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Dr. David Wagner, Director of Graduate Studies

SPATIAL PRIORITIZATION FOR INVASIVE PLANT MANAGEMENT

THESIS

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in the College of Agriculture at the University of Kentucky

By

Abraham Michael Levin-Nielsen

Lexington, Kentucky

Co-Directors: Dr. Songlin Fei, Assistant Professor of Forestry

and Dr. Mary Arthur, Professor of Forest Ecology

2012

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ABSTRACT OF THESIS

SPATIAL PRIORITIZATION FOR INVASIVE PLANT MANAGEMENT

Invasive exotic plant species have been recognized as serious threats to ecosystems. Extensive research on invasive exotic plant species has primarily focused on the impacts, characteristics, and potential treatments. Decision tools and management models that incorporate these findings often lack input from managers and have limited use in differing invasion scenarios. Therefore, in this study, I created a scientifically-driven framework that incorporates expert input to prioritize watersheds for management within the Inner Bluegrass region of Kentucky. The widely distributed invasive exotic plant Amur honeysuckle (*Lonicera maackii*) was used as an example species. The framework is built around the Analytic Hierarchy Process and highlights areas in most need of invasive exotic plant management by incorporating weighted landscape variables associated with the invasion process. Results of the prioritization provide useful information for natural resource managers by aiding in the development of control strategies while also creating a valuable framework that can be adapted to various invasive exotic plant species.

KEYWORDS: Invasive exotic plants, GIS, Analytic Hierarchy Process, *Lonicera maackii*, spatial analysis

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April 27, 2012

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Acknowledgments

I am very grateful to the members of my committee who provided guidance and support throughout the entirety of my graduate career. I would like to thank Dr. Songlin Fei for taking me on as a research assistant and teaching me valuable research skills. I would also like to thank Dr. Liang Liang for guiding me through various remote sensing techniques. I am grateful for the support of Dr. Mary Arthur, who invited me into her lab group and provided supervision that allowed me to complete this project on schedule. I would also like to thank my fellow graduate student Michael Shouse for offering valued insights that improved my research methodologies. This research would have been unsuccessful without data supplied by the Kentucky State Nature Preserves Commission and input from Joyce Bender and Dr. Ryan McEwan. Finally, I thank my family for their support, especially my parents for their constant encouragement and love.

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Chapter One: Introduction

Many researchers and natural resource managers have recognized invasive exotic species as a growing problem with both economic and ecological implications. In particular, invasive exotic plant (IEP) species are serious threats to natural resource management within various ecosystems. IEPs threaten ecosystem function, native biodiversity, and put rare and endangered species at risk (Wilcove et al. 1998, Byers et al. 2002, Ehrenfeld 2010). Additionally, factors pertaining to IEP control and their potential damages of ecosystem services result in high economic costs annually (Pimentel et al. 2005).

Research has identified basic invasive characteristics that many IEPs share. Traits such as high resource use efficiency, high reproductive output, natural robustness, and high dispersability contribute to invasibility and make IEPs good competitors (Webster et al. 2006). Habitats that tend to have fewer IEPs include dense or mature forests and large non-fragmented areas (Alpert et al. 2000). Recently disturbed habitats with high light levels and proximity to an abundant seed source may lead to an increase in forest invasibility for certain IEPs (Hutchinson and Vankat 1997, Hansen and Clevenger 2005).

Most IEPs follow a generalized invasion process that is comprised of four stages; introduction, establishment, spread, and impact (Lockwood et al. 2007). The time period within each stage can be variable and invaders must overcome a series of barriers before moving on to the next invasion stage (Webster et al. 2006). For example, after an invader has been transported and introduced into a novel habitat, it must become established before it can begin the spread stage. Though most invasions display basic similarities, subtle differences are noted when analyzing the invasion process across different

ecosystem types. The first stage of the invasion process essentially addresses the introduction of the invader. Depending upon the IEP, introduction can occur accidentally or sometimes purposely such as when introduced for landscaping, erosion control, or horticulture purposes (Reichard and Hamilton 1997, Reichard and White 2001).

Once introduced into a new habitat, IEPs have the potential for establishing a viable population. Various research efforts have focused on the establishment stage, especially studying how or why invaders become established in certain habitats over others. For example, disturbances may act as pathways for IEP invasion and establishment (Hansen and Clevenger 2005). Disturbed areas such as roadways may provide suitable habitat for IEPs (Parendes and Jones 2000), while fire or other disturbances such as tree harvesting create openings that may allow for new IEP establishment (Keeley 2006, Oswalt et al. 2007, Mandle et al. 2011).

With an established reproducing population, dispersal and spread of IEPs is possible and facilitated by numerous mechanisms. For example, roadways can act as corridors that provide connectivity and potentially increase spread rates (Parendes and Jones 2000, Gadagkar et al. 2007), while propagule spread into forest systems can be aided by cars and machinery (Von der Lippe and Kowarik 2007). Furthermore, particular IEPs have the potential to disperse significantly farther in forests that experience litter disturbance or removal (Marshall and Buckley 2008). Finally, spread can also be facilitated by natural mechanisms, such as avian fruit dispersal (Bartuszevige and Gorchov 2006).

The impact stage represents the final phase of the invasion process. One can analyze impacts from different perspectives or levels. For instance, when hybridization

occurs between invaders and native species the gene pool is altered, thus impacting the genetic level (Barbour et al. 2006). In addition, invaders that outcompete natives may affect genetic variability at the population level. Therefore, competition from invaders operates at both the individual and population level, as a more competitive plant can better compete for resources, often at the expense of other species (Holmes et al. 2009). Finally, IEPs can impact the structure and functions of ecosystems by altering species diversity, primary productivity, and the flow of energy, water, or nutrients (Walker and Smith 1997, Ehrenfeld 2010).

As IEPs continue to spread and invade new regions, managing to reduce the impacts of IEPs becomes crucial (Byers et al. 2002). Within the United States, exotic species including pathogens, pests, and plants cause environmental damages and losses totaling \$120 billion annually (Pimentel et al. 2005). With an estimated 5000 exotic plants naturalized within the United States, many ecosystems are experiencing the economic and ecological impacts (Morse et al. 1995). For example, the invasive exotic woody shrub *Tamarix spp.*, which alters water regimes and affects sedimentation, reportedly costs the western United States 280 - 450 dollars per ha annually (Zavaleta 2000).

As impacts rise, identifying vectors of introduction and preventing the spread of IEPs become important management goals. Early detection and rapid response to invasions are essential for management, as actions are needed to quickly address the problem and generate rapid solutions to either eradicate or control the invader (Webster et al. 2006). In addition, proactive approaches that employ adaptive management are needed to further reduce the impacts on our conservation areas (Webster et al. 2006).

However, managers need to know distributions and densities of invaders to effectively direct control operations, as a lack of knowledge about IEP distributions can significantly hinder management actions (Bradley and Marvin 2011).

Consequently, for management purposes, there is a need for accurate IEP distribution information. However, agencies with large management areas need a cost effective estimation process that is relatively accurate. Large field surveys may require too many resources, especially for managers that may have limited personnel or finances. Fortunately for some IEPs, acquiring data through remote sensing is an alternative to sole reliance on field surveys.

Remote sensing is the act of acquiring data without a physical sample in the field. Sensors can acquire data from various means such as satellite imagery, aerial photographs, or airborne multi-spectral scanners (Joshi et al. 2004). Remote sensing allows researchers to collect data at large study sites more quickly than if data were collected solely through field work. Remote sensing also enables data collection in habitats that may be difficult to access in person.

Researchers can recommend IEP control operations to natural resource managers based on pertinent remotely sensed data. Furthermore, remote sensing may facilitate control operations by collecting data that detects new invasions while also creating an accurate distribution of the invader. Remotely sensed data can lead to estimations of historical distributions, resulting in studies of IEP dispersal patterns that can be adapted into land use and landscape invasion analyses. Finally, managers can use remote sensing techniques in conjunction with other spatial data to critically analyze larger regions for IEP management. For instance, GIS systems can integrate spatial data with remotely

sensed data to create spread models or analyze conditions that may facilitate invasion (Peterson et al. 2009). In addition, organizations that incorporate GIS allow for sharing of data between agencies and the public. For example, Bradley and Marvin (2011) suggested that knowledge of plant invasions and their general distributions exist within local agencies and experts were prepared to participate in regional sharing of such data. Thus, the combined use of remote sensing and GIS for analyzing invasive exotic species has been increasing and provides the possibility for creating a framework that aides in guiding IEP management.

Due to limited resources, managers often face widely established IEP populations in more areas than can be quickly managed, making it a necessity to prioritize management actions (Hiebert 1997). Creating a framework that directs management actions to priority areas would be useful for managers. Such a framework could be created by spatially prioritizing landscape units based on the IEP distributions, impacts, and land use characteristics (Byers et al. 2002). Furthermore, it would be beneficial to build this framework based on scientifically-driven planning at the watershed level, as the invasion risk of a particular area is often related to its environmental factors (Blossey 1999, With 2002).

Additionally, we are acknowledging that certain watersheds may be more vulnerable to invasion and experience various levels of impacts. Prioritization at the watershed level permits for eradication of the most ecologically damaging populations and creates a system that uses limited labor in areas of most need. A prioritization framework needs to incorporate the attributes of relevant invaders, such as widely distributed and high impact understory IEPs. However, these invaders prove to be

problems for remote sensing as the reflectance values correspond to canopy species rather than understory IEPs, signifying a need to develop new management frameworks that address such invaders (Joshi et al. 2004).

Amur honeysuckle (*Lonicera maackii*) is a common understory IEP in the eastern United States. Management of the invader is important to natural resource managers because of its increasing distribution and ecosystem impacts. Amur honeysuckle can quickly develop into dense thickets that negatively impact understory plants (McKinney and Goodell 2010). In addition, natural regeneration of secondary forests may be adversely affected by Amur honeysuckle's impacts to native tree seedlings (Gorchov and Trisel 2003). Amur honeysuckle has also been linked to altering native forest amphibian communities (Watling et al. 2011) and changing habitat characteristics resulting in unusual behavior of some small mammals (Dutra et al. 2011). Finally, stands of Amur honeysuckle are also linked with reducing the nesting success of forest birds while also altering breeding bird communities (Borgmann and Rodewald 2004, McCusker et al. 2010, Rodewald et al. 2010).

Amur honeysuckle occurs mostly in urban or urban-fringe landscapes and has a high reproductive output with seeds that are effectively dispersed by birds (Luken and Thieret 1996). Rather than invading from an advancing front, Amur honeysuckle often invades from multiple loci and is associated with distance to nearest town or city centers (Bartuszevige et al. 2006, Trammell and Carreiro 2011). Its distribution is significantly affected by distance to nearest road and forest connectivity may facilitate more extensive spread (Hutchinson and Vankat 1998, Flory and Clay 2006). Finally, areas that are not

actively managed, such as roadsides and fence lines, provide suitable habitat for the invader (Luken 1988).

As Amur honeysuckle is a high impact and widely distributed invader, it would be beneficial to managers to use this invader as a model species for a management prioritization framework. Yet, to create the framework, we are highly dependent on knowing the invader's current distribution, as it is critical to develop comprehensive distribution and abundance data for modeling (Bradley and Marvin 2011). Fortunately, Amur honeysuckle has distinct phenological characteristics that allow researchers to estimate its distribution using satellite imagery and remote sensing techniques (Resasco et al. 2007, Wilfong et al. 2009).

My research had two primary foci. My first objective, addressed in chapter 2, was to use remote sensing techniques to estimate the distribution of Amur honeysuckle within the Inner Bluegrass physiographic region of Kentucky. My second objective, the focus of chapter 3, was to incorporate Amur honeysuckle distribution data and other spatial variables into a framework that prioritizes landscape units for IEP management based on expert input. This study is significant because it highlights areas in most need of IEP management by incorporating weighted landscape variables associated with the invasion process. Furthermore, this study will provide the basis for a framework that can be used by managers to address their goals for prioritizing IEP management within regions experiencing varying stages of the invasion process.

Chapter Two: Supervised Classification of Amur Honeysuckle within the Inner Bluegrass Region of Kentucky

INTRODUCTION

For successful management of invasive exotic plants (IEPs), early detection, prevention of new introductions, and determined efforts for eradication are needed (Rejmanek 2000). Understanding IEP characteristics alone is inadequate to handle the problem of increased exotic plant invasions. Rather, efficient IEP management requires scientifically-driven planning and implementation of management actions (Hobbs and Humphries 1995, Blossey 1999). More specifically, managers need to know distributions and densities of invaders to effectively direct control operations, as a lack of knowledge about IEP distributions can hinder strategic management planning (Bradley and Marvin 2011).

Knowledge of IEP spatial distributions can allow for the creation of models for management prioritization and invasion risk assessment. Yet, managers first need a cost effective and reasonably accurate process for estimating such distributions. Remote sensing has proven to be a valuable tool for gathering ecological data. Remote sensing is the act of acquiring data without an extensive physical sample in the field. The data is acquired from sensors on multiple platforms such as satellite imagery, aerial photographs, or airborne multi-spectral scanners (Joshi et al. 2004).

Early IEP remote sensing research often focused on spectral reflectance measurements, specifically testing if it was possible for computer systems to quantitatively differentiate IEPs from native vegetation (Everitt et al. 1987). Everitt et al.

(1987) studied two IEPs that were found in rangeland habitat, broom snakeweed (*Gutierrezia sarotbrae*) and spiny aster (*Aster spinosus*). The researchers found that both invaders had lower near-infrared reflectance values than the common rangeland shrubs and herbaceous vegetation of the area. These lower values caused the invaders to have a distinct color on color-infrared aerial photographs, thus allowing computer-based image analyses to calculate distributions of the invaders from aerial photographs. When such studies were effective, the remotely sensed data was often integrated into a GIS to create distribution maps that were used for monitoring and treatment of invasive populations (Everitt et al. 1995).

Within the past few decades, researchers have been persistently improving and using new remote sensing methodologies to aide in IEP management. Research focuses on the use of three main remote sensing data acquisition systems: hyperspectral, high spatial resolution (HSR), and medium spatial resolution (MSR) sensors. Varying spatial and spectral resolutions are the two factors that differentiate these systems from one another. Researchers may choose specific sensors depending upon their goals, study area, and focal IEP, as each system has advantages and disadvantages depending upon the invasion or research scenario.

Hyperspectral remote sensing has a high spectral resolution that acquires images across hundreds of spectral bands (Vane and Goetz 1993). The main benefit of hyperspectral remote sensing is the ability of the sensor to capture images within many narrow bands that may better differentiate the object of interest from its background based on unique reflectance properties (Jensen 2005). Consequently, hyperspectral remote sensing has been effective at mapping IEPs that exhibit distinct spectral

reflectance values (Noujdina and Ustin 2008). Furthermore, hyperspectral imagery is especially useful when the invader has a low distribution density or scattered spatial pattern (He et al. 2011). Thus, mapping of IEPs has been successful in habitats where the invader is inter-mixed and spread among native vegetation (Lawrence et al. 2006).

Though hyperspectral remote sensing is beneficial for mapping IEPs with low densities, it has its drawbacks. For instance, acquiring hyperspectral data is very expensive; typical cost for a 20 x 40 km area with 2 -3 m spatial resolution ranges between 60,000 to 100,000 dollars (Lass et al. 2005). Furthermore, hyperspectral imagery requires large data storing capacity, long processing times, and complex procedures that may be technologically beyond the grasp of most ecologists (He et al. 2011). Finally, most hyperspectral sensors are airborne, meaning their flight patterns are limited and may only cover certain regions of the world and at only certain times.

HSR remote sensing, typically with a resolution of 5 m or less, records data in multiple bands of the electromagnetic spectrum (Jensen 2005). The goal of these HSR sensors is to cover large extents, while being able to collect data in the same detail as aerial photographs (Mehner et al. 2004). HSR data acquisition is advantageous for many researchers, as it may allow for regular monitoring of vegetation (Slater and Brown 2000). Therefore researchers or land managers can update land cover and vegetation distribution maps quicker than if solely assessed through fieldwork. In addition, HSR sensors have been successfully used to detect and map IEP distributions (Carter et al. 2009). Unfortunately, HSR imagery is still not necessarily cost effective, as a 20 x 40 km image area with 1 m spatial resolution with four spectral bands can cost between 17,000 to 35,000 dollars (Lass et al. 2005). Furthermore, HSR imagery may not be favorable

when the object of interest is larger than a pixel, making HSR use not ideal for certain studies (Song and Woodcock 2002).

MSR sensors acquire data at lower spatial resolutions, such as on the Landsat 7 platform which produces a pixel size of 30 x 30 m. Researchers often use MSR sensors for studies that assess land cover classes, land change, and land use (Ringrose and Matheson 1987, Dewey et al. 1991, Morissette et al. 2006). In IEP studies, MSR images have been used to create IEP habitat suitability maps and future invasion risk maps (Shafii et al. 2004, Bradley and Mustard 2006, Morissette et al. 2006). For example, Bradley and Mustard (2006) used historical distribution maps of cheatgrass (*Bromus tectorum*) and integrated its extent with six landscape variables derived from Landsat imagery to create a risk map that is useful for land management.

With the limited spatial resolution, MSR imagery may not be ideal for IEP distribution mapping, especially for newly invaded areas (Carter et al. 2009). This is because newly established IEP patches are frequently much smaller than the pixel size, which results in the mixing of vegetation types within a pixel, making classification problematic for low IEP density areas (Foschi 1994, Carson et al. 1995).

On the other hand, MSR can be effective when the infested area is large and the target species have a distinct phenology (Everitt et al. 1995, Resasco et al. 2007). For instance, researchers have characterized the phenological features of understory bamboo and successfully mapped its spatial distribution with MODIS imagery (Tuanmu et al. 2010). Finding the optimal phenological time periods for remote sensing has also allowed other researchers to calculate distributions of IEPs such as false broomweed (*Ericameria austrotexana*) (Anderson et al. 1993). Furthermore, researchers have used phenological

traits to calculate distributions of saltcedar (*Tamarix ramosissima*) by using Landsat imagery (Groeneveld and Watson 2008). Saltcedar displays dark stems that make it distinguishable from other vegetation during the leafless winter period. These research studies demonstrate the importance of knowing the characteristics of the study plant, as certain seasonal times may be more appropriate for MSR based IEP classification.

When IEPs have large invasion patches and distinct phenological characteristics that allow for separation from background vegetation, it may be more beneficial to use MSR imagery over other sensors for a few reasons. First, MSR sensors frequently produce images that are provided by the government free of charge, a significant factor for managers and agencies that are fiscally constrained. Another benefit of using MSR sensors such as Landsat thematic mapper is the global coverage and approximately 16 day temporal resolution of the sensor, providing images of the same geographic location every 16 days since 1982. This temporal resolution is a great tool for researchers, especially those interested in studying IEP distributions and habitat invasibility, as the repetitive visits of the sensor allows for historical analysis of IEP distributions that permit analyses of spread and habitat invasion.

