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Research

Forecasting Weed Distributions using Climate Data: A GIS Early Warning Tool

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The number of invasive exotic plant species establishing in the United States is continuing to rise. When prevention of exotic species from entering into a country fails at the national level and the species establishes, reproduces, spreads, and becomes invasive, the most successful action at a local level is early detection followed by eradication. We have developed a simple geographic information system (GIS) analysis for developing watch lists for early detection of invasive exotic plants that relies upon currently available species distribution data coupled with environmental data to aid in describing coarse-scale potential distributions. This GIS analysis tool develops environmental envelopes for species based upon the known distribution of a species thought to be invasive and represents the first approximation of its potential habitat while the necessary data are collected to perform more in-depth analyses. To validate this method we looked at a time series of species distributions for 66 species in Pacific Northwest and northern Rocky Mountain counties. The time series analysis presented here did select counties that the invasive exotic weeds invaded in subsequent years, showing that this technique could be useful in developing watch lists for the spread of particular exotic species. We applied this same habitat-matching model based upon bioclimatic envelopes to 100 invasive exotics with various levels of known distributions within continental U.S. counties. For species with climatically limited distributions, county watch lists describe county-specific vulnerability to invasion. Species with matching habitats in a county would be added to that county's list. These watch lists can influence management decisions for early warning, control prioritization, and targeted research to determine specific locations within vulnerable counties. This tool provides useful information for rapid assessment of the potential distribution based upon climate envelopes of current distributions for new invasive exotic species.

Key words: Exotic species, geographic information system, invasive species, iterative sampling, modeling, rapid assessment, weeds.

Invasive exotic plant species are one of the major threats of the 21st century, negatively impacting human health (Mack et al. 2000), the economy (Pimentel et al. 2005), native species, and ecosystem processes (Vitousek et al. 1996; Wilcove et al. 1998). The rate of exotic species' introductions appears to be increasing with globalization (Levine and D'Antonio 2003; Stohlgren et al. 2008; Work et al. 2005), exacerbating these potential negative impacts. In invasive exotic species management, prevention of a novel exotic species reaching a new location is key to reducing unwanted invasions (Rejmanek and Pitcairn 2002). Prior to species establishment, early detection quickly followed by control and eradication is the most effective course of action in reducing spread. The cost of eradicating an exotic species increases exponentially as an infestation grows (Rejmanek and Pitcairn 2002). The large number of species already established or currently entering the United States coupled with the time and labor demands of screening for potential invasiveness and early detection of key species makes the problem seem intractable (Levine and D'Antonio 2003). Therefore, an early warning system is necessary in the prevention of new infestations (Lodge et al. 2006); the creation of watch lists such as those suggested here are an important component of such a system.

Regrettably, there is often a dearth of specific biological knowledge about any particular exotic species. Although

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Interpretive Summary

The rapid-assessment geographic information system tool described in this paper is very applicable to management of invasive exotic species. County-level records for weed distributions for large geographic areas are readily available on Websites, unlike point location data. This tool is easy to use and creates potential distribution maps based on climate variables. These maps can then be used to generate watch lists for early detection of the weeds. Early detection can help efforts to eradicate a problem species before a large infestation occurs that is much more difficult to control.

The tool creates an environmental envelope for each environmental variable for each species; this envelope describes the range of environmental variability over which the species can survive. For example, we obtained the lowest recorded temperature and the highest recorded temperature for a species in counties where it is present. We then compared this range to counties where the species is absent and recorded if the county's value fell inside (assigned a value of one) or outside (assigned a value of zero) the range of the recorded presence locations. Finally, we summed these values of one or zero for all of the variables by county. The sum indicates the number of variables for each county that fell within the environmental envelope of the species.

