seeds of *Tamarix ramosissima*. *J. Range Manag.* 57:475-481.
- Youden, W. 1950. Index for rating diagnostic tests. *Cancer* 3:32-35.
- Zavaleta, E. 2000. Valuing ecosystem services lost to *Tamarix* invasion in the United States. Pages 261-299 in H.A. Mooney and R. J. Hobbs, eds. *Invasive species in a changing world*. Washington, D.C: Island Press.
- Zhai, S.H. and M.X. Li. 1986. Chromosome number of *Tamarix* L., *Acta Phytotax. Sin.* 24:273-274.

Zhang, D., L. Yin and B. Pan. 2003. Biological and ecological characteristics of *Tamarix* L. and its effect on the ecological environment. *Sci. China* 45:18-22.

CHAPTER 8 – CONCLUSIONS AND CONTRIBUTION TO NEW KNOWLEDGE

8.1 Summary

This dissertation provided a critical evaluation of current biosecurity policy instruments and provided recommendations on how to modernize the biosecurity toolbox. This dissertation extended the use of spatial predictive modeling in addressing the risks two invasive plants in Prairie Canada. In this study, spatial predictive modeling and geographic information were integrated to produce new spatial models. These techniques should be applied by biosecurity agencies to modernize their risk-based regulatory frameworks and to direct risk-based surveillance programs. This dissertation also provided the first models of the potential distributions of saltcedar and purple loosestrife in Prairie Canada. The ability to identify emerging quarantine pests, and to predict where they may establish and spread, has tremendous economic value to biosecurity agencies, and is also of immense geographic interest (Mack et al. 2000).

8.2 Applications of New Knowledge

8.2.1 Biosecurity Decision-Making

The best strategy against invasive plants is to keep them out. Prevention is the most cost effective and efficient strategy against pest incursions (Simberloff 2003). From a biosecurity perspective, tools and general approaches that have the potential to predict pest incursions are required. Biosecurity agencies can utilize the techniques and

approaches used in this study to build informative models that can guide policy decisions (e.g., that either allow or prohibit plants for importation into a country). The modelling methods used in this study can be applied by biosecurity agencies to meet their obligations under international and national policy instruments and to support biosecurity decision-making. In the absence of predictive tools, signatory parties of the IPPC are restricted in their ability to develop effective policies against invasive plants. Predictive modelling can not only be useful in an examination of geographic consideration, but help with determining the economic importance of a potential pest, both requirements of biosecurity risk analysis. Spatial predictive models can also be used to determine habitats where a species cannot establish, for example if a pest arrives in an area projected to be unsuitable for establishment, no risk exists (Venette et al. 2010).

8.2.2 An RSPM on Spatial Predictive Modelling

Biosecurity agencies can incorporate new practices or techniques such as spatial predictive modelling into their risk analysis frameworks by developing phytosanitary standards. International Standards for Phytosanitary Measures (ISPM) are developed by the United Nation's Food and Agriculture Organization (FAO 2006) as part of their global program on policy and plant protection. Under the International Plant Protection Convention (IPPC), each signatory country is required to establish a National Plant Protection Organization (NPPO). The NPPO's can also develop Regional Standards for Phytosanitary Measures (RSPMs) which serve as guidelines to protect resources against regulated plant pests (Petter et al. 2008). Presently, there are no standards that attempt to

incorporate spatial predictive modelling tools into an IPPC risk analysis. In some standards the use of climatic matching is briefly eluded to however no details are provided. For example, RSPM No. 32 (2008), *Pest Risk Assessment for Plants for Planting as Quarantine Pests*, suggests that climate matching and climatic modelling systems can be used to compare ecological data from known distributions to novel areas in a pest risk assessment (see Chapter 3 for a more detailed discussion). Hence, there is opportunity to develop a standard or a RSPM that guides the use of spatial predictive modelling. Below is a proposed RSPM, the format follows that of a traditional IPPC RSPM.