The goal of this study was to map the distribution of Amur honeysuckle (*Lonicera maackii*), an ecologically damaging IEP in the Bluegrass Region of Kentucky, to facilitate management planning. The specific objective of this study was to (1) examine a classification process that uses a Landsat satellite image to estimate the distribution of Amur honeysuckle and (2) explore the reliability of a supervised classification technique and analyze the importance of imagery pre-processing methods to enhance the accuracy of the classification. With limited budgets, using a methodology that incorporates free

Landsat imagery into the analysis may be more attractive to managers in other regions facing similar IEP problems.

METHODS

Study area

The study area was created to fit the general boundary of the Inner Bluegrass physiographic region of Kentucky (Lobeck 1932). The study area covers approximately 5,000 km² and was further edited to fit within one Landsat satellite image, causing the northern tip of the Inner Bluegrass region to be clipped from the study area (Figure 2.1). The Inner Bluegrass region is largely defined by limestone formations and soils that tend to be phosphate-rich silt loams (Wharton and Barbour 1991). The regional climate is characterized as temperate, humid, and continental (Wharton and Barbour 1991).

Study species

Amur honeysuckle is distributed widely throughout the Inner Bluegrass region and can quickly develop into dense thickets, negatively impacting understory plants and natural regeneration (Gorchov and Trisel 2003, McKinney and Goodell 2010). Amur honeysuckle has also been linked to altering native forest amphibian communities (Watling et al. 2011), changing habitat characteristics (Dutra et al. 2011), reducing nesting success of forest birds (Borgmann and Rodewald 2004, Rodewald et al. 2010), and altering breeding bird communities (McCusker et al. 2010).

Amur honeysuckle occurs mostly in urban or urban-fringe landscapes and has a high reproductive output with seeds that are effectively dispersed by birds (Luken and

Thieret 1996). Rather than invading from an advancing front, Amur honeysuckle often invades from multiple loci and is associated with distance to nearest town or city centers (Bartuszevige et al. 2006, Trammell and Carreiro 2011). Its distribution is significantly affected by distance to nearest road and forest connectivity may further affect its spread (Hutchinson and Vankat 1998, Flory and Clay 2006). Finally, areas that are not actively managed, such as roadsides and fence lines, also provide suitable habitat for the invader (Luken 1988).

Amur honeysuckle has phenological characteristics that enable the plant to obtain leaves longer than most deciduous trees and shrubs, and its leaf expansion occurs well before native plants (Trisel and Gorchov 1994, McEwan et al. 2009). This distinctive phenological characteristic has allowed researchers to estimate the invader's distribution using Landsat satellite imagery, even though it is typically found under forest canopies (Wilfong et al. 2009).

Field work

Accurate vegetation classification relies on precise field data of various land cover classes. Field work locations were selected by an opportunistic sampling methodology of public lands and parks within the study area. Between May and July of 2011, 28 sites were visited for data collection (Figure 2.2). Once on site, perimeter locations of distinct land cover patches were collected using a Juno series Trimble handheld GPS unit. Perimeters were collected at a minimum size of 30 x 30 m (size of a Landsat pixel) to ensure that the training data for the classification process represented an entire pixel.

Field notes were taken at each location regarding site characteristics such as land cover type (forest, grass, shrub), local attributes (stream, road, fence), and general attributes (urban park, dense forest, open field). The field points were placed into one of five classes: Amur honeysuckle, tree urban, tree rural, grass natural, or grass managed. The tree points were assigned by their sampling location (rural or urban), while the grass points were assigned based on the management of the grass. For instance, “grass managed” represented open grass areas that were mowed frequently, such as in parks. Areas of unmanaged grass and small shrubs were placed into the class “grass natural”. Overall, a total of 161 Amur honeysuckle presence and 108 absence locations were collected.

Image pre-processing

Landsat scenes (row 34, path 20) were obtained from the USGS Global Visualization Viewer for a late fall date of November 7, 2009 and for a mid-winter date of January 23, 2009. The late fall date of November 7 allowed for the green leaf exposure of Amur honeysuckle while deciduous trees were leaf off. The image captured in January allowed for a comparable site when all deciduous species were leaf off, including Amur honeysuckle. I also obtained a November 12, 2005 image for classification purposes, thus allowing for Amur honeysuckle change analysis over the 4 year period. All images were of high quality and had no cloud cover within the study site. The seven bands of the Landsat image were first spectrally stacked and processed based on methods outlined in Wilfing et al. (2009). The Landsat images were then clipped to the outline of the study area (Figure 2.3).

Four additional steps were taken to remove unwanted pixels prior to Amur honeysuckle classification. These steps included (1) removing pixels that displayed non-vegetated areas (roads, buildings, and water), (2) removing pixels that could be spectrally confused with Amur honeysuckle, such as evergreen species, (3) using change in Normalized Difference Vegetation Index (NDVI) values to further remove unwanted pixels, and (4) determining which bands provided the best possibility of land cover discrimination.

Non-vegetated pixels, including urban and water, were removed first using an unsupervised classification and verified with field data and aerial photography (Figure 2.4). Pixels associated with the absence of Amur honeysuckle were removed based on the differences between November and January images. Both the November and January 2009 Landsat images were converted to NDVI values. NDVI uses bands of near infrared and red to estimate the health and greenness of vegetation.

$$\text{NDVI} = (\text{NIR} - \text{R}) / (\text{NIR} + \text{R})$$

Within the January image, pixels with high winter NDVI values would most likely represent the greenness of evergreen species. Yet at the same point in time, leaf off deciduous species would display very low NDVI values. Therefore, pixels with high January NDVI values were assumed to be associated with evergreen species and were removed from the image.

Next, a new NDVI value was generated by subtracting the January NDVI from the November NDVI, following the algorithm outlined by Wilfong et al. (2009). In

theory, pixels that represent leaf off deciduous trees in November would experience little change in NDVI values because they would still be leaf off in January. However, forests that were invaded by Amur honeysuckle would display a higher NDVI value in November but a lower value during January when the invader was leaf off, consequently displaying a noticeable change in NDVI values. This method was used to remove pixels that experience little or no change in NDVI value, which likely represented un-invaded deciduous forest land. Aerial imagery and field data were used to analyze the NDVI values and decide the cut off points to ensure that pixels were not incorrectly removed.

The final pre-processing step was to determine which bands of the Landsat scene were most effective in discriminating the land cover classes from each other without providing redundant spectral information (Jensen 2005). The mean spectral values of each land cover were graphed within each of the 7 bands for analysis (Figure 2.5). Bands 3, 4, and 5 were found to be the best candidates for class discrimination without redundant information (Figure 2.6). The resulting pre-processed Landsat image represented the area and pixels that would be subjected to the classification process (Figure 2.7). The same mask was applied to the November 12, 2005 image to allow for a similar classification analysis.

Classification and accuracy assessment

I chose only to use field points that covered an entire Landsat pixel for the classification process in order to improve accuracy. Thus, 62 Amur honeysuckle data points were used for the supervised classification. A stratified random sample was applied to split the field data, of which 2/3 were used for classification and 1/3 for

accuracy assessment (Table 2.1). Classification points were used to collect signatures for their respective classes. The averaged class signatures were applied to the maximum likelihood decision model which resulted in the placement of each pixel into one of the five classes (Amur honeysuckle, tree urban, tree rural, grass natural, or grass managed) for the November 7, 2009 image. The same point locations were used to collect new signature data and classify the November 12, 2005 image.

The remaining 1/3 of points were used for the accuracy assessment. The accuracy assessment was evaluated based on three merged classes; Amur honeysuckle, forest, and grass. The resulting classified image was checked for three accuracy types; producer's (based on the perspective of the map maker), user's (based on the perspective of the map user), and overall accuracy of the final classified image. This included accounting for the number of times that the field data matched correctly with the classified map and noting which classes were incorrect when the two data sets did not agree. Again, the same methodology was applied to the November 12, 2005 image.

RESULTS

In this study, we took a traditional pixel based classification method and increased the relative amount of imagery pre-processing to estimate the distribution of Amur honeysuckle. The results for the classification of the 2009 image were formulated into an error matrix to calculate the user's, producer's and overall accuracies and resulted in an overall classification accuracy of 71.93% (Table 2.2). Of the three classified land cover groups, the tree class had the highest producer's accuracy, followed by Amur honeysuckle, and then grass. Amur honeysuckle had the highest user's accuracy,

followed by grass and then the tree class. Most importantly for this study were the accuracies associated with Amur honeysuckle (producer's accuracy of 71% and user's accuracy of 75%). Amur honeysuckle field points were incorrectly classified as other classes in 6 of 21 points, 3 misclassified as tree and 3 as grass. Furthermore, other land cover classes were incorrectly classified as Amur honeysuckle in some instances. The classification misidentified 5 pixels as Amur honeysuckle, 4 were truly grass and 1 was a tree location.

In a similar fashion, the results for the classification of the 2005 image were grouped into an error matrix for analysis (Table 2.3). The overall accuracy was slightly higher than the classification of the 2009 image, with an accuracy of 77.2%. In addition, both producer's accuracy (85.7%) and user's accuracy (81.8%) for Amur honeysuckle were higher in the 2005 image when compared to their 2009 image accuracies. Overall, the producer's accuracy for the grass class displayed the lowest accuracy under both models.

The final classification map represents the overall distribution of the three land cover classes (Figure 2.8). Large patches of forested areas and open grass fields dominate the classified image. Throughout the region, stands of Amur honeysuckle are intermixed between these two classes (Figure 2.9). Amur honeysuckle seems to most densely populate the south-central region, the part of the study area where edge between forested and agricultural land is dominant. Furthermore, within the urban areas, patches of Amur honeysuckle are potentially interconnected by invaded road edges and tree corridors (Figure 2.10).

DISCUSSION

The supervised classification methodology was successful in estimating the species-level distribution of Amur honeysuckle within the study area for both 2009 and 2005 images with moderate accuracy. This methodology is similar to previous research that has used remote sensing to analyze IEP distributions (Wilfong et al. 2009). However, I altered this basic methodology by incorporating various pre-processing techniques and extended the classification to a regional scale.

Image pre-processing

Non-vegetated areas such as roads and buildings are often removed before classifying images. Yet, it may also be favorable to remove certain vegetated pixels that are not associated with the study species to lessen the potential of incorrectly classifying pixels. This is especially useful in studies that use MSR systems, such as Landsat imagery, where the possibility for spectral mixing is high. Therefore, it was beneficial to use the NDVI values and imagery dates in accordance with the specific phenological characteristics of Amur honeysuckle to remove pixels that could be spectrally confused with the invader.

The ability of each spectral band to discriminate Amur honeysuckle from other land cover classes was evaluated in the final pre-processing step. The combination of bands 3, 4, and 5 displayed the greatest spectral variability among classes. According to NASA, band 3, the visible red band, is one of the most important bands for discriminating among various vegetation types. Band 4, the near infrared band, helps to convey the amount of vegetation biomass. Finally band 5, the mid-infrared band, is

sensitive to the amount of water within plants (NASA 2011). In areas where Amur honeysuckle is present, the abundance of these green leaves would result in different reflectance values than areas with withered leaves or showing an empty canopy. Therefore, this band combination (3, 4, and 5) was useful in discriminating Amur honeysuckle from other vegetation types.

Classification

The pixel based supervised classification resulted in a relatively accurate estimation of Amur honeysuckle when compared to similar research. Wilfong, et al. (2009), used a comparable methodology to predict Amur honeysuckle presence and found that their verification model had a $R^2 = .77$. Furthermore, another research study that used Landsat imagery to identify IEP distributions had a similar accuracy of 72% (Bradley and Mustard 2005).

With a user's accuracy of 75%, my classification displays the estimated locations and general IEP density levels of the invader throughout the region. The user's accuracy reports when other land cover classes are incorrectly classified as Amur honeysuckle. What I learned from the user's accuracy is that the grass pixel was most often misclassified as Amur honeysuckle. Reasons for this may be associated with the invaders establishment of forest edges; areas which are similar to the natural shrub transition zones between open fields and forests.

The producer's accuracy reports when Amur honeysuckle field points are incorrectly classified as other land cover classes. With a 70% producer's accuracy not all of the Amur honeysuckle in the field is correctly identified on the map. However, the

supervised classification still provides managers with a general estimation of the invader's distribution. When Amur honeysuckle was incorrectly classified, it was evenly distributed between the grass and tree classes. This misclassification may depend on the invaders location within various land cover types. For example, along a fence line within a park, Amur honeysuckle may be incorrectly classified as a natural grass pixel. However, when found within a dense forest, the invader may be more likely misclassified as a forest pixel.

The overall accuracy of the classified image, 71.93%, is also of interest. Low producer's accuracy for grass pixels and low user's accuracy for tree pixels might be associated with limited field points of these land cover classes. The overall accuracy may be increased by collecting additional points within these land cover classes. However, as my main goal was to identify Amur honeysuckle distribution, it was beneficial to allocate more sampling points to collecting the locations of the invader.

Similar research

Researchers first attempts at classifying Amur honeysuckle discovered that using late fall dates of Landsat imagery provided the best possibility for capturing the invaders locations (Resasco et al. 2007). Researchers then used regression models to predict Amur honeysuckle cover by converting November and January images into NDVI values (Wilfong et al. 2009). My research aimed to identify Amur honeysuckle within a complicated landscape at a regional scale, extending the application by implementing new pre-processing techniques.

By recognizing the attributes of the MSR Landsat imagery and evaluating the phenological characteristics of Amur honeysuckle, I spent more time pre-processing the image to remove un-wanted pixels before the classification. Furthermore, I concentrated on the spectral reflectance values within a supervised classification technique rather than using NDVI values within a regression analysis to predict Amur honeysuckle presence. The supervised classification technique relies not only on Amur honeysuckle locations but also incorporates other vegetation classes absent of the invader. By separating the absence data among various vegetation types, I was able to provide the model with more options for classifying a pixel, which may be useful in cases of spectral mixing. Overall, I believe that the pre-processing and supervised classification techniques were best suited for the widespread variability found within the regional scale of my study area.

Limitations

This study demonstrated that MSR imagery is useful for estimating IEP distributions that have distinct phenological characteristics. However, it is necessary to address the limitations of both this approach and MSR imagery. First, researchers and managers need to be certain that imagery dates fall within the specific time frame of Amur honeysuckle leaf on and deciduous tree leaf off. Generally, within the Inner Bluegrass region of Kentucky, it was found that native vegetation was mostly leaf off by the first week of November (McEwan et al. 2009), and therefore our image date falls within this time period.

When using MSR imagery, spectral mixing is another issue. Narrow strips of Amur honeysuckle along roads may incorrectly be associated with road pixels because

these stands typically do not cover most of a pixel, resulting in spectral mixing. As these two spectral values are dissimilar, the spectral mixing would potentially result in a value not associated with Amur honeysuckle, even though the invader is present. This ultimately means that some locations of Amur honeysuckle are not correctly classified. Furthermore, even though the classified map had relatively high accuracies for MSR imagery, this methodology only displays estimated locations and densities of the invader. Managers might consider these limitations when examining distribution maps and planning possible control operations.

Future research

The supervised classification and pre-processing steps could be improved for future research. For instance, increasing the field collection process to more accurately locate and delineate absence classes from Amur honeysuckle may improve the classification. I found that the grass layer was most often incorrectly classified as Amur honeysuckle. Therefore, it would be advantageous to obtain more grass absence locations and possibly further divide them into many sub-classes to better differentiate it from Amur honeysuckle.

Future research should focus on removing more grass pixels by increasing the pre-processing efforts before the classification occurs. Also, further separating the study region into urban and rural areas may improve classification accuracy. From field notes, forests in rural areas tended to contain larger stands of Amur honeysuckle, while urban park systems tended to include smaller and more sporadic patches of the invader. The differences in stand structure and background land cover classes could alter the

reflectance values associated with Amur honeysuckle pixels between these general locations. Therefore, I suggest that future research should classify the invader separately within urban and rural areas to better obtain any differences in Amur honeysuckle reflectance values.

Research and management implications

IEP modelers generally prefer HSR imagery to MSR imagery. However, MSR imagery may be more useful for management agencies because these platforms are cost effective, have a high temporal resolution, and allow for land change analysis over large geographic extents. Therefore, it is beneficial to managers when researchers create methodologies that incorporate MSR imagery. My adapted pre-processing methodologies provide techniques that researchers can apply to other MSR platforms and IEPs for management purposes.

In addition, my methodologies demonstrate how managers can use Landsat imagery to help identify IEP distributions. This study has successfully classified the distribution of an IEP at a scale that is useful for numerous managers. The results can be given to agencies to inform them of the various levels of invasion within their lands and be made available to public landowners for education purposes. Furthermore, this same methodology could be applied to other regions to identify Amur honeysuckle invasion, which would increase information on the current distributions and spread of the invader. Using Landsat images, managers can create historical distribution maps of Amur honeysuckle, thus opening the door for further invasion analysis. Overall, this framework

builds on the use of MSR imagery for IEP management and provides a basic methodology that estimates the distribution of Amur honeysuckle.

CONCLUSION

Knowledge of IEP distributions is an important and essential tool for management purposes. Early detection of IEPs maximizes the potential for long-term management and helps to reduce negative environmental impacts. Remote sensing can facilitate early detection by aiding IEP distribution modeling, thus leading to quick eradication and prevention of spread. Here, I have created a methodology that uses the phenological characteristics of Amur honeysuckle, along with pre-processing techniques, and a supervised classification system to estimate the distribution of the invader. My research has created not only useful IEP presence/absence data for managers but also provided a basic methodology that can be used to estimate locations of the invader in different regions.

Unfortunately though, ecologists and managers underutilize remote sensing. One reason for this may be the lack of interdisciplinary training between ecologists and geographers. Integration is needed that introduces ecologists and IEP researchers to the benefits and potential uses of remote sensing in order to fully construct a useful network of IEP distributions based on remote sensing methodologies. Further remote sensing research is needed to create additional cost effective and basic classification frameworks that allow managers to estimate the distributions of various IEP species.