We developed bioclimatic envelopes using climate data for invasive exotic plant species at the county level in the United States. Using these envelopes, we determined the likelihood of a species establishing in a county. These results can be used to develop county-level watch lists of species whose envelope includes the county. This method is not limited to the county-level data sets used here, but could be applied to other taxonomic groups and other data sets such as national park species lists.

several different methods exist for predicting the potential distribution of an exotic in a new range (Caley and Kuhnert 2006; Krivanek and Pysek 2006; Richardson and Thuiller 2007), these methods generally are used at the scale of countries, and require specific information about the native range of the species (see Ficetola et al. 2007; Richardson and Thuiller 2007). Data on country distributions are generally easily obtained. Herbarium collections may be used to generate lists of invasive exotics for political entities such as countries, states, or counties, but such lists are not inclusive; the species listed are not systematically collected nor are the species lists developed for this purpose. Ecological data concerning a potential invasive exotic species, including its life history requirements, may often be lacking unless the species has displayed invasive characteristics elsewhere or it has been well studied throughout its native range. Collecting these data for new invaders can often be time intensive. When a new exotic species is located, managers may not be able to wait for detailed data collection and analysis before taking action. A quick, general way to prioritize species watch lists at the scale of a management unit such as a U.S. county would be a useful tool for field managers involved in early detection and rapid response activities.

There are many techniques available for predicting species ranges (see recent review by Elith et al. 2006), typically requiring point locations for a species or an overlaid grid with cells identified as present or absent based upon field data. Unfortunately, these types of location data are often not obtained easily by resource managers. Occurrence data for invasive exotic plant species across large spatial extents are often only readily available at county-level (or even state-level) distributions (or as species lists for areas such as national parks or wildlife refuges), although there are several online systems being developed to synthesize disparate field data sets for invasive exotic species. Because of the varied size and shape of U.S. counties, it can be difficult to transform these data into the required point locations or grid of presence locations.

There are two suites of environmental niche models that are useful in determining species occurrences, those requiring presence-only data and those requiring presence and absence data. These models can be generated with location data from many sources, including museum and herbarium records, research survey data such as plot data and transects, and inventories of species for specific areas. Models using presence and absence data will be more discerning and can distinguish between factors related to species absence as well as presence (Brotons et al. 2004; Zaniewski et al. 2002). However, when reliable absence data are unavailable different strategies may be recommended. Generally, absence locations are not implicitly collected in weed surveys (Barnett et al. 2007; North American Weed Management Association 2002), and often may only be inferred if an entire area has been surveyed or all inspected locations are known. However, this information is generally not included in online databases that make presence data readily available (e.g., Invasive Plant Atlas of New England [University of Connecticut 2007]). Other data sets, including those from museums and herbaria and species lists for areas such as counties or national parks, also lack absence data, again resulting from our lack of knowledge about survey locations or because of lack of information on survey targeting and extent for species occurrence data. Where available, absence data has the potential of false absences (e.g., where a species is cryptic or present as a buried seed; Crossman and Bass 2008; Rouget et al. 2001), and the species could be unreported or absent even in highly suitable habitat. Detection of an exotic species can often be difficult early in the invasion process as some exotic species often grow in relatively small numbers for a period of time after the introduction, which is called the lag phase (Crooks 2005). Missing these presence locations can cause errors in models by missing important suitable habitats (Hortal et al. 2008, but see Loiselle et al. 2008). Another kind of false absence may result from the fact that there is a high probability that the new invading species has not yet had the opportunity to establish itself at a particular location, and so is out of equilibrium with its environment. Given opportunity and time, the invader could eventually establish itself and spread into areas where it is currently absent. In these situations, where a species does not occupy all suitable habitat, presence-only models have out-performed presence/absence methods (Brotons et al. 2004; Hirzel et al. 2001) and have been used instead (Gibson et al. 2007). Thus, we choose to use presence-only data in this paper for exotic species distribution modeling.