Draft RSPM

Incorporating Spatial Predictive Modeling into Risk Analysis for the Plants for Planting Pathway

INTRODUCTION

SCOPE

This standard provides guidance to National Plant Protection Organizations (NPPOs) in how to use spatial predictive modeling in the pest risk analysis process, specifically for plants for planting and for the purposes of preparing phytosanitary regulations.

The primary scope of this RSPM is plants imported through the plants for planting pathway, that may establish, spread, and become a pest (e.g., invasive plants) in either managed or unmanaged systems. The probability of establishment in protected environments (e.g., in glasshouses) is not in the scope of this standard.

REFERENCES

- Agreement on the Application of Sanitary and Phytosanitary Measures*, 1994. World Trade Organization, Geneva.
- International Plant Protection Convention*, 1997. FAO, Rome.
- Principles of plant quarantine as related to international trade*, 1995. ISPM No. 1, FAO, Rome.
- Guidelines for pest risk analysis*, 1996. ISPM No. 2, FAO, Rome.
- International Plant Protection Convention*, 1997. FAO, Rome.
- Pest risk analysis for quarantine pests*, 2001. ISPM No. 11, FAO, Rome.
- Pest risk analysis for quarantine pests including analysis of environmental risks and living modified organisms*, 2004. ISPM No. 11, FAO, Rome.
- Glossary supplement No. 2: Guidelines on the understanding of potential economic importance and related terms including reference to environmental considerations*, 2003. ISPM No. 5, FAO, Rome.
- Convention on Biological Diversity*, 1992. CBD, Montreal.
- Pest risk assessment for plants for planting as quarantine pests*, RSPM No. 32, 2008. The Secretariat of the North American Plant Protection Organization. Ottawa, Ontario.
- Stockwell, D.R. and D.P. Peters. 1999. The GARP modeling system: problems and solutions to automated spatial prediction. *International Journal Inf. Sci.* 13:143-158.

DEFINITIONS

Definitions of phytosanitary terms used in the present standard can be found in ISPM No. 5 (*Glossary of Phytosanitary Terms*).

OUTLINE OF REQUIREMENTS

The International Plant Protection Convention (IPPC) is based on securing common and effective action to prevent the spread and introduction of pests of plants and plant products, and the promotion of appropriate measures for their control (Article I of the IPPC, 1997). A specific requirement of plant quarantine as related to international trade is to determine which pests are quarantine pests and the strength of the measures to be taken against them, countries shall use pest risk analysis methods based on biological and economic evidence and, wherever possible, follow procedures developed within the framework of the IPPC.

Pest risk analysis (PRA) consists of three stages: initiating the process for analyzing risk, assessing pest risk, and managing pest risk. The application of spatial predictive modeling provides quantitative and spatial information that can be incorporated into the pest risk assessment stage and overall into risk analysis.

In using spatial predictive modeling, a National Plant Protection Organization (NPPO) can make an informed determination of the potential risk to a PRA area, leading to spatially informed decision making.

BACKGROUND

Spatial predictive modelling and geographic information systems (GIS) have proven to be effective tools in predicting the potential distribution of a pest, and these need to be incorporated into the biosecurity risk analysis process. Incorporating these tools would facilitate a shift in the biosecurity paradigm from a reactive to proactive regulatory approach that might anticipate new emerging pests. The best strategy for addressing invasive plants is to proactively assess their risk before they establish and spread. Spatial predictive modeling is a tool that can be used by NPPO's to proactively assess geographic risk.

Once established, invasive plants are difficult and costly to eradicate, hence the importance of using predictive tools that would also allow for early detection of, and rapid response to, new or emerging invasion plants. Specifically, the Genetic Algorithm for Rule Set Production (GARP) (Stockwell and Peters 1999) is an spatial predictive tool that NPPOs may incorporate into their pest risk analysis frameworks. It uses species occurrence data from a species native area to predict geographical distribution into a novel area. It allows a NPPO's to spatially predict a pests potential distribution and risk to an area of concern.