Table 2.1. The distribution of field points for either model or accuracy assessment purposes within the supervised classification process

Land cover	Points for model	Points for assessment
Amur honeysuckle	41	21
Tree urban	11	5
Tree rural	20	10
Grass natural	22	11
Grass managed	19	10

Table 2.2. Error matrix and supervised classification accuracies of three land cover classes that were classified on a 2009 Landsat image

	Field work			Row Total	User's accuracy
	Amur honeysuckle	Tree	Grass		
Map					
Amur honeysuckle	15	1	4	20	75.0%
Tree	3	12	3	18	66.7%
Grass	3	2	14	19	73.7%
Column total	21	15	21	57	
Producer's accuracy	71.4%	80.0%	66.7%		71.9%

Table 2.3. Error matrix and supervised classification accuracies of three land cover classes that were classified on a 2005 Landsat image

	Field work			Row Total	User's accuracy
	Amur honeysuckle	Tree	Grass		
Map					
Amur honeysuckle	18	0	4	22	81.8%
Tree	1	12	3	16	75.0%
Grass	2	3	14	19	73.7%
Column total	21	15	21	57	
Producer's accuracy	85.7%	80.0%	66.7%		77.2%

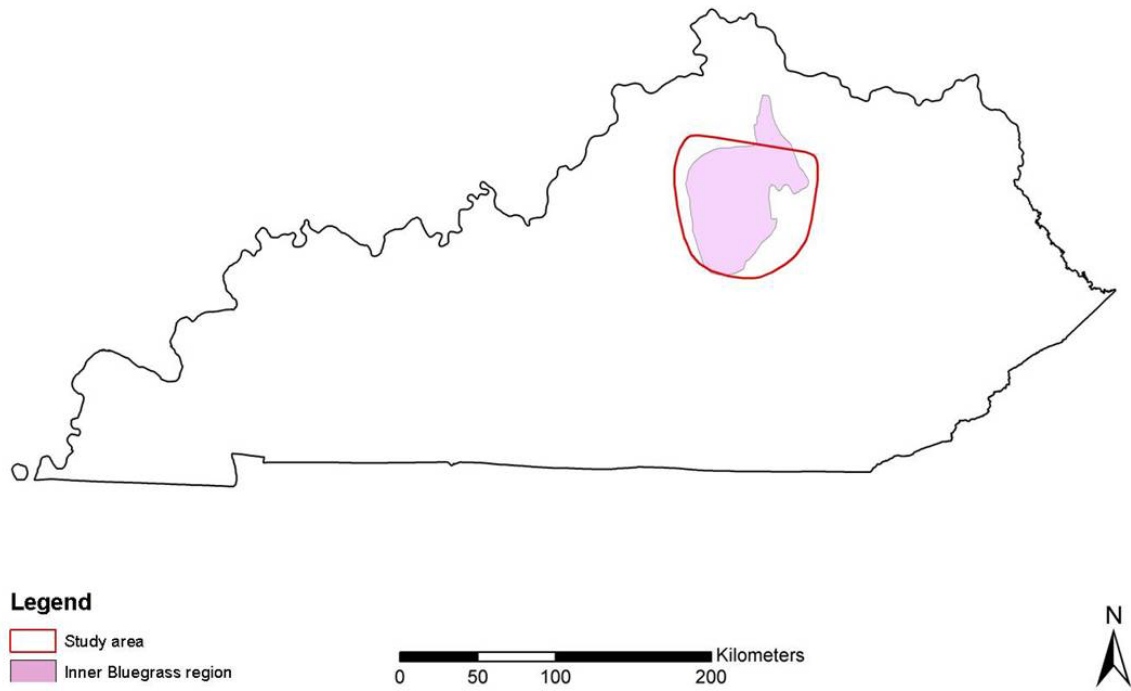


Figure 2.1. Map of the study area created to fit the general outline of the Inner Bluegrass region of Kentucky

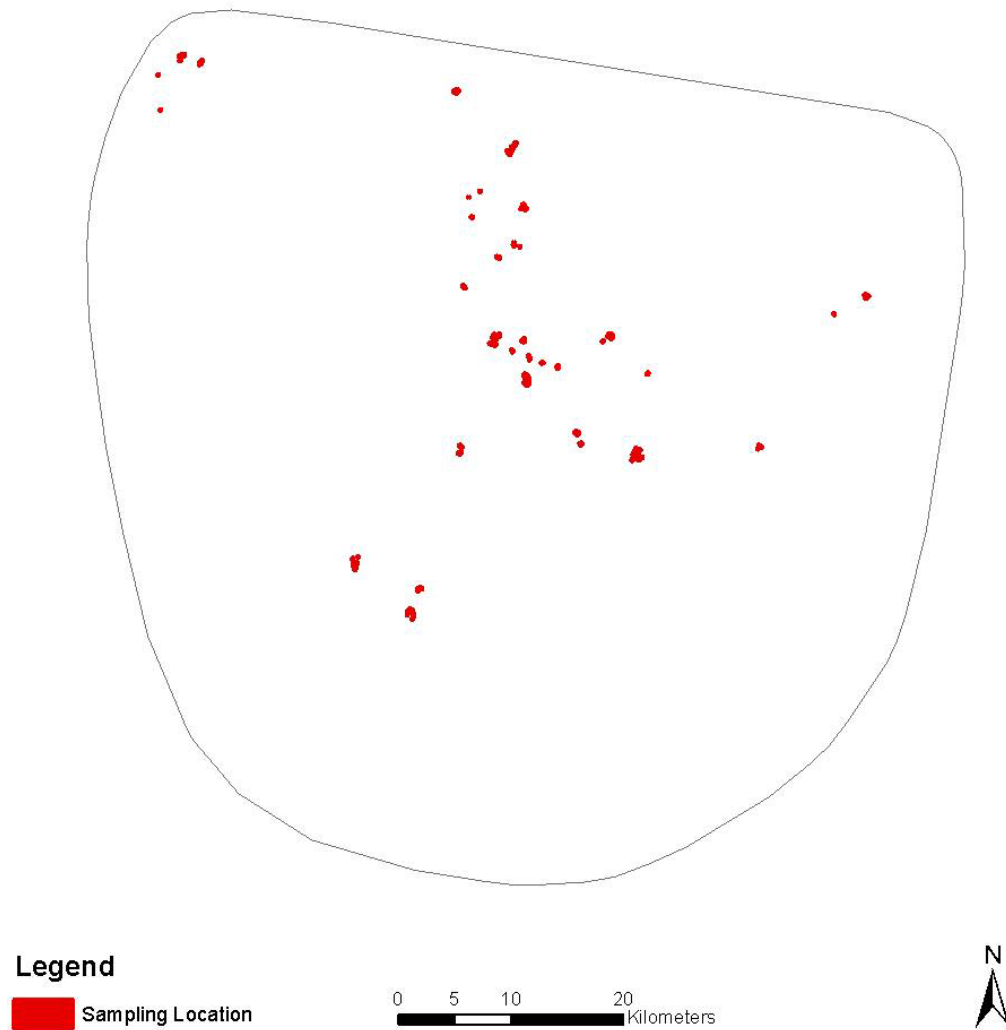


Figure 2.2. Sampling locations within the study area based on an opportunistic sampling methodology

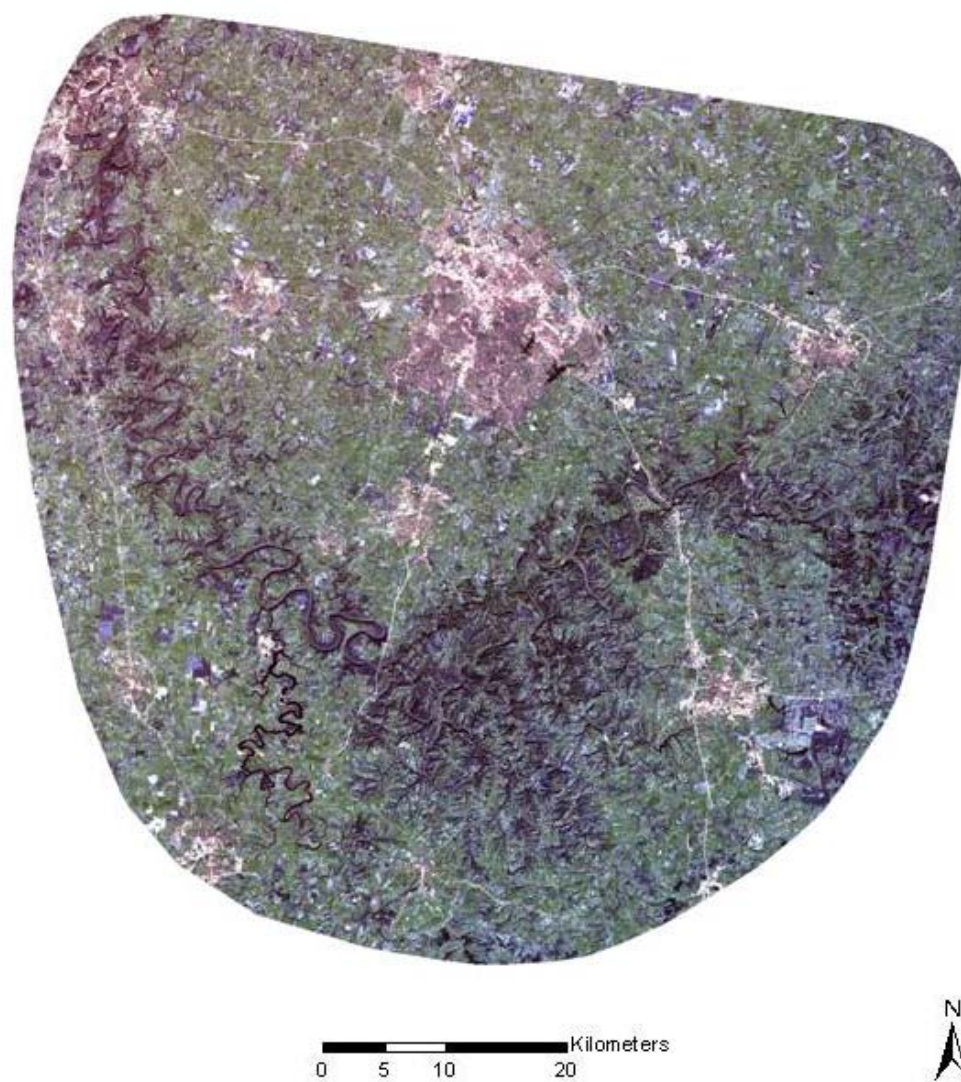


Figure 2.3. Landsat image of the study area displaying the full coverage of pixels prior to image pre-processing



Figure 2.4. Landsat image of the study area displaying vegetation pixels and also showing areas in white where pixels have been removed

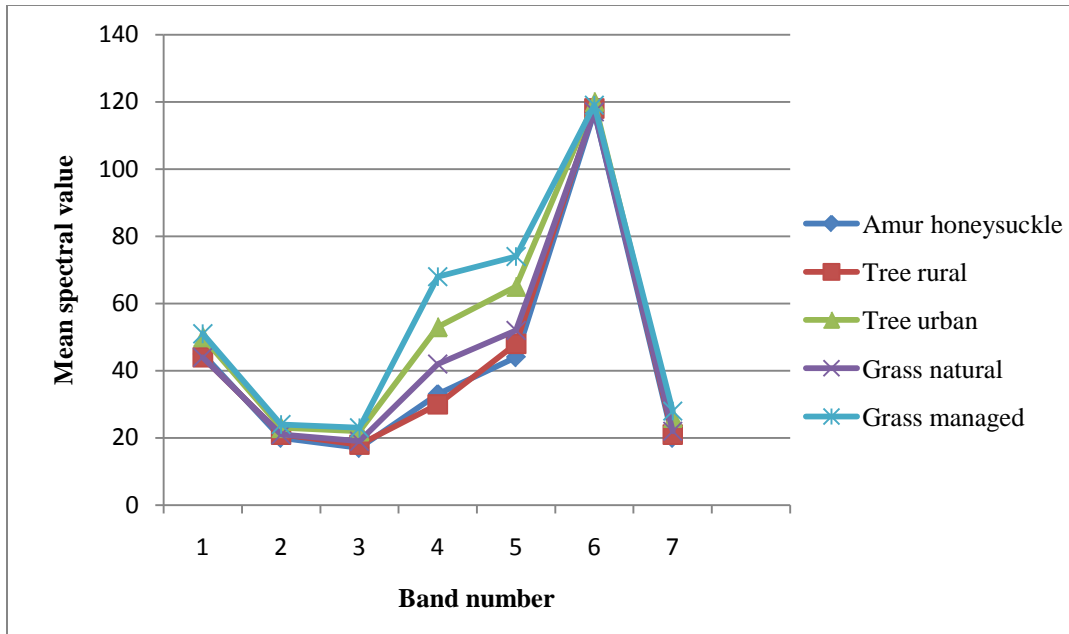


Figure 2.5. Mean spectral values for the five land cover classes of the November 7, 2009 Landsat image

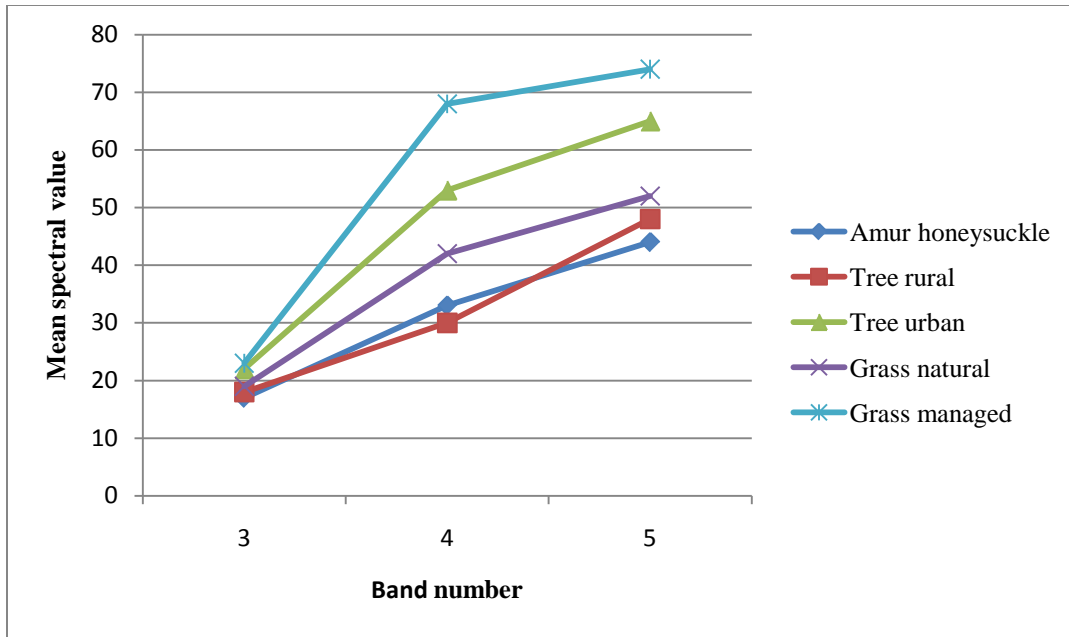


Figure 2.6. Mean spectral values for bands 3, 4, and 5 of the November 7, 2009 Landsat image

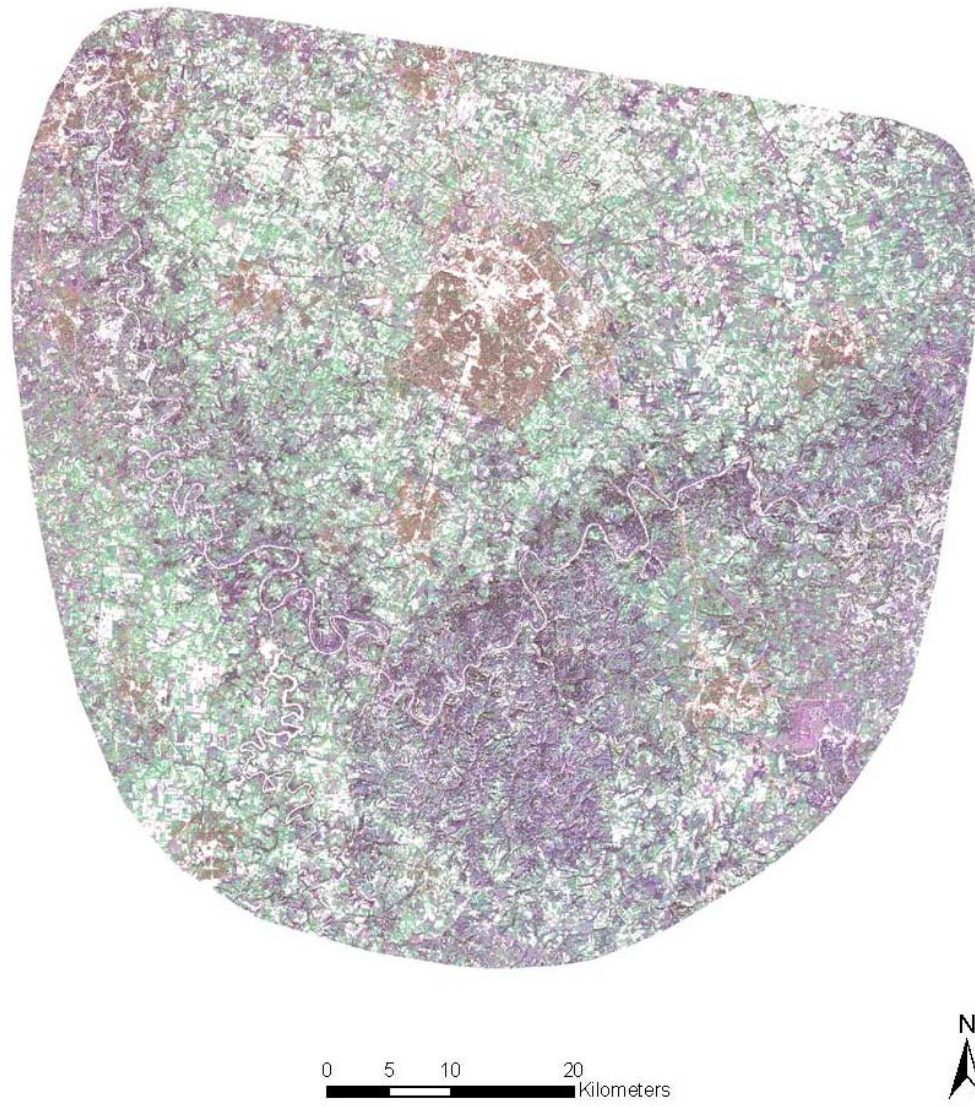


Figure 2.7. Landsat image displaying the pixels that were used in the classification process and also showing areas in white where pixels have been removed