Given the challenges of obtaining species-specific data for exotic plants, data format (point locations or regular grid) limitations, and inaccuracies of absence data along with the issues associated with species distribution models, we have developed what we believe to be a quick and effective method of providing information early in the invasion process to guide management decisions until the information and resources to develop more detailed and specific models become available. This geographic information system (GIS) program is adapted from an earlier program that we created, which incorporates known point location data to create an environmental envelope for a species (Barnett et al. 2007; Evangelista et al. 2008). This method is simple enough for users who may not have the statistical background necessary to understand more complex predictive modeling techniques. It incorporates county-level species lists and ancillary data layers such as air temperature and annual precipitation as parameters; in this example we chose general bioclimatic parameters (although other environmental parameters such as topographic parameters could be used) that are fundamentally important for most plant species' growth and establishment rather than parameters necessary for a particular species. Here, we detail our system for generating "watch lists" of species based upon currently reported county-level distribution data in association with various bioclimatic factors. We plan to make this system available for use at the National Institute for Invasive Species Science (National Institute of Invasive Species Science 2008). This GIS program will create a bioclimatic envelope of a species' potential distribution based upon where the species is known to currently occur. These envelopes are defined by the range in bioclimatic conditions where a species is currently known and can be used to assess the potential spread of the species and develop watch lists for early detection activities. Information is quickly available while more detailed assessments are gathered.

Materials and Methods

Invasive Exotic Weed Data. We obtained county-level presence data from 2004 and 2007 for the top 100 most problematic invasive exotic plant species within the contiguous 48 states of the United States from the Biota of North America Program (BONAP; Kartesz 2004, 2007). BONAP maintains a county-level database of current occurrence data and historic herbarium records for all known vascular plants in the United States. The top-100 list includes the most problematic invasive exotic species. These species covered a broad range of spatial distributions, from mesquite [*Prosopis juliflora* (Sw.) DC.] found in one county to curly dock (*Rumex crispus* L.) found in 1,846 counties across 47 states.

Validating our method required a temporal data set because we were predicting the potential range of an exotic species given an initial distribution after introduction. We used a county time series data set from the INVADERS database (Rice 2006), which records exotic plant occurrence records for all counties in the Pacific Northwest and northern Rocky Mountain states of Washington, Oregon, Idaho, Montana, and Wyoming, hereafter called the Northwest. We queried county-level distributions for all 100 species for 1930, 1960, 1990, and 2005. Some of the species documented only a single occurrence record for a time-step and 27 species were undocumented for these states for all four time periods (not recorded), precluding their use. Thus, sample sizes varied for each time period, resulting in envelopes for 44 species for 1930, 57 for 1960, 66 for 1990, and 69 for 2005.

Climate Data Layers. We derived 19 bioclimatic raster data layers (Appendix A) from average monthly precipitation, minimum temperature, and maximum temperature (Nix 1986) using an ArcAML script (Hijmans 2006). These variables represent annual trends, seasonality, and extreme or limiting bioclimatic factors. To represent current climate conditions and species habitat we used the PRISM data set, (Daly et al. 2000; PRISM Group 2007), an 800-m (2,625-ft) resolution 30-yr average data set for 1971–2000. We then summarized the bioclimatic variables for each county using ArcGIS's Spatial Analyst Zonal Statistics tool[1] to calculate the minimum, maximum, mean, and range for each variable for each county. From these four metrics we chose the statistic that matched the variable most closely, for example for Bio1, annual mean temperature, we chose the mean, and for Bio6, minimum temperature of the coldest month, we chose the minimum. This method allowed us to take the extremes in counties rather than simply using an average across the county.

Bioclimatic Envelope Tool. We developed an ArcGIS script to determine the bioclimatic envelope of a species defined by its known polygonal presence locations (in this case, counties). We created a bioclimatic envelope for each variable for each species; we define a bioclimatic envelope as the range of bioclimatic variability over which the species can survive. For example, we obtained the lowest recorded temperature and the highest recorded temperature for a species in counties where it is present. We then compared

Table 1. Results from predicted distribution with the envelope model compared to actual distribution.

Envelope model	Actual distribution	Species sample size	Average % of new records predicted	Sensitivity[a]	Specificity[b]	Range in number of county watch lists including a certain species
NW1930	NW1960	18	85%	92	27	63–151
NW1960	NW1990	37	95%	94	24	26–148
NW1990	NW2005	50	80%	96	25	40–150
NW1930	BONAP2007	18	86%	86	37	63–151
NW1960	BONAP2007	37	93%	91	29	26–148
NW1990	BONAP2007	50	95%	95	25	40–150

[a] Sensitivity is the proportion of true positives, or the number of counties predicted as present where the species was actually recorded as present in the future.