PURPOSE OF THE STANDARD

The objectives of the standard are to:

- increase the ability of NPPO's to model the potential distribution of a pest in the plants for planting pathway by using spatial predictive modelling,
- provide NPPO's with general guidance for incorporating spatial predictive modelling into their pest risk analysis.

GENERAL PROVISIONS OF THE IPPC AS THEY RELATE TO SPATIAL PREDICTIVE MODELING

1. Pest Risk Analysis

The NPPO of the importing country should determine whether a potentially invasive plant is required to be subjected to pest risk analysis (PRA). The process for pest risk assessment can be broadly divided into three interrelated steps pest categorization, assessment of the probability of introduction and spread, and assessment of the potential economic consequences.

As part of the PRA process, a pest risk assessment should be conducted in accordance with ISPM No. 2 (*Guidelines for pest risk analysis*) and/or stage 2 of ISPM No. 11 (*Pest risk analysis for quarantine pests including analysis of environmental risks and living modified*). In this RSPM, spatial predictive modeling is considered to be an integral part a pest risk assessment, as well as part of an overall pest risk analysis framework.

1.1 Potential for establishment in PRA area

Spatial predictive modeling can provide evidence to support the conclusion that an invasive plant could potentially become established in the PRA area. For example, the PRA area may have suitable ecological conditions allowing for the establishment and spread of the plant in the PRA area.

Considerations:

- the intended habitat is the place where the plants are intended to grow and the unintended habitat is the place where the plants are not intended to grow,
- in the case of plants to be imported, the concepts of entry, establishment and spread should be considered differently,
- plants for planting that are imported will enter and establish in a unintended habitat, probably in substantial numbers and for an indeterminate period,
- imported plants, not intended to be planted, may be used for different purposes (e.g. used as bird seed, as fodder, or for processing). The risk arises because of the probability that the plant may escape or be diverted from the intended use to an unintended habitat and establish and spread,
- in the case of plants to be imported, the assessment of the probability of establishment concerns the unintended habitats.

1.2 Predicting suitability of the PRA environment

Factors in the environment that are critical to the development of a plant, and its ability to survive periods of stress and complete life cycles, can be considered as predictive variables in developing the spatial predictive models. These are largely abiotic factors. How each predictive variable contributes to model should be evaluated statistically as well as by using expert evaluation.

Examples of predictive variables to consider include:

- topography (i.e., slope, aspect, elevation)
- temperature (i.e., mean annual temperature, temperature of warmest and coldest months)
- precipitation
- growing degree-day's
- land use patterns

1.3 Conclusion on the spatial risk

The overall pest risk should be expressed geographically in terms of the potential distribution of the pest. Expert evaluation should be considered in assessing the potential distribution model. A decision maybe reached as to if the pest can establish in the PRA area, or further extend its current range. The spatial conclusions should be brought forward into considering Risk Management options.

SPECIFIC REQUIREMENTS FOR SPATIAL PREDICTIVE MODELING

1. Data Sources

One of the major limitations of predictive spatial modeling is the lack of quality data on which to build spatial predictive models. Modelling data can include existing creditable data or data from an NPPO's surveys.

1.1 Species occurrence data

Point occurrence data for a invasive plant of concern should be collected as part of an NPPOs surveillance program. Surveillance data can be supplemented by data available on a number of websites (giving careful consideration to data quality and accuracy) including:

- Government databases (e.g., USDA Plants Database)
- University databases
- Herbarium databases
- EDRR databases
- Regional databases

1.2 Environmental data

Predictive raster datasets can be found at a number of different locations or developed specifically for an application. Raster datasets at various spatial extents and resolutions can be found on the:

- Intergovernmental Panel on Climate Change website
- Environment Canada's National Climate Data and Information Archive
- World Meteorological Organization
- WorldClim – Global Climate Data

1.3 Surveys

Presence data can be obtained by the NPPO by conducting a carefully planned survey.

3. Geographic Information Systems – ArcMap

3.1 ArcMap

ESRI's ArcMap (Environmental Systems Research Institute, Redlands, California, USA) is the recommended GIS tool to process the spatial predictive results.