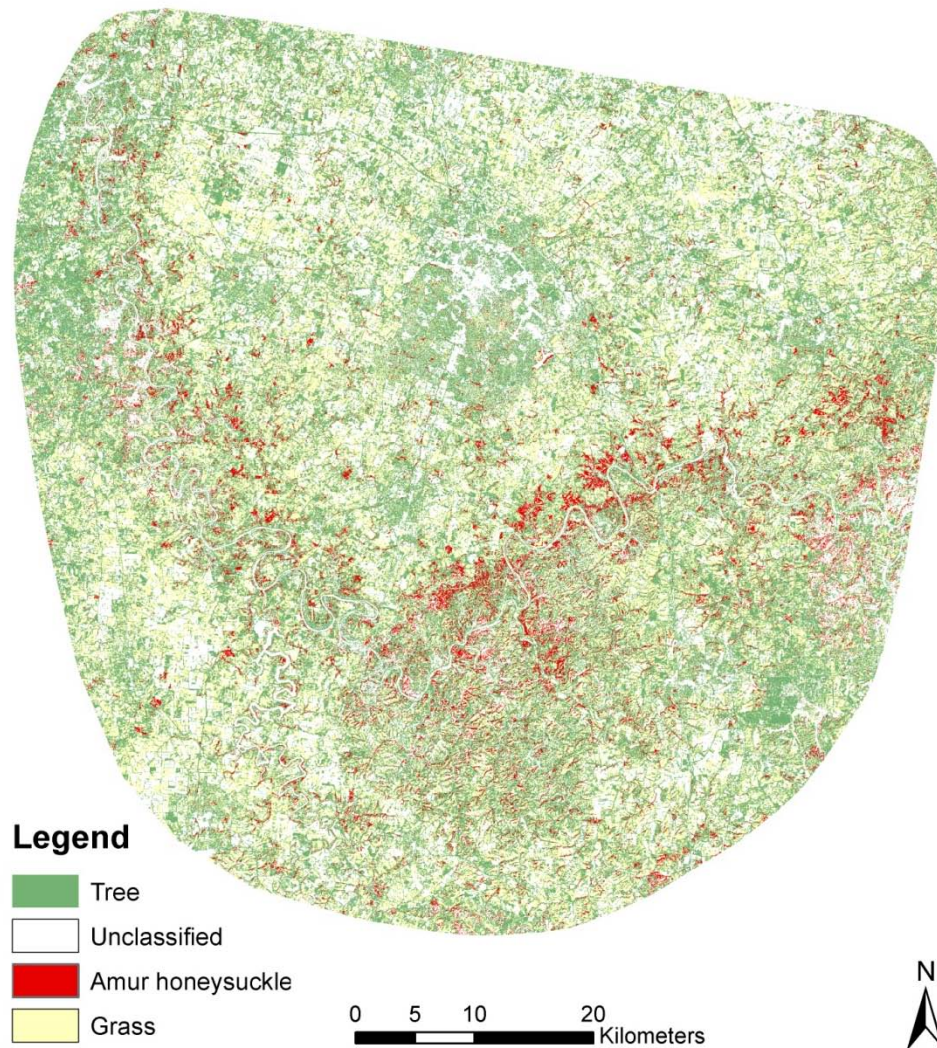
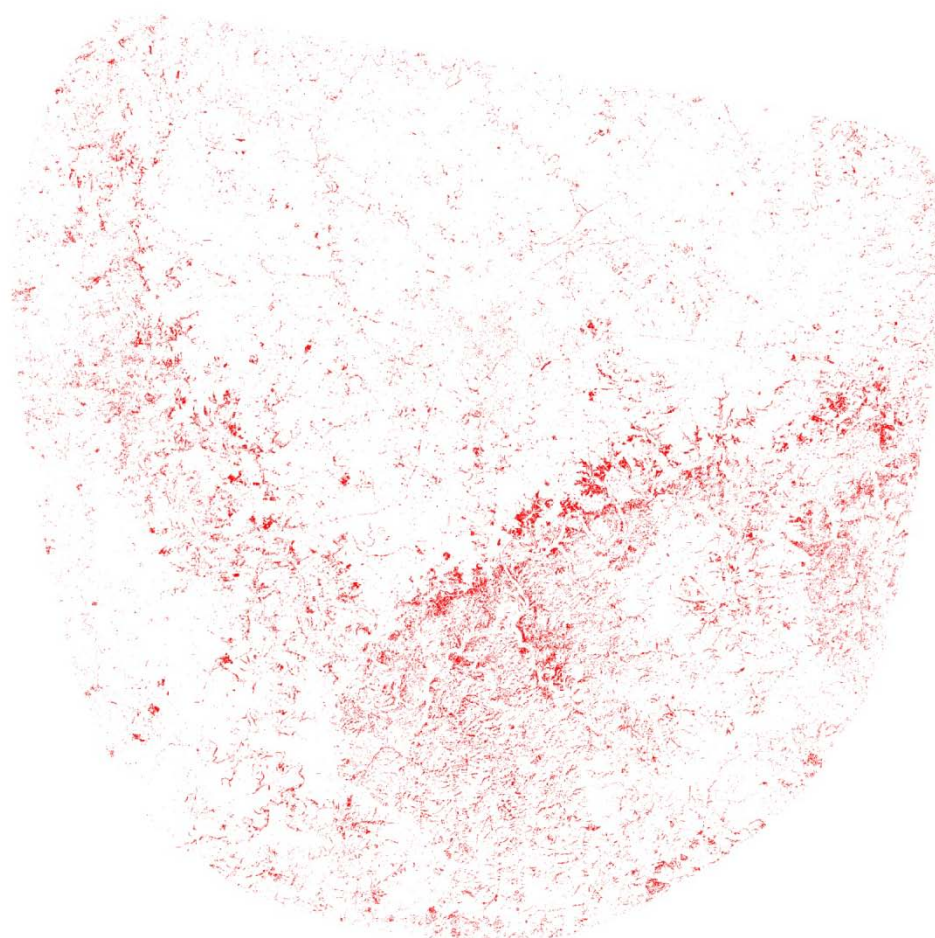


Figure 2.8. The 2009 classified image displaying the distribution of the three land cover classes



Legend



Amur honeysuckle

0 5 10 20
Kilometers



Figure 2.9. The 2009 classified image displaying only Amur honeysuckle presence

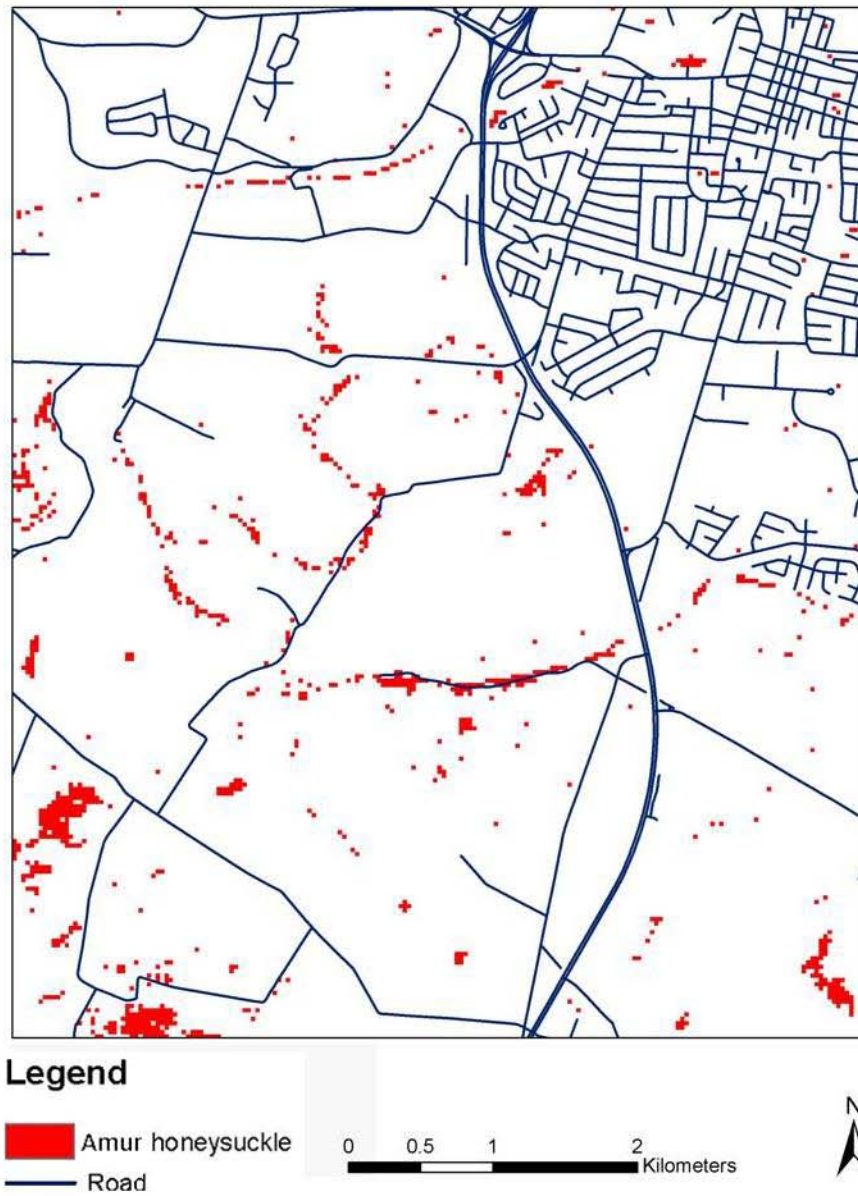


Figure 2.10. Connectivity of Amur honeysuckle along roads within an urban area

Chapter Three: Prioritization Framework for IEP Management

INTRODUCTION

Invasive exotic plants (IEP) are a threat to conservation, ecosystem services, and biodiversity (Mack et al. 2000, Ehrenfeld 2010). Though IEPs are widely researched, most studies focus on the characteristics, spread, and impacts of the invaders. Such studies tend to center their goals on a particular step of the invasion process, leading to generalizations about invasion ecology (Davis et al. 2000, Byers 2002, Gelbard and Belnap 2003, Coutts et al. 2011, Pergl et al. 2011). Researchers use this essential knowledge to further explore IEPs by creating models to analyze the invasibility of recipient ecosystems (Alpert et al. 2000, Hansen and Clevenger 2005), forecast future invasion spread (Coutts et al. 2011, Pergl et al. 2011), and predict potential impacts (Cook et al. 2007).

However, research that directly leads to IEP management actions is often limited. As IEPs continue to spread and further impact native ecosystems, managing these invasions becomes vital. Managers often face widely established IEP populations in more areas than can be quickly managed due to limited resources, making it a necessity to prioritize management actions (Webster et al. 2006). Yet, the extensive knowledge about invasion ecology is inadequate to guide such management actions. To optimize effective IEP management, there is a need for scientifically-driven strategic planning implemented at the landscape level that includes characteristics of the invaded ecosystem (Hobbs and Humphries 1995, Blossey 1999, Byers et al. 2002).

Hiebert (1997) was one of the first researchers to call upon the need for scientifically guided management strategies for IEP control. He stressed the need for managers to objectively assess the feasibility of control, the impacts, and the potential for spread when evaluating management options. Based on such guidelines, there is a need for decision tools and models to address the allocation of limited resources to areas of management priority. While decision tools have been used for various purposes, including prioritizing areas for conservation (Jane 1995, Sarakinos et al. 2001, Moilanen et al. 2005), the IEP management field has only recently begun using decision tools and models to prioritize management actions.

These IEP prioritization frameworks share a common component, in which models are created specifically to address one stage or characteristic of the invasion process. For instance, researchers have argued the need for prevention (Leung et al. 2002) and thus models have been created that focus on preventing the introduction of high impact IEPs (Cunningham et al. 2004). However, other researchers stress that it may be more beneficial to focus management on already established IEPs and therefore have created models to address IEP detection (Mehta et al. 2007). Models are also built that focus on the spread of the invaders by analyzing their distributions and densities to address populations most likely to disperse into adjacent areas (Taylor and Hastings 2004). In other instances, models can prioritize management options based on potential economic impacts (Cook et al. 2007).

These models address different stages of the invasion process, resulting in several approaches for prioritizing IEP management. Unfortunately, these static models are generally not flexible for application between differing invasion stages. Thus, a stage-

specific prioritization framework could be problematic if a manager has multiple management goals. For example, the manager might be interested in prioritizing IEP management operations associated with prevention and monitoring of newly emerging species in one area, while wanting to prioritize removal operations of well-established species in another location. Static models could be too rigid and not applicable to both management goals. Furthermore, model creation typically does not include manager input. Thus, models created by researchers may not completely address the specific goals or perspectives of managers. Managers need to be able to add their input into models and weight the level of importance of the included variables. Finally, models need to be intuitive and relatively easy for managers to implement.

We therefore argue the need for a flexible modeling framework that is adjustable to the differing stages of invasion while also allowing for the inclusion and manipulation of important variables that represent the various goals of managers. Such a framework could be important for management because it would not limit managers to a specific invasion stage and could be applicable to different regions. A model that incorporates all these factors will be more attractive to managers and have a higher likelihood of actual application in the field.

With this in mind, we designed a prioritization framework that uses the Analytic Hierarchy Process (AHP) as a basis for manager input and adjustability. The AHP employs a pair wise comparison method in a manner in which a goal is set and associated variables are arranged in a hierarchical fashion so that relative weights of importance can be compared (Saaty 1990). This methodology can be used to build a hierarchical foundation around the invasion process while also allowing managers to address their

management goals by weighing the importance of the variables built into the model. The adaptable AHP methodology has been used in broad studies to prioritize areas for forest conservation (Valente and Vettorazzi 2008) and landfill site selection in Serbia (Zelenović Vasiljević et al. 2012).

Application of the AHP methodology has been applied in the field of IEP management to assess invasion risks by different species (Ou et al. 2008, Roura-Pascual et al. 2009) and to determine management activities (van Wilgen et al. 2008). The goal of this research was to create a prioritization framework using the AHP methodology that was applicable to various invasion stages while allowing expert input to prioritize watershed units for IEP management. In addition, we analyzed how the expert weighting of variables affected the final prioritizations. To demonstrate our modeling framework, Amur honeysuckle (*Lonicera maackii*), a widely distributed and high-impact IEP, was selected as our study species.

METHODS

Study area

The study area was created to fit the general boundary of the Inner Bluegrass region of Kentucky as created by Lobeck (1932). The study area covers approximately 5,000 km² and was further edited to fit within one Landsat satellite image, causing the northern tip of the Inner Bluegrass region to be clipped from the study area (Figure 3.1). The Inner Bluegrass region is largely defined by limestone formations and soils that tend to be phosphate rich silt loams (Wharton and Barbour 1991). Amur honeysuckle is widespread and distributed throughout this region. The highest densities of the invader

are found in the south-central region of the study area, where there are large segments of edge between forested and agricultural land.

Source of data

Spatial data relevant to IEP management were collected to build our prioritization model and were designated as separate indicators (Table 3.1). An indicator is an individual data set that addresses a specific characteristic of the invasion process. To fit the framework of the AHP, the indicators were organized into a hierarchy (Table 3.2). At the highest level, the indicators were placed into one of three categories: IEP attributes, ecological impacts, or land use characteristics. At the lowest level, the indicators were broken down into detailed criteria. Full descriptions of the indicators, along with explanations of data sources and detailed criteria, can be found in Table 3.1.

To address management priority, the study area was separated into different units. We used the 14-digit hydrological unit (HUC14) as our base unit for the prioritization framework. Spatial distributions of the indicators within each of the 286 HUC14 units are displayed in Figures 3.2 - 3.8. Data were manipulated within ArcGIS 10 and Geospatial Modeling Environment.

Prioritization framework

We built the prioritization framework around the AHP, which allows for expert input and model flexibility to address differing invasion stages. This methodology works within a hierarchical association to weight the overall importance of variables in meeting the assigned goal. Our goal was to “prioritize watersheds for IEP management”.

Therefore, to assign weights to the variables, each hierarchical level was assessed by a pair wise comparison methodology.

At the highest level, the categories, the pair wise methodology assigned relative weights by comparing all categories with one another. The comparisons were completed by asking, “when prioritizing watersheds for IEP management, is it more important to know the ecological impacts or IEP attributes?” In this pair wise manner, all categories were compared (IEP attributes against ecological impacts, ecological impacts against land use characteristics, and IEP attributes against land use characteristics). The answers to each of these comparisons resulted in ratio-scale weights that were calculated within Expert Choice decision software, version 11.5.

The same method was used to weight the next two levels of the hierarchy, the indicators and detailed criteria, by asking in a pair wise manner the same question of importance among all the variables. For instance, at the indicator level, “is it more important to know the presence/absence of rare species or to know the presence/absence of ecologically important sites when prioritizing watersheds for IEP management?” Again, the pair wise comparisons were conducted for each indicator and detailed criteria within the model, resulting in ratio-scale scores that represented the relative weight each variable carried in addressing the management goal.

In our study, we used a natural resource manager and an ecologist to provide responses to the pair wise comparisons. To gain insights from both perspectives, the two experts were interviewed separately. The AHP methodology was introduced and an explanation of the purpose and goal of the prioritization model were given to the experts. Their responses to each of the pair wise comparisons were recorded and because of their

parsimonious responses, we combined their expert opinion. We then used their combined responses to calculate the ratio-scale weighted values of all the variables within the framework.

Prioritization models

One framework can create different models by varying the model inputs and the ranking of indicators to address, for example, the current invasion stage. Expert input regarding indicator importance may vary among invasion stages, as one indicator may be more important in a highly infested invasion scenario, but not as important in a newly invaded scenario. Therefore, to test the flexibility of our framework, two separate models were created that represented the same region, one pertaining to the current invasion stage and the other to a hypothetical stage of invasion.

The first model addresses the current invasion stage of Amur honeysuckle in the Inner Bluegrass region of Kentucky. This model was labeled the “established invasion scenario” because Amur honeysuckle is widely established and distributed throughout this region, having high ecological and economic impacts. The second model was created to prioritize the same Inner Bluegrass region but the expert responses were based on a hypothetical invasion scenario related to recent invasion and limited impacts. This model was labeled “new invasion scenario” because it was created to represent a stage of invasion in which the density levels of Amur honeysuckle are hypothetically much lower than what the region is currently experiencing.

Therefore, the two invasion scenarios represent the same Inner Bluegrass region and use the same data. Again, the only difference is that even though Amur honeysuckle

is heavily established in this region, we are hypothetically claiming that in the new invasion scenario, the invader is newly invading. We believe that it is acceptable to use the same IEP density data for both scenarios because the class levels for density (lowest, low, medium, high, highest) are only relative density percentages and can be altered to fit our hypothetical scenario. For instance, we can make the class level densities hypothetically different between the scenarios by suggesting that within the new invasion scenario the five levels are made of lower densities. For example, within the established invasion scenario, the five class levels may include IEP densities from 0 - 70%, but we can hypothetically say that these same five levels represent smaller intervals of IEP density from 0 - 15% within the new invasion scenario. This would give us the spatial distribution data of the IEP that is needed to help differentiate the watersheds from one another. By using the same data, we are allowing the experts to apply different weights to the indicators depending on their altered importance within either invasion scenario. Furthermore, using the same study area allows for easy comparisons of change in management priority between the invasion scenarios.

For both invasion scenarios, the expert responses created different weighted ratios of importance at each hierarchy level. The ratios, which are essentially percentages, were then converted to scores to represent the priority level of management for each watershed. For example, the ecological impacts category received a weighted ratio of 0.661 (66%), while the last 34% was divided among the other two categories. The 66% assigned to the ecological impacts category was converted to 66 points, which was then divided proportionally among the three indicators within this category. Again, this allocation of points to the indicator was dependent on the weights assigned by the expert

responses. For instance, the rarity-weighted species richness index received a weighted value of 49%, ecologically important sites 41%, and GAP diversity 10%. These weights were converted to points based on the indicators' percentage of the 66 points possible, resulting in the rarity-weighted species richness index with 32 points, ecologically important sites with 27 points, and GAP diversity with 7 points.