[b] Specificity is the proportion of true negatives, or the number of counties predicted as absent where the species was not recorded as present in the future.

this range to counties where the species is absent according to the BONAP data set and recorded if the county's value fell inside (assigned a value of one) or outside (assigned a value of zero) the range of the recorded presence locations. Finally, we summed these values of one or zero for all of the variables by county. The sum indicates the number of variables for each county that fell within the bioclimatic envelope of the species. Since 19 variables were used, a value of 10 would mean that the county was within the range of 10 variables and outside the range of nine variables. We did not differentiate between the variables, so counties with a value of 10 would not necessarily fall within the range of the exact same 10 variables.

For validation of the method we developed a bioclimatic envelope for each of the 100 worst exotic species present in the Northwest in 1930 and compared it to the species' recorded distribution in 1960, 1990, and 2004. We used the Northwest data set because we could use the time periods to check validity. We performed the same comparison using the updated envelopes based upon the new species location records for both 1960 and 1990 to further validate the technique. Assessment metrics included percentage of new occurrences captured by the envelope, sensitivity and specificity (Fielding and Bell 1997), and the number of counties added to the watch list. Sensitivity is the probability that observed presence locations were predicted correctly; specificity is the probability that absence locations were predicted correctly. Because the assessment metrics required binary data, we defined anything with an envelope value of at least 15 as present. We selected 15 as the cutoff by examining the number of presence locations in future years that fell into each of the 19 envelope count classes and selected the one where the values leveled off for all species. The envelope from each time period for the Northwest and the envelope from 2004 were also compared to the 2007 BONAP data set. After validation we examined an application of this bioclimatic envelope method, calculating the bioclimatic envelope in the United States for each of the 100 worst invasive exotics in the BONAP data set to examine potential species distributions.

Results and Discussion

Validation with Time Period Analysis. Because we examined 100 species, we present general trends and a few detailed examples (for all 100 species and occurrences see Appendix B). A minimum of 15 occurrence records was required to capture future occurrences, as determined by examination of sensitivity and sample size, thus we used this value as a cutoff for including species within further analyses reported here. For all species in the time series, average sensitivity of the envelope was 92, 95, and 96% for 1930 applied to 1960, 1960 applied to 1990, and 1990 applied to 2005, respectively (Table 1). However, specificity, which was calculated by defining all counties not reporting a species as "absence" locations, was much lower, meaning that the envelope overpredicted the species distribution (27, 24, and 25%, respectively; Table 1). These low specificity values could be caused by calculating the metrics using absence locations that were not necessarily unsuitable locations for the species to grow. Rather, these were places where the species has not been recorded either because of sampling errors (these data are based on museum records and not a statistical sampling design) or because of suitable habitat where the exotic species has not yet arrived. All species have continued to be recorded in new locations for the time period, including the most recent, although this period was half that of the others. Although this could be a result of failing to detect or report a species, in previous analyses using the INVADERS data, we determined that at least some of the new records through time are due to species spread (Stohlgren et al. 2008). Another reason for the drastically different