4. Outcome of Spatial Predictive Modelling

The outcome of predictive spatial modeling will be a map representing the potential distribution of the pest of interest. The outcome can support the pest risk assessment in determining the areas at risk within the PRA area, and to provide spatial information to support policy decision making.

8.2.3 Risk-based Early Detection and Rapid Response (EDRR) Programs

The results of spatial predictive modelling can be used to direct risk-based biosecurity surveillance programs, specifically early detection and rapid response (EDRR) programs. Early detection and rapid response are widely recognized as the most efficient strategy for the control of invasive pests (Westbrooks et al. 2000, Worrall 2002). The overall purpose of EDRR is to prevent the establishment of an invasive pest

before it can begin to reproduce and spread (Waugh 2009) increasing the likelihood that a response will be effective and cause less collateral damage (Wotton and Hewitt 2004). It is a cost effective approach to biosecurity in that it does not restrict trade and movement of species, only addresses species that have established free-living self-perpetuating populations, causes minimal impacts on invaded habitats, and usually aims to restore invaded habitats (Westbrooks 2004). Early detection and rapid response programs are implemented by biosecurity agencies when pest exclusion has failed. The likelihood of successful eradication may then be improved, and costs minimized, if a newly detected pest can be responded to rapidly (Simberloff 2003). Worrall (2002) provided the following definitions for EDRR:

Early detection is a comprehensive, integrated system of active or passive surveillance to find and verify the identity of new invasive species as early after entry as possible, when eradication and control are still feasible and less costly. It may be targeted at areas where introductions are likely, such as near pathways of introduction; or sensitive ecosystems where impacts are likely to be great or invasion is likely to be rapid.

Rapid response is a systematic effort to eradicate, contain or control invasive species while the infestation is still localized. It may be implemented in response to new introductions or to isolated infestations of a previously established, non-native organism.

Early detection through biosecurity surveys and inspections are primary methods for detecting new pests prior to range expansion (Porter et al. 2007). As part of an EDRR program, response plans should be developed prior to pest incursions. Responding to pest incursions in non-agricultural systems (e.g., saltcedar and purple loosestrife) including natural areas has created new challenges for plant health both to policymaking and program implementation (Porter et al. 2007). Early detection surveys and inspections

can be risk-based and directed if the approaches used in this study are adopted to target areas for resources. GARP ecological niche modelling can be used to direct risk-based surveillance efforts. For example, biosecurity agencies with limited surveillance budgets should direct pest surveys into areas predicted by GARP as suitable for pest establishment and spread.

8.3 Contributions to New Knowledge

1. In Chapter 3, I critically reviewed how international and national biosecurity policy instruments addressed invasive plants as pests and concluded that these instruments did not incorporate spatial predictive modelling into risk analysis toolboxes. This chapter has been published in a peer-reviewed science journal *Risk Analysis*.

2. In Chapter 5, I provided new seasonal growth and seed production data which was found to be lacking for purple loosestrife. This chapter data been published in the peer-reviewed science journal *Wetlands*.

3. In Chapter 5, I contributed the first statistical model of seasonal growth using a three parameter logistic function for purple loosestrife. This data been published in the peer-reviewed science journal *Wetlands*.

4. In Chapter 5, I interpolated a new growing degree-day (GDD's) risk surface specific to purple loosestrife which demonstrated GDD's as a constraining variable on its spatial distribution. This data has been published in the peer-reviewed science journal *Wetlands*.

5. In Chapter 6, I contributed a new spatial predictive model for purple loosestrife map using the Genetic Algorithm for Rule-set Production (GARP) using GDD's, climate, and topography as predictive variables. This data has been published in the peer-reviewed science journal *The Canadian Field Naturalist*.

6. In Chapter 6 and Chapter 7, I investigated how different geographic sub-setting methods, use of performance measures, and predictive variables influenced the spatial predictive models. These methods represent a new contribution to knowledge.