The points assigned to each indicator had to be further divided among the last level of the hierarchy, the detailed criteria. The detailed criteria represented the attributes of the indicators and each watershed could only be assigned one level of the detailed criteria. For instance, the detailed criteria of the GAP diversity indicator was represented as “high”, “medium”, or “low” diversity levels. Depending on the expert weighting, the detailed criteria received either the total allotment of points from its indicator or only a proportion of points. For example, the experts indicated that “high” GAP diversity levels were most important, and therefore this level received all 7 possible points from the indicator. The “medium” level was next important and received 4 of the possible 7 points, while the “low” diversity level was ranked least important and received only 1 of the 7 points. The points of all the detailed criteria were assigned to the watersheds in this way. Weights and allocation of points accordingly can be seen in detail in Table 3.3. Point totals were calculated, resulting in a final prioritization score for each watershed (Figure 3.9). The higher the score a watershed received, the higher the need for IEP management.

Model analysis

By creating two invasion scenarios that use the same data and represent the same region, we can identify which indicators are of most importance for management priority

based on the stage of invasion. Yet, we also wanted to address how expert input affects the allocation of management priority within each individual invasion scenario. To do this, “null” models were created for comparison. For each invasion scenario, a null model was created by making the relative weights of the three categories equal. The indicators were also assigned equal weight within each category, thus allowing for change analysis between models that were weighted by experts or weighted equally.

Overall, for both invasion scenarios, two models were created, an expert model and its associated null model, resulting in a total of four models for analysis. Differences between expert and null models were analyzed by comparing scores across HUC14 units in ArcGIS. The absolute value of differences in score were created to display the overall change in priority score between the models. Finally, we were also interested in knowing how changes in point allocation may alter the priority level of a watershed between the differing models. Therefore, watersheds were placed into one of four management priority levels, based on their final point total (Table 3.4). Differences between models were analyzed by comparing the change in priority level across watersheds.

RESULTS

Established invasion scenario

For the established invasion model, results from the AHP indicated that the ecological impacts category carried the most importance in prioritizing management areas, followed by IEP attributes, and land use characteristics (Table 3.3). The indicators of greatest influence were the rarity weighted species richness index, followed by

ecologically important sites, and IEP density. The remaining five indicators had limited influence, with high invasion pressure and road density having the lowest weights.

We created four separate priority levels based on the scores of the established invasion expert model (Figure 3.10). The lowest priority score for a watershed was 17 while the highest was 91. The results for the established invasion null model varied from its expert model (Figure 3.11, Table 3.5). The lowest priority score for a watershed was 23, with a high of 89.

Though it is important to know the final priority scores a watershed received from the two models, it is more important to know if the different priority scores affect the placement of a watershed into different priority levels. Approximately 2/3 of the watersheds changed priority level based on the expert vs. null models (Figure 3.12). The greatest change in priority was a difference in levels of -1 or -2. These values indicate that the null model prioritized such watersheds either 1 or 2 levels higher than the expert model did. Thus, for the bulk of watersheds that did experience a change in priority, their level was higher in the null model, and the expert model ranked them with less priority.

Furthermore, within the expert model, the top priority level contained watersheds that were mostly found along a narrow strip on the western side of the study area. This general section represents a large area of edge between forested and agricultural land. In the null model, some of the top priority watersheds were found in this same area. However, the null model resulted in most watersheds being distributed across the top three priority levels, while within the expert model, the lowest priority level contained the highest number of watersheds.

New invasion scenario

The responses of the experts altered the weight of the variables within the framework to fit the new invasion scenario. Results from the AHP indicated that the IEP attributes category carried the most weight for this model, followed by land use characteristics, and ecological impacts (Table 3.6). The expert model had the majority of its weight spread amongst five indicators. The IEP density indicator carried the most weight, followed by young IEP density, land cover, road density, and high invasion pressure. The remaining three indicators had little influence on the model, with the GAP diversity indicator receiving the lowest weight.

Total priority scores were again calculated for the watersheds (Figure 3.13). The lowest score for a watershed was 13 while the highest score was 89. Compared to the expert model, the null model resulted in different scoring totals (Figure 3.14). Scores ranged from 10 to 86 for the null model (Table 3.7). The differences in scoring affected the placement of watersheds into different priority levels (Figure 3.15). Approximately 1/3 of watersheds changed priority, favoring a positive level change of 1, indicating that the expert model prioritized such watersheds one rank higher than the null model.

For the expert model, the highest priority level watersheds were in a tight cluster within the center of the study area. This general location was among the areas that displayed the highest Amur honeysuckle densities. For the null model, however, the highest priority watersheds were more scattered throughout the study area, especially along the western portion. In addition, the general number of watersheds placed within each of the four priority levels varied between the two models.

Comparison of the invasion scenarios

By comparing the change in management priority between the two expert models of the differing invasion scenarios, we were able to analyze the flexibility of the framework (Figure 3.16). The change in priority scoring ranged from 0 to 58, which altered the allocation of watershed priority (Figure 3.17). The majority of watersheds displayed a negative priority level change, indicating that most watersheds were prioritized at lower levels within the established invasion scenario when compared to the new invasion scenario.

DISCUSSION

The responses to the pair wise comparisons within the framework served as the basis for the AHP. Using experts to answer the pair wise questions was very important. Interestingly, although the manager and scientist were interviewed separately, their responses were very similar and allowed us to combine their inputs into one “expert” opinion. Furthermore, we believe that their input and feedback gave us insights that improved our prioritization framework.

The prioritization framework was built at the watershed level. It is important to address this scale because the risk of invasion is often related to its environmental factors (With 2002). By using a watershed level approach, we are acknowledging that certain watersheds may be more vulnerable to invasion and experience various levels of impacts. Likewise, prioritization at the this level can facilitate eradication of the most ecologically damaging populations, while creating a system that uses limited labor in areas of most need.

Moreover, deciding how to break up the landscapes in a reasonable manner to allow for prioritization is important. For instance, models could use political boundaries to divide the land. However, we believe that watersheds create the most reasonable boundaries for prioritization at this scale. Watersheds are highly recognizable, and most managers know where their ownership boundaries fall within watersheds. In addition, watersheds provide a natural topographic boundary for analysis compared to political boundaries. Even though we argue the usefulness of the watershed boundary, other boundary layers could easily be applied to our framework to suit managers' needs.

We used the AHP to create a spatial prioritization framework for IEP management that incorporated expert input to alter weights of variables between the various models. The current invasion status within the Inner Bluegrass region of Kentucky resulted in the creation of the established invasion scenario. By using the same data and hypothetically altering the IEP density levels, we created the new invasion model for comparison.

Established invasion expert model

Within this model, experts gave the most weight to the ecological impacts category because of the high impact potential of Amur honeysuckle. Within this category, experts weighted management priority to locations with rare species and ecologically important sites. The GAP diversity indicator did not receive much weight because it is a rough estimate of diversity potential. In contrast, the rarity weighted species richness index and the ecologically important sites are discrete results from fieldwork and species

presence data. These two indicators are far more accurate at displaying areas that would potentially experience high ecological impacts.

Priority was next given to the IEP density indicator. Though it is imperative to identify ecologically important areas, it is also important to recognize known locations of Amur honeysuckle stands. Interestingly, experts gave watersheds with the lowest IEP density levels the highest priority. Since Amur honeysuckle is so thoroughly established in this region, it is more feasible to manage low density sites where the IEP will not quickly re-establish, giving managers a higher likelihood for control. The other indicators, which related to spread and establishment, are not as important because the IEP is already widely established. Consequently, management priority was assigned to locations of high ecological importance and watersheds displaying the best potential for IEP control.

Comparison of the established invasion expert and null models

Approximately 2/3 of watersheds changed priority level between the expert and null model, with most expressing negative level changes. This means that because of its equal weighted inputs, the null model is incorrectly allocating management by giving top priority to watersheds that are not in most need of management. This demonstrates the importance of expert opinion within our framework to direct management actions.

This also shows that if managers are interested in prioritizing management, they need to use a model that incorporates their goals and inputs. Our model took the expert responses and prioritized management areas accordingly. For instance, experts were most interested in preventing ecological impacts, and therefore our framework gave priority to

watersheds that had both rare species and ecologically important sites. This is valuable because experts were able to analyze the invasion scenario and by the pair wise comparison method decide which factors were most important for management. Furthermore, this framework presented how and why priority was given and did so in a comprehensible manner.

New invasion expert model

In the new invasion scenario, experts gave the most weight to the IEP attributes category because of the hypothetically lower IEP density levels. Within this category, the experts weighted most management priority to IEP density indicators because managing watersheds with the highest IEP densities would allow for the most removal before further spread. In addition, the high invasion pressure indicator was important because of its ability to identify watersheds that are experiencing high propagule pressure.

Similarly, the land use characteristics category becomes more important in this hypothetical invasion scenario because its indicators may lead to monitoring and prevention operations. For instance, the land usage and road density indicators identify areas of increased disturbance, which may relate to a higher probability of introduction or establishment. The ecological impacts category and its three indicators did not carry much weight in this scenario. Rather than focusing on potential impacts, experts hypothetically deemed it more important to center activities on removing current stands while also directing operations to monitor and/or prevent new introductions, in an effort to eradicate the IEP.

Comparison of the invasion scenarios

Within the new invasion scenario, approximately 1/3 of the watersheds changed priority between the expert and null models. This again demonstrated the importance of expert input, as the allocation of management priority changed noticeably between the two models. However, this scenario showed less change in watershed priority levels when compared to the established invasion scenario. The expert model of the established invasion scenario had its point allotment dispersed mostly among three indicators, while the expert model of the new invasion scenario had its points dispersed mostly among five indicators. Because more points were allotted to fewer indicators within the established invasion expert model, it created a more dramatic difference compared to its null model.

Depending on the invasion scenario, the experts modified weights at all three hierarchy levels, which ultimately altered the locations receiving management priority. Within the established invasion scenario, the experts weighted the ecological impacts category with most importance, while the IEP attributes received the most weight in the new invasion scenario. In addition, the experts altered their weights at the detailed criteria level. For instance, the low IEP density class received the most weight within the established invasion scenario, while within the new invasion scenario, the highest IEP density class received the most weight that indicator. In addition, the land usage, road density, and young IEP density indicators experienced changes in class weights. These differences in weighting demonstrate the flexibility of the framework and how it can be adjusted to fit different invasion scenarios, which is useful for managers.

Framework analysis

Our modeling approach has created a useful framework for prioritizing IEP management. This approach is valuable because it consolidates characteristics of the invasion process in one framework, making it applicable to diverse regions and distinct invasion scenarios. Our framework is also important because it was implemented at a landscape scale, which allowed for the inclusion of new and relevant data that managers might not have previously considered. The framework also adds to the field of IEP management because of our characterization of Amur honeysuckle. We were able to analyze current stands of the invader and identify watersheds at higher risk of further invasion.

By comparing the indicators in a pair wise manner rather than simply listing importance 1- 8, we are providing managers with a more objective way to rank the most important factors that determine management priority. We are also giving managers the ability to first analyze the region and stage of invasion, and then objectively weight which factors are of most importance to their management goals. Furthermore, our framework takes this input and then interprets the priority locations. Overall, as we have demonstrated the flexibility of our framework, we are giving managers a tool that can be adapted to various regions or IEPs based on their expert input.

Agencies and managers with dissimilar goals could use this one framework to create customized prioritizations. One manager may be more interested in management that removes IEP from areas with high ecological value and can adjust the framework to such goals. On the other hand, a manager with less invaded lands can use this same framework to prioritize management based on preventing introduction or establishment.

Furthermore, managers could fit the framework to different invaders by adding or removing indicators based on the characteristics of the IEP. For example, if the IEP has known dispersal characteristics, such as wind dispersal, then populations of the invader located on higher topographic positions may be prioritized for management (Roura-Pascual et al. 2009). Managers can also adjust the framework to fit special invasion scenarios, such as for regions where the IEP has a potential to alter important hydrological regimes (Ou et al. 2008).

Other factors that this framework did not incorporate, such as management feasibility, may influence control operations. Obviously, without proper resources, the control operations may not be executed. However, this type of information and data are highly variable from agency to agency, and therefore need to be addressed from within when applying prioritization frameworks. Finally, in highly urbanized regions, access to lands may be a management barrier that is difficult to deal with. Agencies may need to initiate incentives to private landowners to gain land access or reward them for individual removal.

A primary goal of this prioritization was to use data that is easily accessible and available for managers, yet possibly one of the most important indicators in our framework, the IEP distribution, may be the hardest for managers to acquire. Our model applied remote sensing techniques to acquire an estimated distribution of Amur honeysuckle within our study area. This stresses the importance and need for accurate distributions maps of IEP species throughout the United States. Employing similar remote sensing methodologies by government agencies or other environmental

organizations to create a more accurate database of IEP distributions would be beneficial for managers.

CONCLUSION

As IEP continue to spread and establish in new regions worldwide, there is an ever-increasing need to manage these invasions. Often times, managers simply do not have the resources to sufficiently address and manage all infested areas under their control. Therefore, it becomes particularly vital that managers use scientifically driven decision tools to prioritize areas in most need of management in order to conserve and protect our native ecosystems. Managers need a flexible framework that incorporates their goals and can be applied to various stages of invasion.

Therefore, our overall approach was to create a prioritization framework that used accessible data, encouraged expert input, and was adaptable to differing invasion scenarios. We applied the working knowledge of the invasion process and the flexible AHP methodology to address managers' goals and input in one framework. Our results detail the important role that expert input plays in making management decisions, as management priority was allocated to watersheds that displayed the key indicators associated with the invasion stage of that region. This framework is useful and can be easily applied by managers. Furthermore, within the finalized prioritization, managers can adjust the number of watersheds grouped within the top priority level to meet budget needs.

Overall, decision tools are and will be important in the fight against IEPs. Such tools will guide managers to areas in most need of management based on their relative

goals. Researchers need to present these tools to managers in a basic manner that allows for ease of use and increases the likelihood of application within their management areas.

Table 3.1. Detailed description of indicators used in the prioritization framework

Indicator	Description	Index Classes
IEP Attributes		
IEP density	Estimated Amur honeysuckle density from a supervised classification of a 2009 Landsat satellite image	5 density levels: lowest, low, medium, high, highest
Young IEP density	Estimated Amur honeysuckle from a supervised classification of a 2005 Landsat satellite image. Subtracted the 2005 distribution from the 2009 distribution	5 density levels: lowest, low, medium, high, highest
High invasion pressure	Calculated average density of Amur honeysuckle for watersheds. Higher densities relate to higher invasion pressure on neighboring watersheds	Is the watershed neighboring an area with a higher than average density of Amur honeysuckle? Yes or no
Ecological Impacts		
Rarity-weighted species richness index	Presence/absence of rare species. Index created by the Kentucky State Nature Preserves Commission. Index incorporates the rare species distribution and number of populations within the state to create a rarity index score.	5 index levels: <u>High</u> = high concentration of rare species and/or rare species that have a very small range. <u>Medium</u> = rare species present. <u>Low</u> = May support rare species, though no occurrences are known. <u>Historic</u> = rare species occurrences that have not been observed for over 20 years and may no longer exist. <u>Absent</u> = no rare species present or historically documented
Ecologically important sites	Ecologically significant areas as identified by the Kentucky State Nature Preserves Commission.	Does the watershed contain an ecologically important area? Yes or no
GAP diversity	Generalized habitat diversity levels as modeled by the GAP analysis program.	3 diversity levels: low, medium, high
Land Use Characteristics		
Land usage	General land usage of each watershed derived from Population Interaction Zones for Agriculture (PIZA) created by the USDA. The index identifies zones of agricultural land and the surrounding levels of increasing population interaction.	3 zones: agricultural land, less impacted land, highly urbanized land
Road density	The road dataset was produced by the Kentucky Transportation Cabinet	5 density levels: lowest, low, medium, high, highest

Table 3.2. Hierarchical association of categories, indicators, and detailed criteria that created the prioritization framework

1. IEP Attributes	2. Ecological Impacts	3. Land Use Characteristics
1.1 IEP density	2.1 Rarity-weighted richness	3.1 Land usage
Lowest	High	Agriculture
Low	Medium	Less impacted
Medium	Low	Highly urban
High	Historic	
Highest	Absent	3.2 Road density
		Lowest
1.2 Young IEP density	2.2 Ecologically important site	Low
Lowest	Yes	Medium
Low	No	High
Medium		Highest
High	2.3 GAP diversity	
Highest	Low	
	Medium	
1.3 High invasion pressure	High	
Yes		
No		

Table 3.3. The AHP results for the established invasion expert model of the prioritization framework

1. IEP Attributes (24%)		2. Ecological Impacts (66%)		3. Land Use Characteristics (10%)	
1.1 IEP density (14)		2.1 Rarity-weighted richness (32)		3.1 Land usage (6)	
Lowest	14	High	32	Agriculture	1
Low	10	Medium	28	Less impacted	6
Medium	5	Low	14	Highly urban	2
High	2	Historic	7		
Highest	0	Absent	0	3.2 Road density (4)	
				Lowest	4
1.2 Young IEP density (6)		2.2 Ecologically important site (27)		Low	3
Lowest	1	Yes	27	Medium	2
Low	2	No	0	High	1
Medium	3			Highest	0
High	4	2.3 GAP diversity (7)			
Highest	6	Low	1		
		Medium	4		
1.3 High invasion pressure (4)		High	7		
Yes	4				
No	1				

Table 3.4. Scoring intervals that created the management priority levels

Scoring Interval	Priority rank	Priority Level
0-30	Lowest	1
31-50	Low	2
51-70	Medium	3
71-91	High	4

Table 3.5. The AHP results for the established invasion null model of the prioritization framework

1. IEP Attributes (33%)		2. Ecological Impacts (33%)		3. Land Use Characteristics (34%)	
1.1 IEP density (11)		2.1 Rarity-weighted richness (11)		3.1 Land usage (17)	
Lowest	11	High	11	Agriculture	2
Low	8	Medium	10	Less impacted	17
Medium	4	Low	5	Highly urban	6
High	2	Historic	2		
Highest	0	Absent	0	3.2 Road density (17)	
				Lowest	17
1.2 Young IEP density (11)		2.2 Ecologically important site (11)		Low	14
Lowest	1	Yes	11	Medium	8
Low	3	No	0	High	4
Medium	5			Highest	1
High	8	2.3 GAP diversity (11)			
Highest	11	Low	2		
		Medium	6		
1.3 High invasion pressure (11)		High	11		
Yes	11				
No	2				

Table 3.6. The AHP results for the new invasion expert model of the prioritization framework