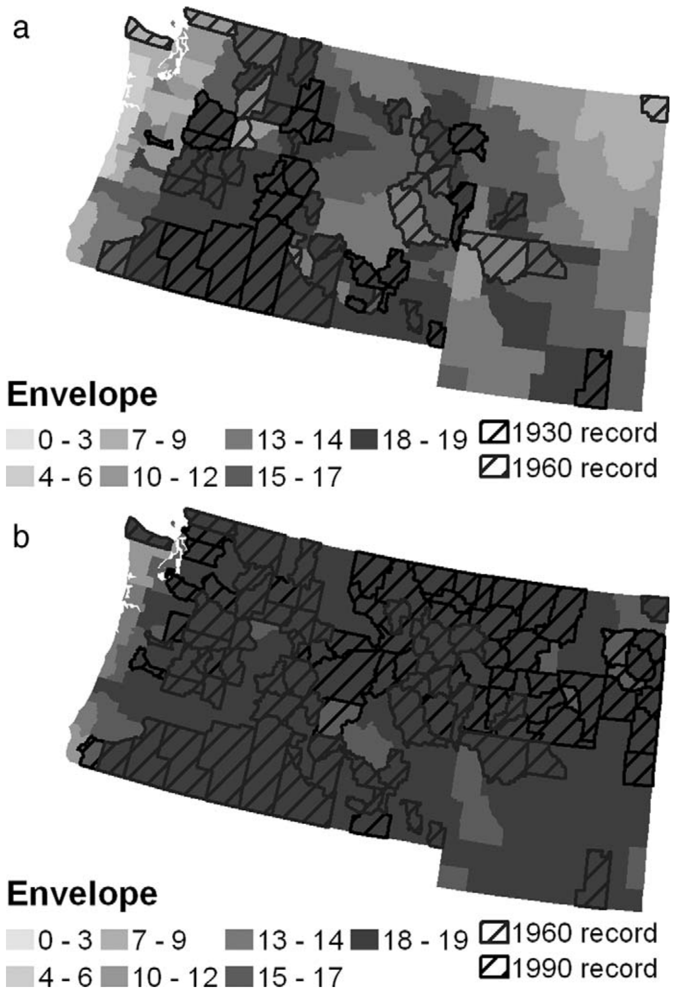

Figure 1. A bioclimatic envelope was generated from all occurrences recorded by (a) 1930 and (b) 1960 for hoary cress. Counties are colored according to the number of bioclimatic variables within the range defined by the bioclimatic envelope. Counties outlined in bold with diagonal lines through them indicate recorded observations by the years (a) 1930 and 1960 and (b) 1960 and 1990. It was found in all counties by 2005.

sensitivity and specificity values relates to the development of the envelope. Factors limiting the distribution of the species may not have been included in the suite of predictors, leading to overprediction. Other methods for determining species distributions that develop statistical relationships with variables using both presence and absence data may be better able to differentiate suitable habitat.

For example, we created a bioclimatic envelope for hoary cress [*Cardaria draba* (L.) Desv.] using the data from 1930 (Figure 1a) and 1960 (Figure 1b) and then compared the envelope's prediction to the reported distribution from the next time periods (1960 and 1990, respectively). The 1930 envelope for hoary cress captured many of the new locations in 1960, but not as great a proportion of the future time-step's new locations. The 1960 envelope captures more of the future time-step's new locations because the species had spread to locations with bioclimatic conditions not encompassed by the 1930 recorded distribution. By rerunning the envelope with the new locations from 1960 the envelope improves by encompassing these novel environments, supporting the need for an iterative approach to improve these models as new records are added to the database (Stohlgren and Schnase 2006).

Selecting all counties with a 1930 envelope score of at least 15 for each of the species, on average 88% of locations reported as present by 2007 were captured by the envelope. The time series results indicate that this is a useful technique to reduce potential locations to watch for such species to appear. County watch lists may be generated by adding species to county lists when the county has a high envelope score.

Based upon the results from the Northwest time series, we found this method to be informative for creating species' watch lists. This simple model captured many of the new occurrences reported in future time steps. The benefits of this approach are that little has to be known about the individual species, which is helpful for unresearched, newly established exotic species. This method provides immediately useful information while more detailed information is being collected and analyzed. More detailed information could be used to predict locations within an at-risk county where the species will be most likely to occur. In every case, the number of counties on a watch list generated from the envelope results was still fewer than the 199 counties in the Northwest region (Table 1).

This method may be especially useful in situations where errors of omission (a species is predicted absent when present) far outweigh those of commission (a species is predicted present when absent). The method performed very well at capturing new locations and new potential locations. However, occasionally it overpredicted, perhaps due to capturing appropriate bioclimatic conditions for growth rather than the subset of those locations a species is limited to by interactions with other organisms. For the species we examined, it is difficult to know if these species have reached the full range of their potential distribution or if they are still spreading. The BONAP data set compiled in 2007 showed increases for all but five of the 100 species from the 2004 data set (an average increase of 99 counties added to a species' distribution), suggesting that the species examined are still being found in new locations.