7. In Chapter 6, I suggested a new approach to selecting the best risk model - a sequential triage approach using (1) measures of predictive accuracy, (2) performance measures and statistics, and finally (3) expert evaluation. This approach to selecting the best model represents a new contribution to knowledge.

8. In Chapter 7, I contributed a comprehensive species review from a Canadian perspective that was found to be previously lacking. This chapter has been published in a peer reviewed science journal *Canadian Journal of Plant Science*.

9. In Chapter 7, I contributed the first regionalized scale spatial predictive model for saltcedar and the results indicate that large areas of Prairie Canada are susceptible to invasion. The model represents a contribution to new knowledge.

10. In Chapter 8, I contributed a new Regional Standard for Phytosanitary Measures (RSPM) that provides suggested guidelines on how to incorporate spatial predictive modelling into the biosecurity risk analysis toolbox. This standard represents a contribution to new knowledge.

11. Overall, I successfully extended the use of spatial predictive modelling for use by biosecurity agencies to help prevent introduction of invasive plants and to support biosecurity policy decision-making. I provided methods on how to incorporate the Genetic Algorithm for Rule-set Production (GARP) into the biosecurity risk analysis toolbox. This represents a contribution to new knowledge.

8.4 References

ISPM. No. 11. 2004. Pest risk analysis for quarantine pests including analysis of environmental risks and living modified organisms. International Standards for Phytosanitary Measures, Secretariat of the International Plant Protection Convention, FAO, Rome, Italy.

ISPM. No. 2. 2007. Framework for pest risk analysis. International Standards for Phytosanitary Measures, Secretariat of the International Plant Protection Convention, FAO, Rome, Italy.

IPPC. 1997. Revised text of the International Plant Protection Convention. FAO.

Mack, R.N., D. Simberloff, W.M. Lonsdale, H. Evans, M. Clout and F.A. Bazzaz. 2000. Biotic invasions: causes epidemiology, global consequences, and control. *Ecological Applications* 10:689-710.

- RSPM. No. 32. 2008. Pest risk assessment for plants for planting as quarantine pests. Regional Standards for Phytosanitary measures, Secretariat of the North American Plant Protection Organization, Ottawa, Canada.
- Petter, F., A.S. Roy and I. Smith. 2008. International standards for the diagnosis of regulated pests. *European Journal of Plant Pathology* 121:331-337.
- Porter, R., L. Goldman, A. Martin, J. McElfish and R. Thomas. 2007. Strategies for Effective State Early Detection/Rapid Response Programs for Plant Pests and Pathogens. The Nature Conservancy and Environmental Law Institute. Research report published by the Environmental Law Institute. 97 pp.
- Simberloff, D. 2003. Eradication – preventing invasions at the outset. *Weed Science* 51: 247-253.
- Simberloff, D., I.M. Parker and P.N. Windle. 2005. Introduced species policy, management, and future research needs. *Frontiers in Ecol. Environ.* 3:12-20.
- Waugh, 2009. Neighbourhood Watch: Early Detection and Rapid Response to Biological Invasion Along US Trade Pathways. Gland, Switzerland: IUCN.
- Westbrooks, R.G., W.P. Gregg and R.E. Eplee. 2001. My View. *Weed Science* 49:0-4.
- Westbrooks, R.G., D.C. Hayes and W.P. Gregg. 2000. National early warning and rapid response system for invasive plants – proposed strategies for early detection, reporting, rapid assessment, and rapid response to new invasive plants in the United States of America. Early Warning Sub-Committee, Federal Interagency Committee for the Management of Noxious and Exotic Weeds.
- Wittenberg, R. and M.W. Cock. (eds.). 2001. *Invasive Alien Species: A Toolkit of*

Best Prevention and Management Practices. CAB International, Wallingford, Oxon, UK.

Wotton, D.M. and C.L. Hewitt. 2004. Marine biosecurity post-border management: developing incursion response systems for New Zealand. *N.Z. J. Marine Freshwater Research* 38:553-559.

Worrall, J. 2002. Review of systems for early detection and rapid response. Unpublished report to the National Invasive Species Council, Washington, D.C., USA.