1. IEP Attributes (62%)		2. Ecological Impacts (9%)		3. Land Use Characteristics (29%)	
1.1 IEP density (30)		2.1 Rarity-weighted richness (4)		3.1 Land usage (17)	
Lowest	6	High	4	Agriculture	1
Low	14	Medium	3	Less impacted	12
Medium	19	Low	2	Highly urban	17
High	25	Historic	1		
Highest	30	Absent	0	3.2 Road density (12)	
				Lowest	1
1.2 Young IEP density (21)		2.2 Ecologically important site (4)		Low	4
Lowest	4	Yes	4	Medium	7
Low	10	No	0	High	10
Medium	15			Highest	12
High	19	2.3 GAP diversity (1)			
Highest	21	Low	1		
		Medium	1		
		High	1		
1.3 High invasion pressure (11)					
Yes	11				
No	1				

Table 3.7. The AHP results for the new invasion null model of the prioritization framework

1. IEP Attributes (33%)		2. Ecological Impacts (33%)		3. Land Use Characteristics (34%)	
1.1 IEP density (11)		2.1 Rarity-weighted richness (11)		3.1 Land usage (17)	
Lowest	2	High	11	Agriculture	1
Lowest	5	Medium	10	Less impacted	12
Medium	7	Low	6	Highly urban	17
High	9	Historic	2		
Highest	11	Absent	0	3.2 Road density (17)	
				Lowest	2
1.2 Young IEP density (11)		2.2 Ecologically important site (11)		Low	5
Lowest	2	Yes	11	Medium	10
Low	5	No	0	High	14
Medium	8			Highest	17
High	10	2.3 GAP diversity (11)			
Highest	11	Low	2		
		Medium	6		
1.3 High invasion pressure (11)		High	11		
Yes	11				
No	1				

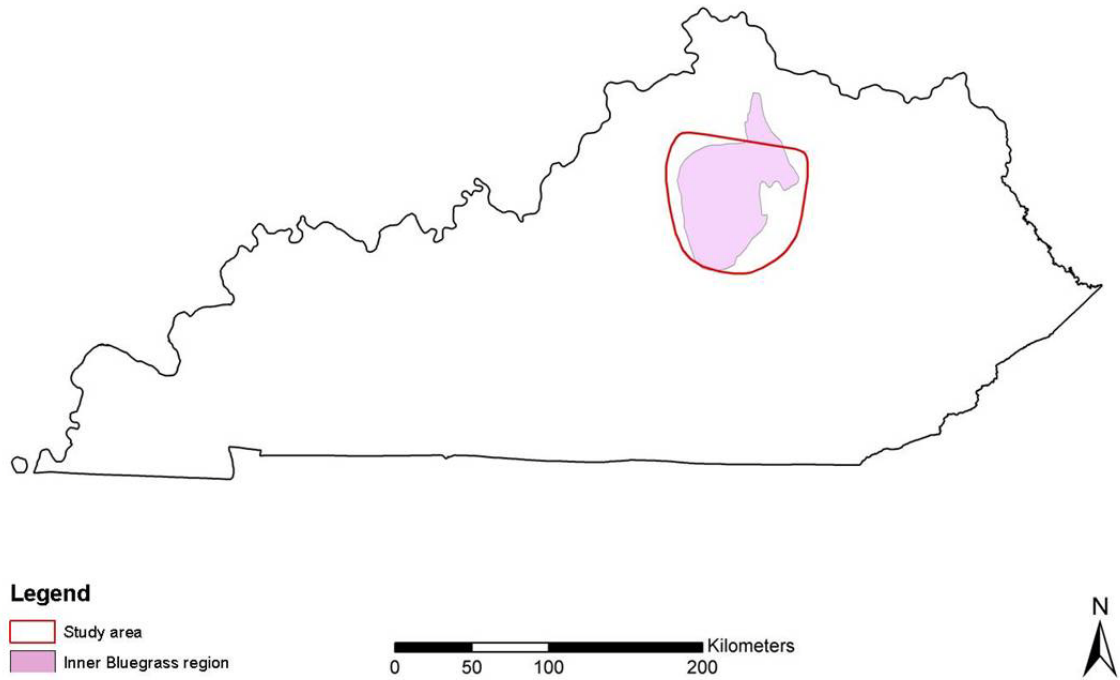


Figure 3.1. Map of the study area created to fit the general outline of the Inner Bluegrass region of Kentucky

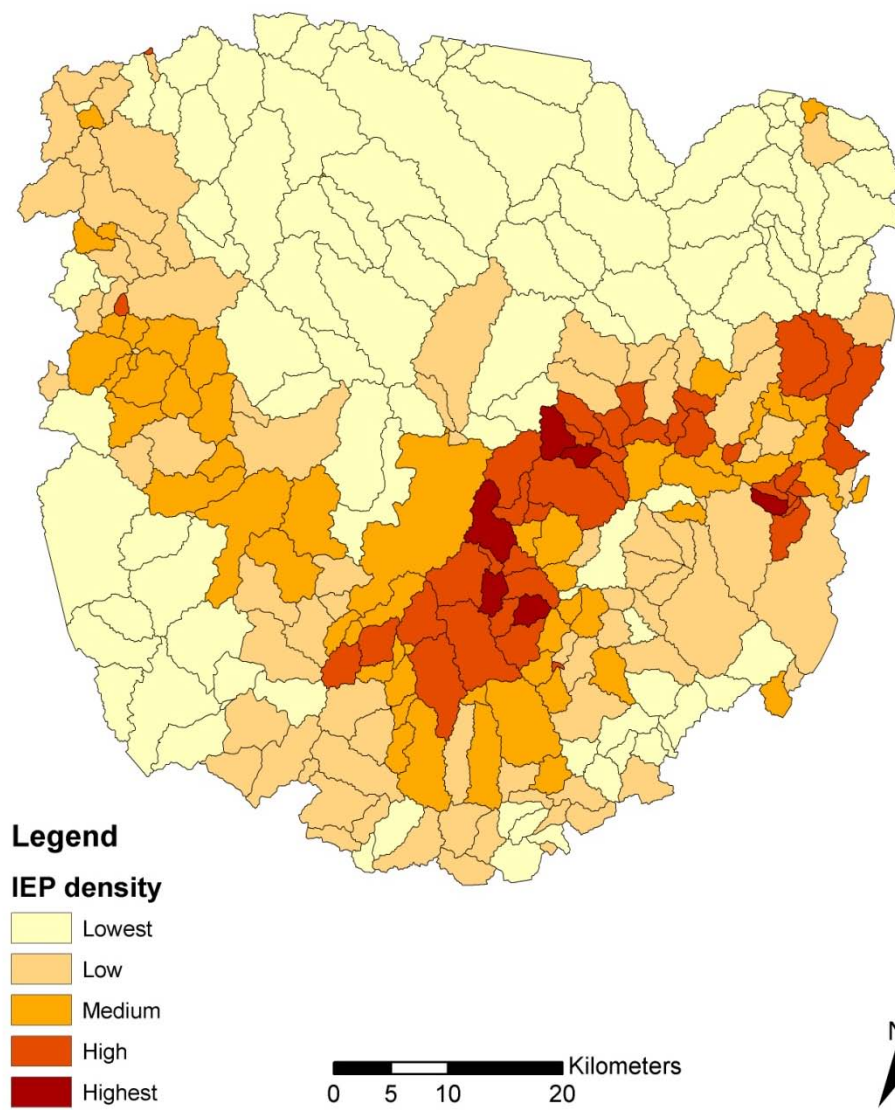


Figure 3.2. The distribution of Amur honeysuckle density displayed within HUC 14 watershed boundaries

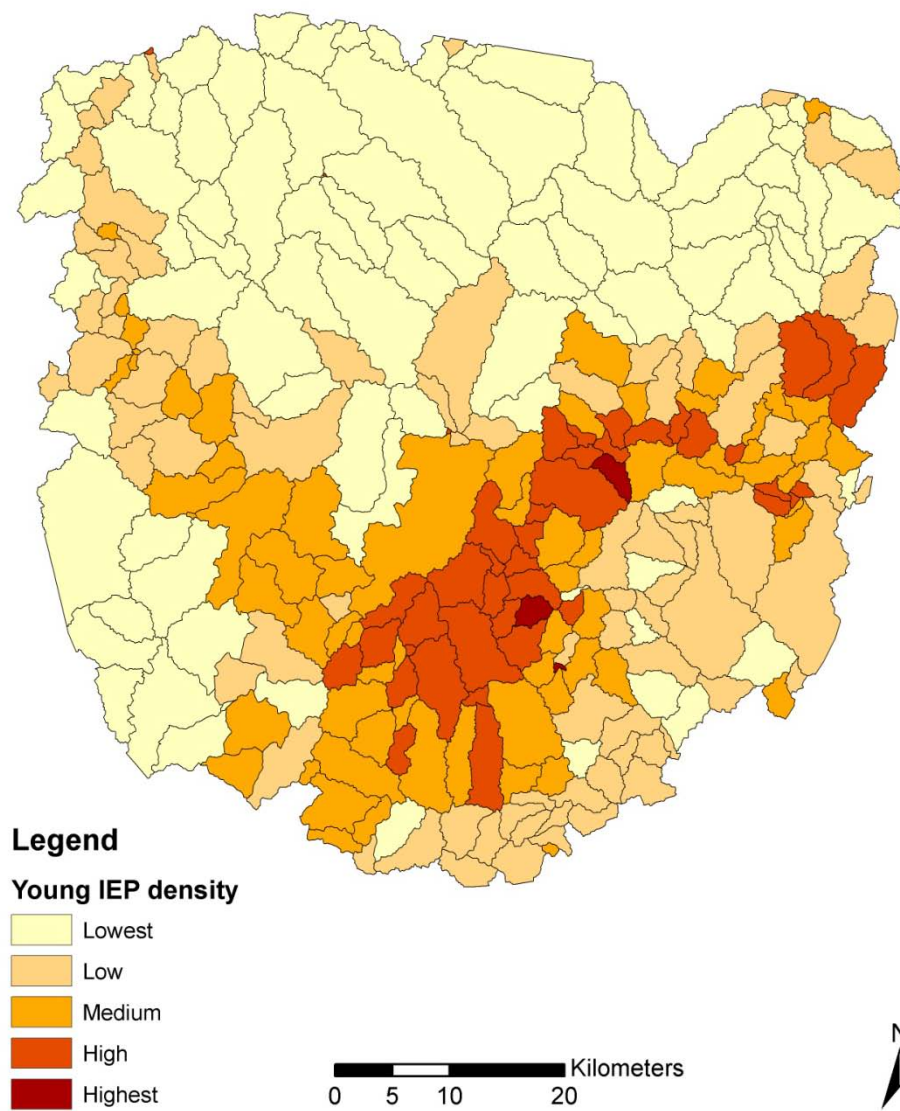


Figure 3.3. The distribution of young Amur honeysuckle density displayed within HUC 14 watershed boundaries

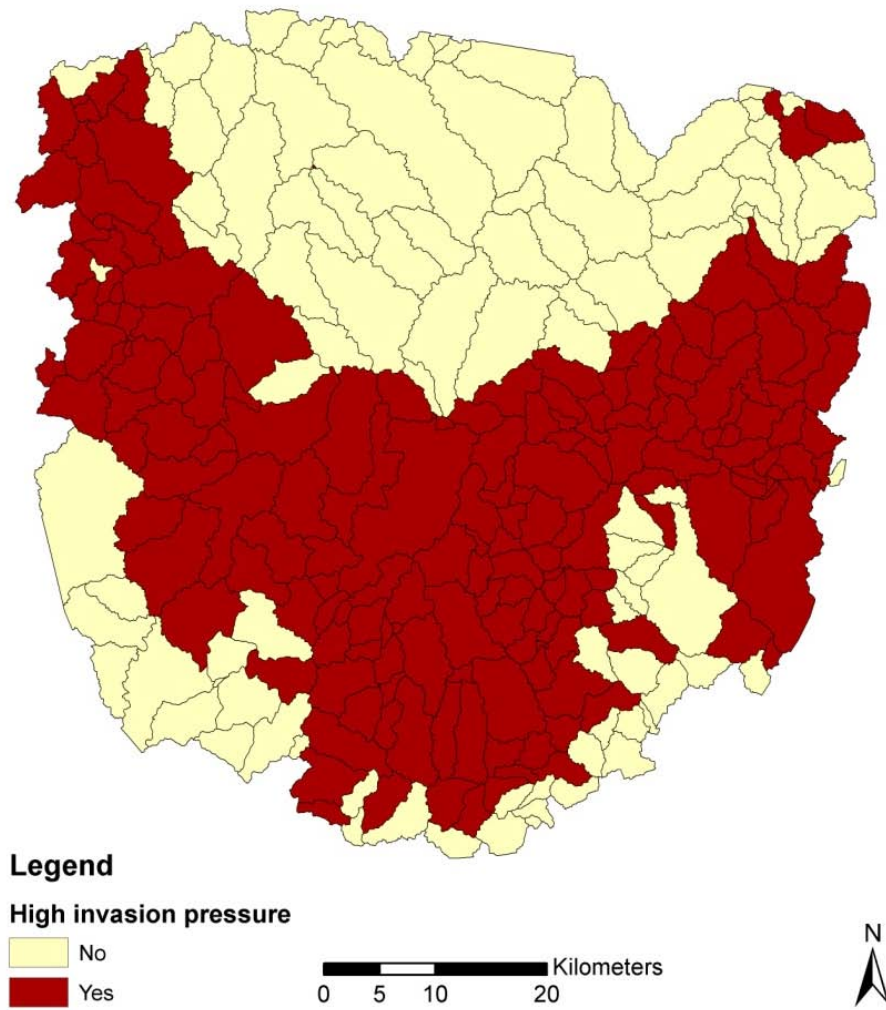


Figure 3.4. The locations of high invasion pressure displayed within HUC 14 watershed boundaries

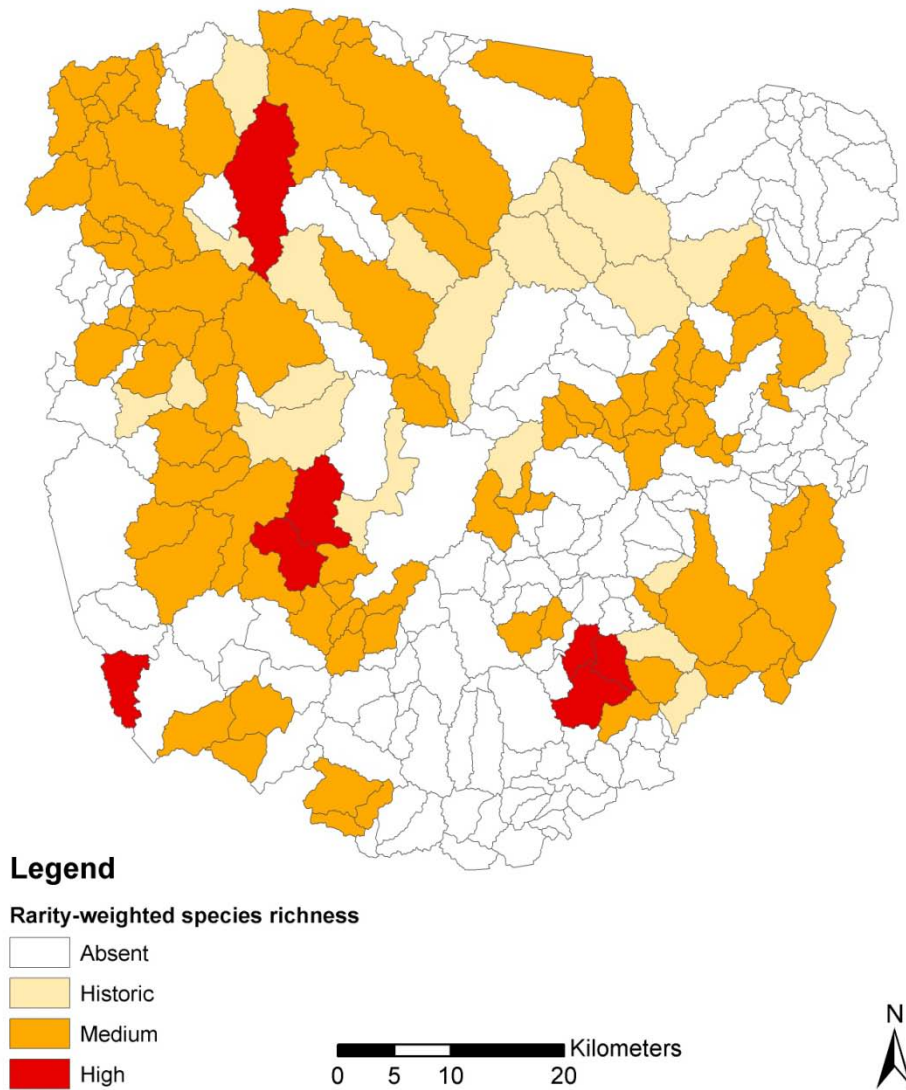


Figure 3.5. The distribution of the rarity-weighted species richness index displayed within HUC 14 watershed boundaries

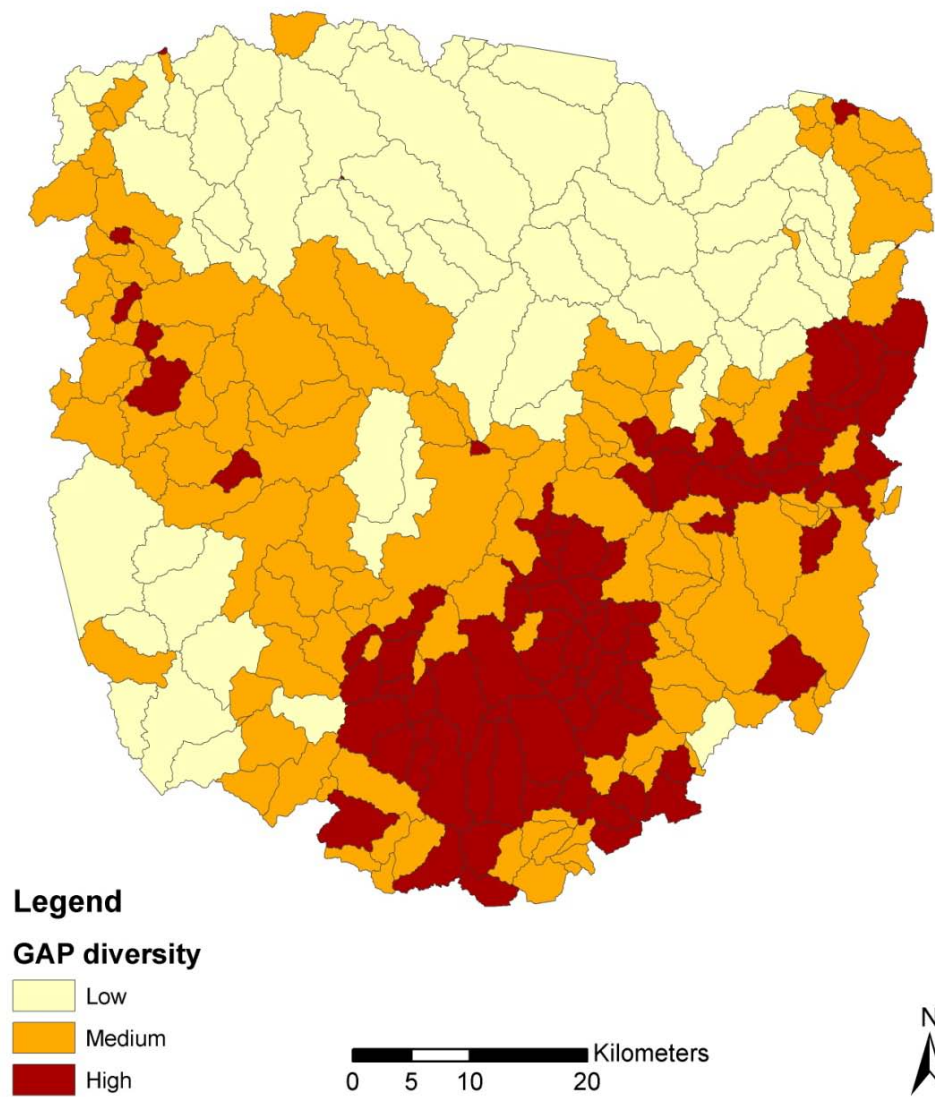


Figure 3.6. The distribution of GAP diversity classes displayed within HUC 14 watershed boundaries