Model Applications. Application of the bioclimatic envelope for the 100 worst invasive exotics suggested that all species could spread relative to the 2004 BONAP data set distribution. On average, species were recorded in 635 counties in 29 states. The average number of counties for each species with an envelope value of at least 15 (e.g., at least 15 of the 19 parameters for the county were within the range of the envelope) was 2,513 counties in 43 states, for a predicted average increase of 1,878 counties in 14 states from the 2004 distribution. Thus, a species could be added to an average number of 1,878 county watch lists. Although this number is large, the envelope for 45 of the 100 species included fewer than 10 new states, meaning that 45 of the species would be added to the watch lists of fewer than 10 states.

Almost all species in the BONAP data set did have increased occurrence records between 2004 and 2007. Eleven species could not be compared due to changes in taxonomy, which made it difficult to differentiate between distribution changes based upon renaming a species and actual spread. For the remaining 89 species, the average number of species per county increased from 635 counties in 29 states in 2004 to 686 counties in 31 states in 2007, an average increase of 98 counties over the 3-yr period. These data again suggest that the selected species are still increasing in distribution, further validating the method as the bioclimatic envelope models based upon the 2004 distributions showed potential increase in distribution.

As an example of the results, we selected two species with different current distributions—clustered vs. highly dispersed—to discuss in detail. Mary's-grass [*Microstegium vimineum* (Trin.) A. Camus var. *imberbe* (Nees) Honda], introduced into Tennessee in 1919, was found in 325 counties in 23 states in the eastern United States in 2004 and had a small predicted bioclimatic envelope (Figure 2a). Yellow starthistle (*Centaurea solstitialis* L.), introduced in the mid-1800s, was also found in small number of counties (218 counties in 32 states), but these locations were widely distributed across the United States and in more states rather than clumped (Figure 2b). The predicted envelope subsequently had a larger predicted distribution. Species such as curly dock and green foxtail [*Setaria viridis* (L.) Beauv.] were reported in at least half the counties within the contiguous United States and had predicted extents covering most counties. However, even for these species, unique counties such as hot, dry counties in the Southwest and hot, moist ones in the southern tip of Florida had a lower habitat match value and therefore lower number of parameters within the envelope. The species Mary's-grass would then be added to the watch lists of a fewer counties than yellow starthistle, which would be added to almost all counties' lists. This method for generating watch lists may be more beneficial for species such as Mary's-grass (species only on a few counties' lists) than potentially widespread species.

Generalist species such as thistles tend to spread easily due in part to their plumose seed dispersion method, and such coarse-scale modeling techniques may not be beneficial, as with yellow starthistle. These generalist species do well in most habitats and tend to have potential