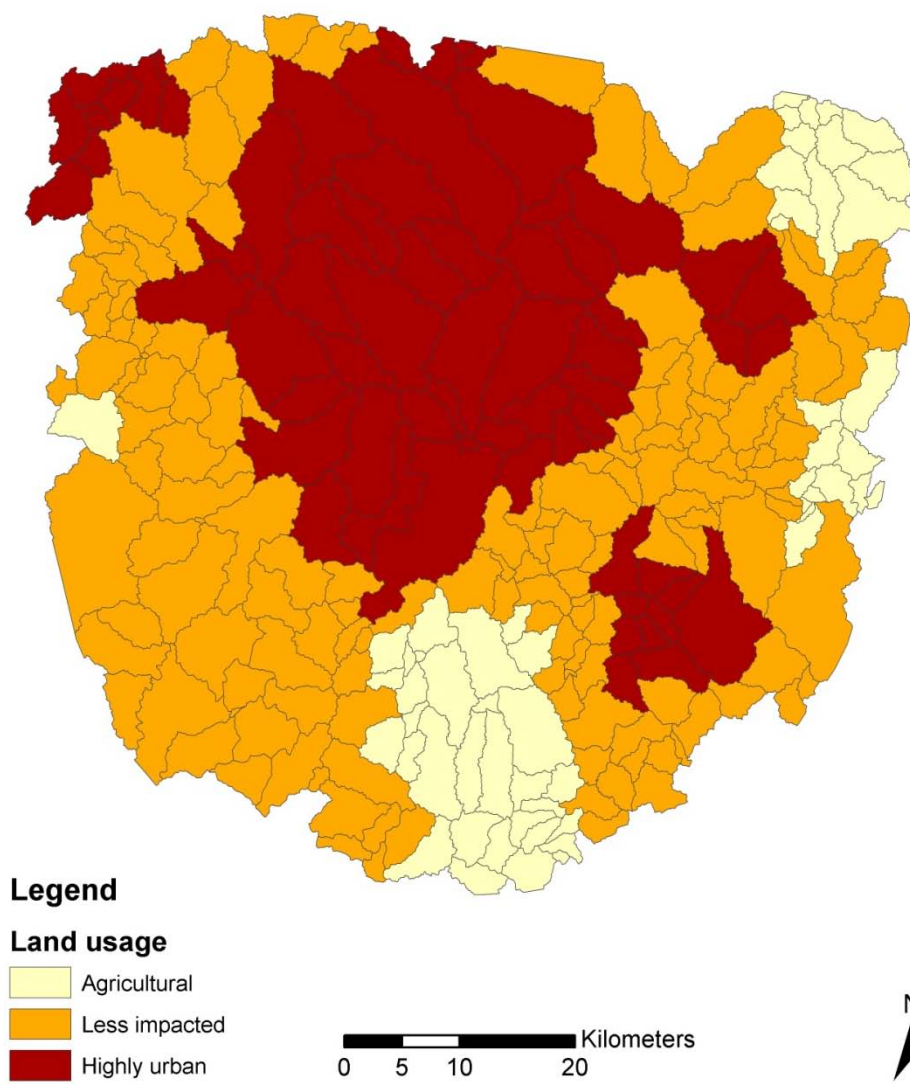


Figure 3.7. The distribution of the land usage classes displayed within HUC 14 watershed boundaries

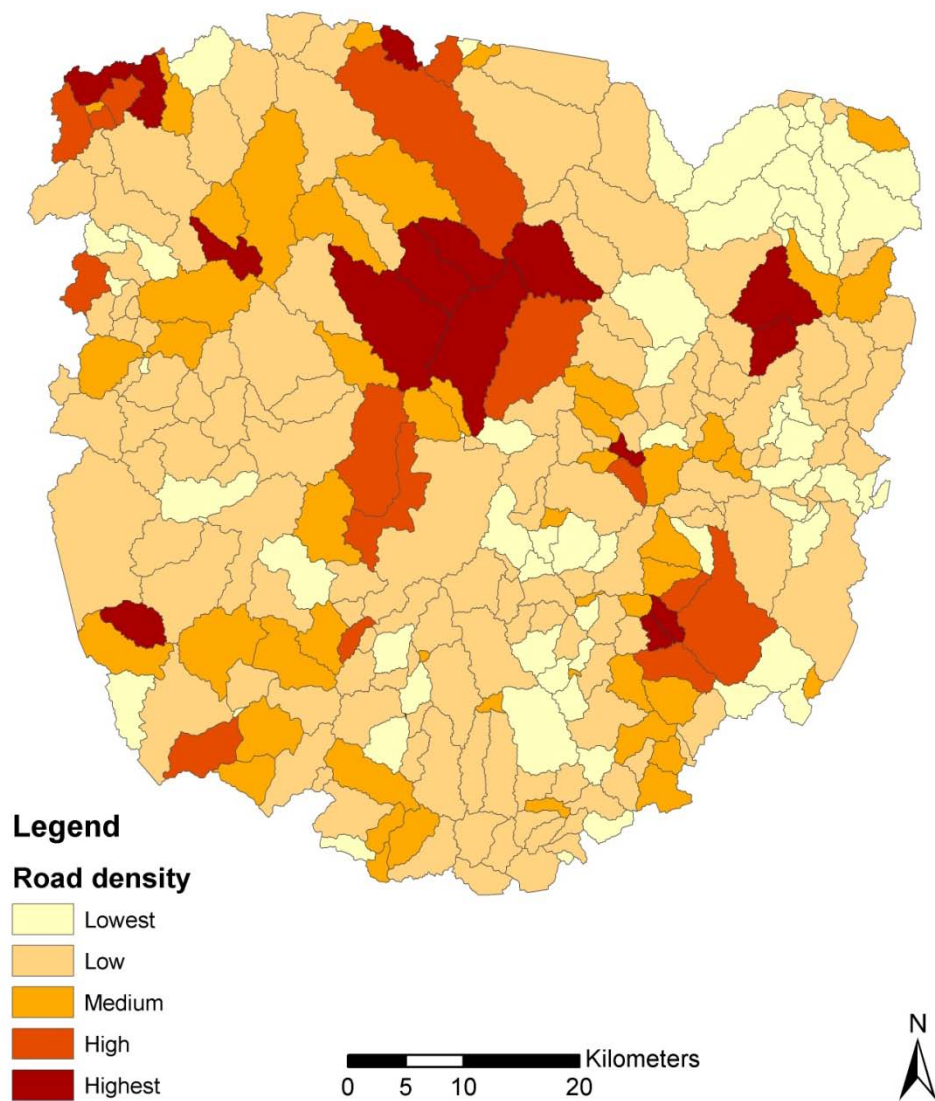


Figure 3.8. The distribution of road density displayed within HUC 14 watershed boundaries

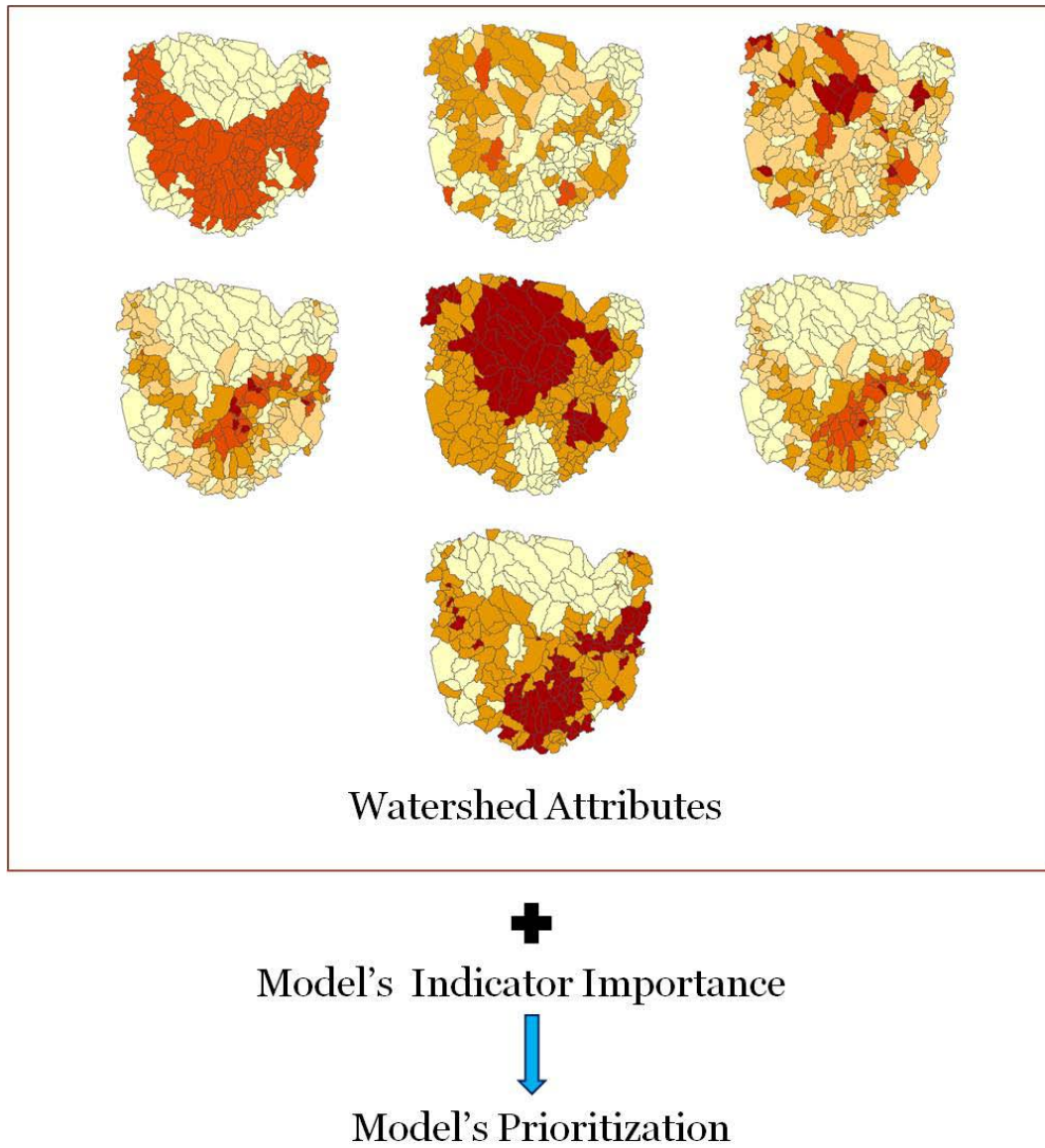


Figure 3.9. Workflow showing how the watershed attributes and the model's weights result in the final watershed prioritization

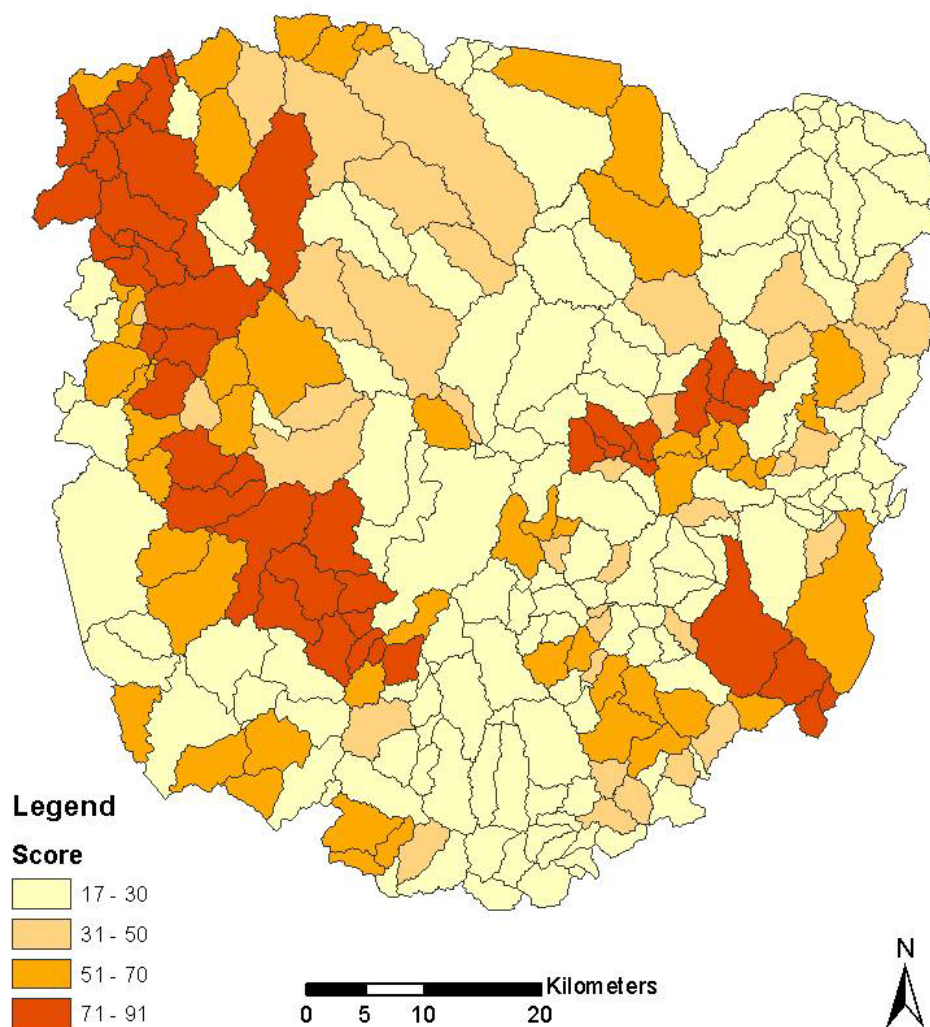


Figure 3.10. The watershed priority scores calculated for the established invasion expert model

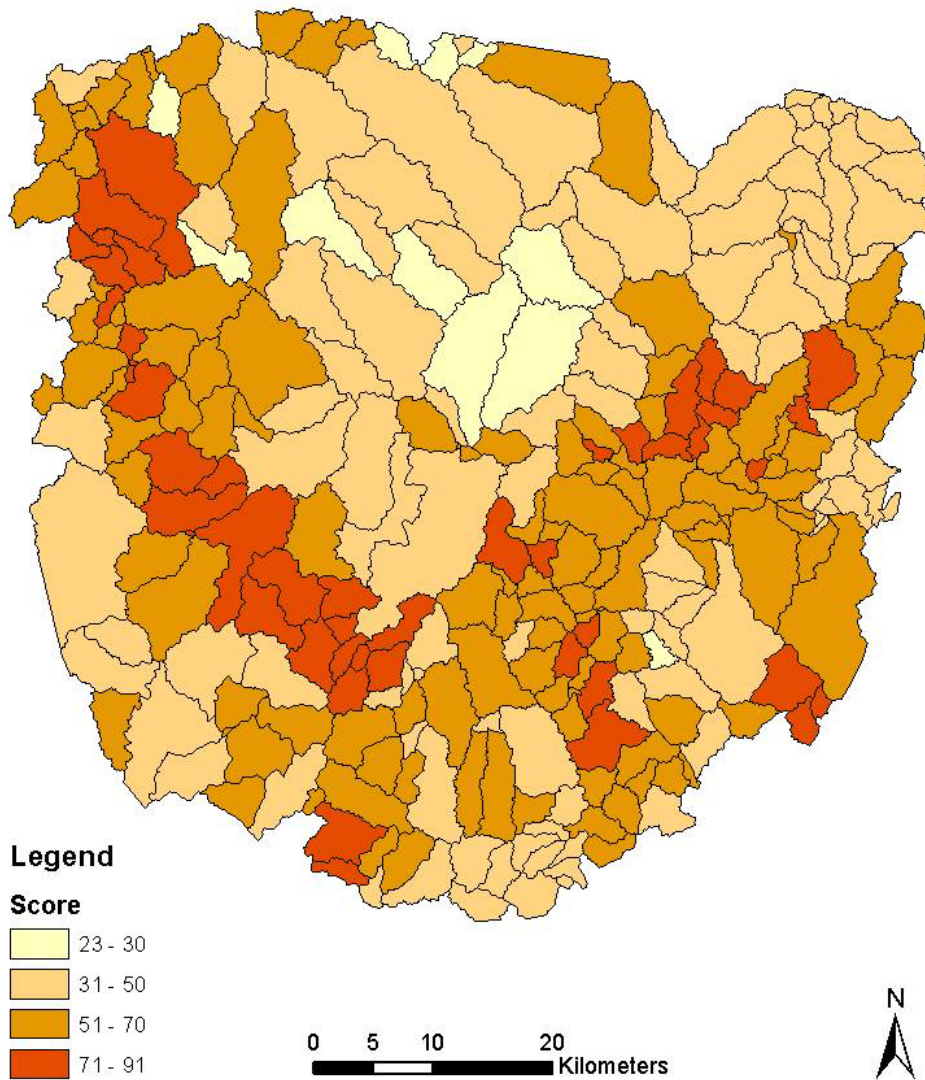


Figure 3.11. The watershed priority scores calculated for the established invasion null model

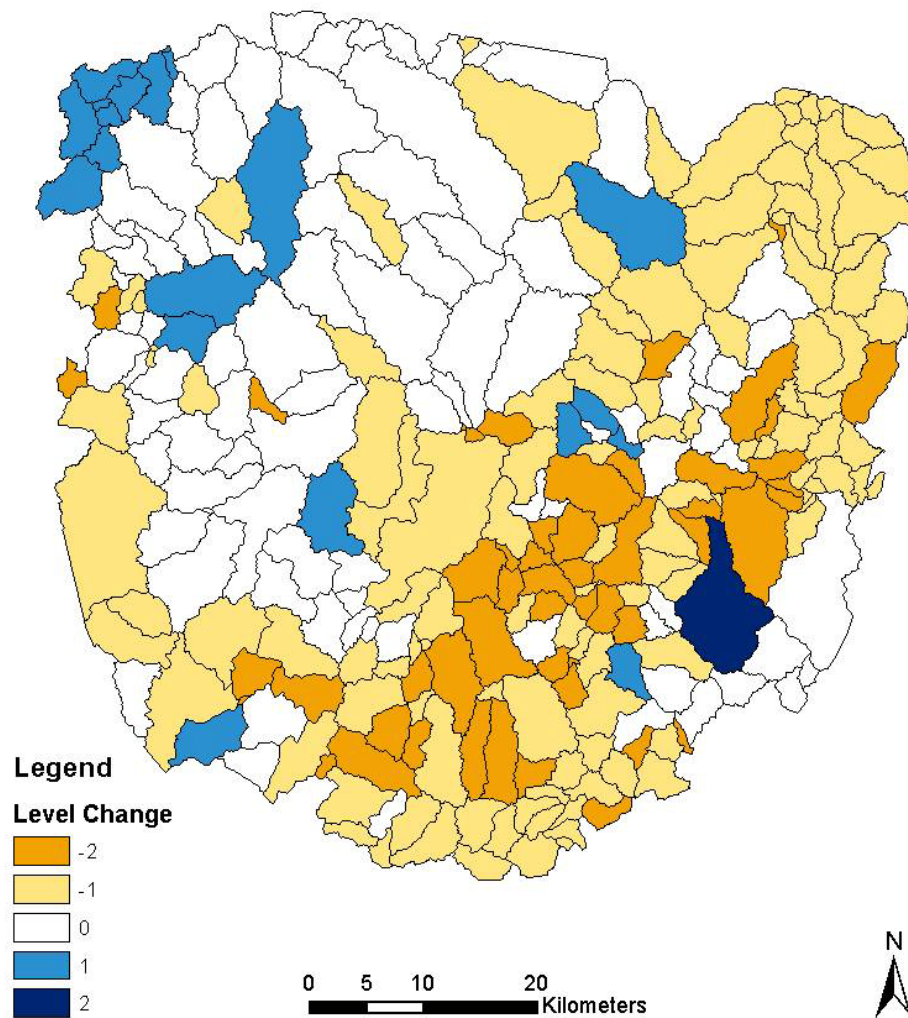


Figure 3.12. The change in watershed priority level between the expert and null models of the established invasion scenario

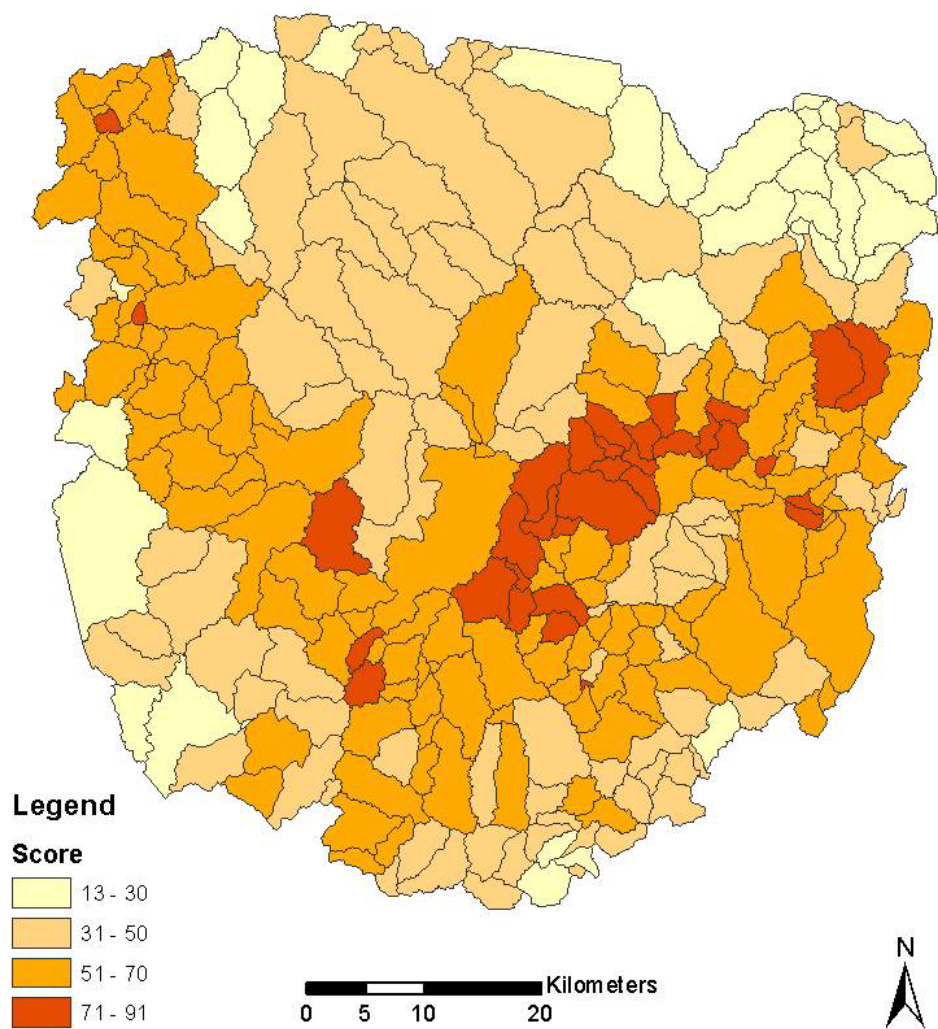


Figure 3.13. The watershed priority scores calculated for the new invasion expert model

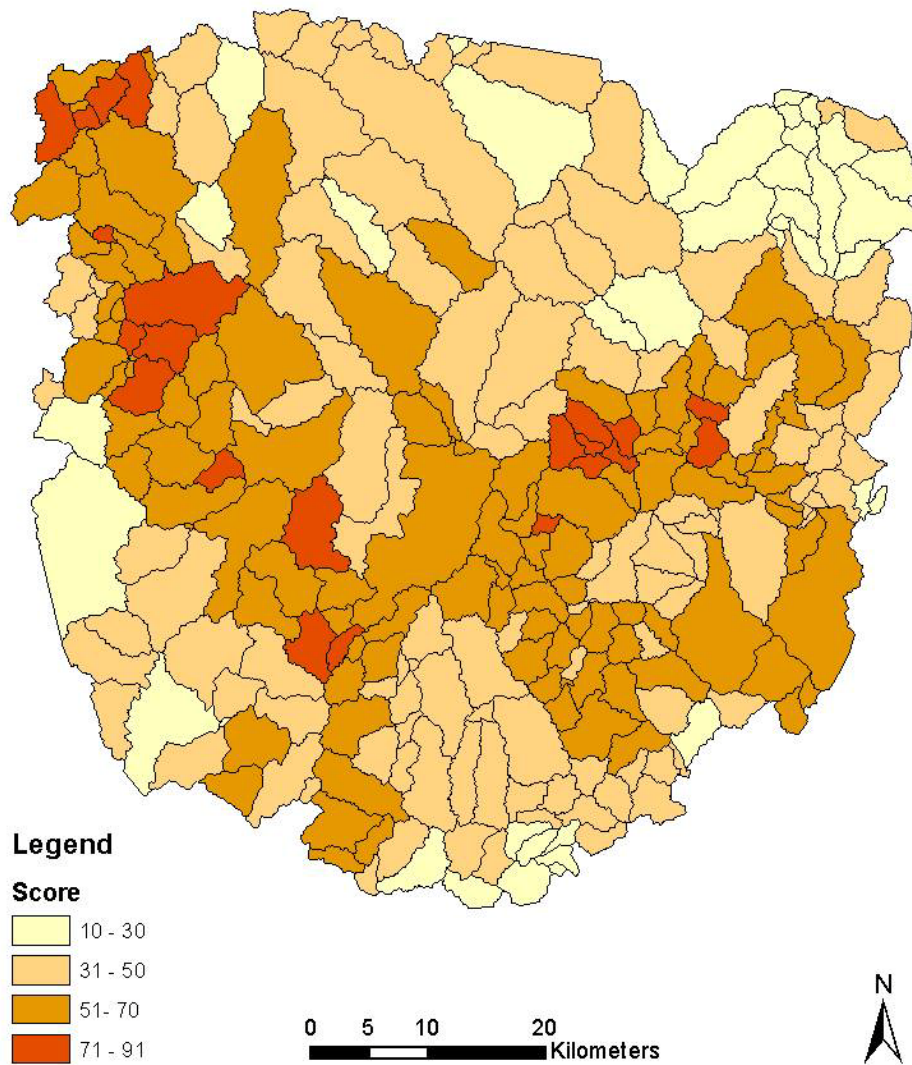


Figure 3.14. The watershed priority scores calculated for the new invasion null model

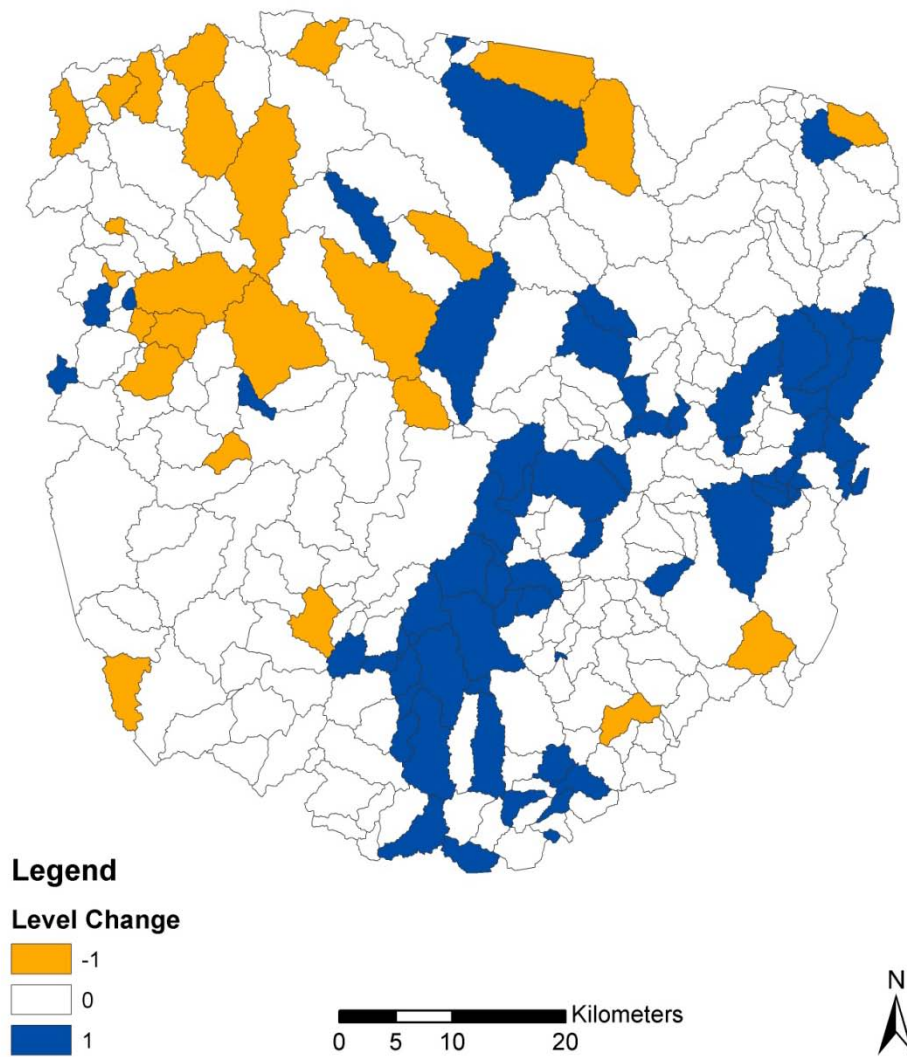


Figure 3.15. The change in watershed priority level between the expert and null models of the new invasion scenario

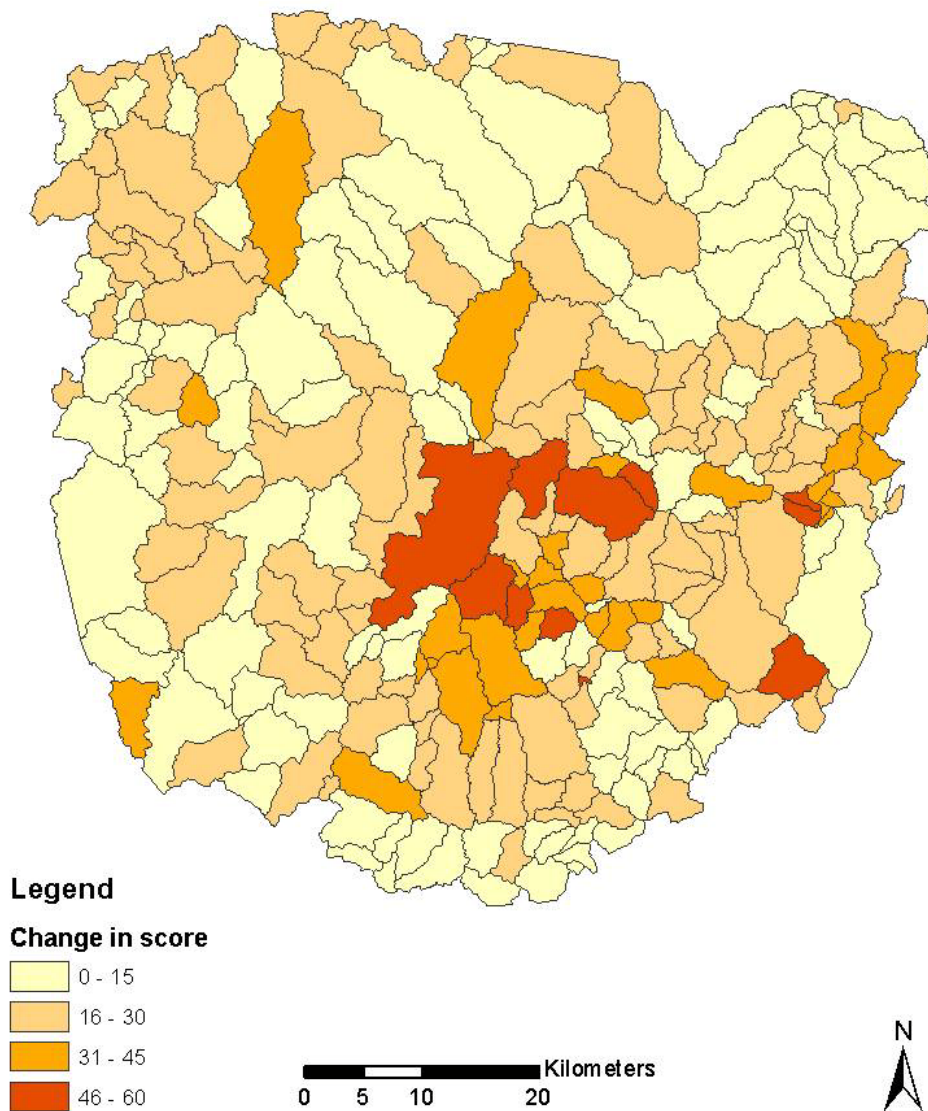


Figure 3.16. The change in priority score between the expert models of the established invasion and new invasion scenarios

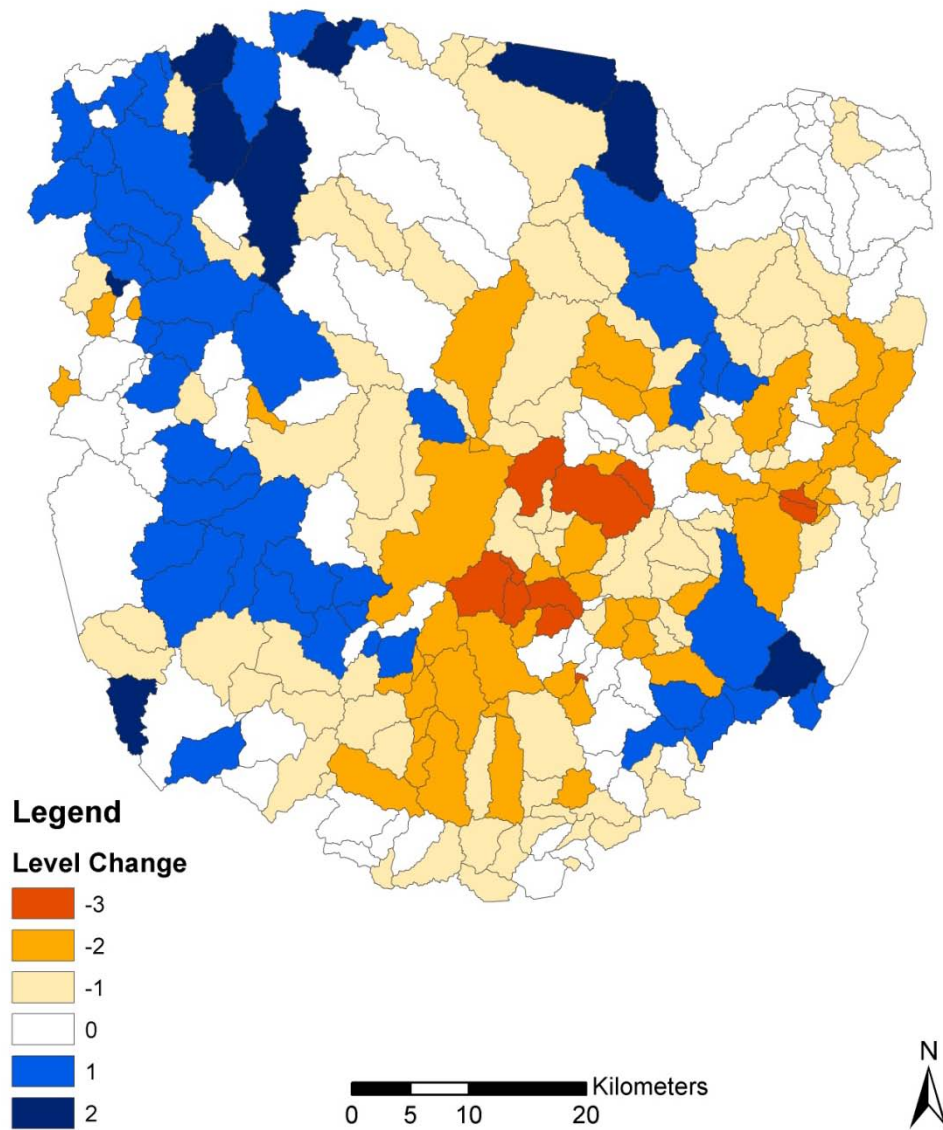


Figure 3.17. The change in watershed priority level between the expert models of the established invasion and new invasion scenarios

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PRESENTATIONS

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