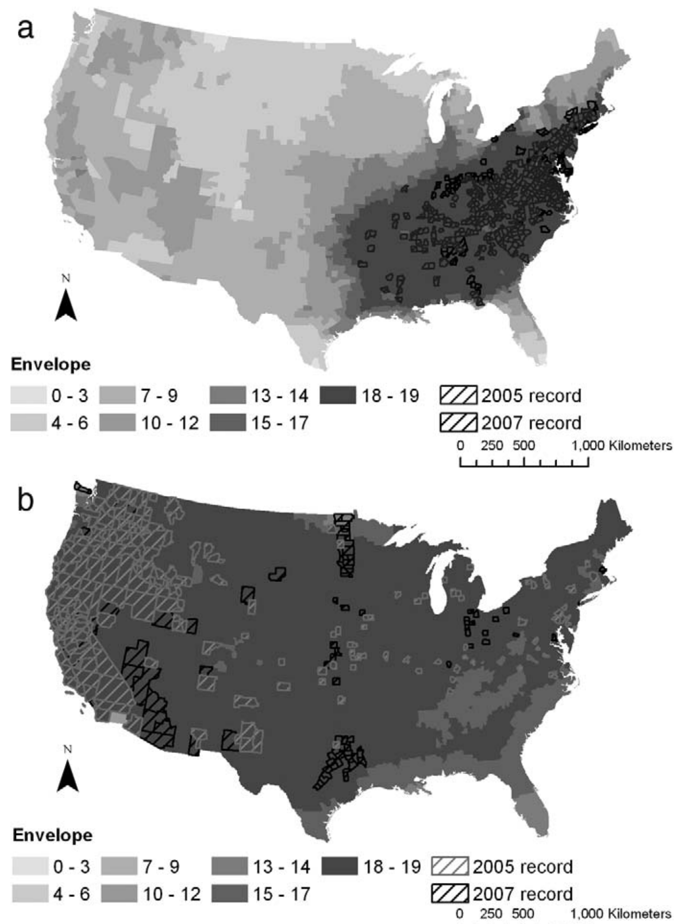

Figure 2. County-level distribution with the current distribution (defined as the counties where the Biota of North America Program [BONAP] data set recorded the species as present) are filled with slashed lines in black (2004) and grey (2007) for (a) Mary's-grass and (b) yellow starthistle. Counties are colored according to the number of predictor variables that fell within the range of the bioclimatic envelope generated from the 2004 BONAP distribution, where higher values indicate greater habitat suitability.

habitat in the vast majority of counties within the United States, and may be more difficult to model (Evangelista et al. 2008). However, for species that are highly restricted by environment in their distributions, such melaleuca [*Melaleuca quinquenervia* (Cav.) Blake], this technique could inform resource managers in diverse locations whether or not they need to monitor for the appearance of this plant. Melaleuca grows primarily in hot and wet conditions, which means that the bioclimatic envelope of this species is very specific. Managers working in the desert southwest or cold mountainous regions can probably rule out the need to monitor for such a plant. Although Mary's-grass is not as specialized as melaleuca, it still appears more restricted in its distribution than a thistle, and managers in the western

United States could again leave it off a watch list (Figure 2a). It is this ability to rule out species for an area that is particularly helpful in the development of species watch lists.

If data were available for watersheds or ecoregions rather than politically defined units such as counties, we would recommend using these data because they would be less prone to the errors associated with amalgamating climatic data across a large, diverse county. However, data for politically defined regions are much more readily available, and despite the issues associated with a single county encompassing very diverse conditions, this technique still has some value. Also, by using metrics other than simply means for the county, we were able to capture some of the extremes that do exist (e.g., if minimum temperature is limiting, using the lowest minimum temperature found anywhere within the county would indicate whether the species could survive anywhere within the county). Additionally, this technique is not limited to the bioclimatic predictors used here. Other variables deemed important for a particular species or a suite of species could be used to define the environmental envelope of a species.

This method is not meant to replace other, more detailed methods. It only predicts locations that may be suitable climatically, and with the variables chosen in the example presented in this paper, and does not explore other potentially limiting factors such as biotic interactions. It can be used as a first approximation of potential habitat after the establishment of a species thought to be invasive while the necessary data are collected to perform more in-depth analyses. As illustrated by the time series data, the methods described here could provide a useful means to quickly develop watch lists for the network of county weed coordinators across the country requiring few additional resources. The models may also be useful in selecting priority weed species for control based on their potential spread, and can certainly provide utility as a first-iteration modeling approach to inform immediate actions while more detailed data are collected.

Sources of Materials

[1] ArcGIS, ESRI, Redlands, CA.

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Appendix A. Nineteen bioclimatic variables derived from average monthly precipitation, minimum temperature, and maximum temperature, based on Nix (1986).

Name	Description
BIO1	Annual mean temperature
BIO2	Mean diurnal range (mean of monthly [maximum temperature − minimum temperature])
BIO3	Isothermality (BIO2/BIO7) ($\times$ 100)
BIO4	Temperature seasonality (standard deviation $\times$ 100)
BIO5	Maximum temperature of warmest month
BIO6	Minimum temperature of coldest month
BIO7	Temperature annual range (BIO5–BIO6)
BIO8	Mean temperature of wettest quarter
BIO9	Mean temperature of driest quarter
BIO10	Mean temperature of warmest quarter
BIO11	Mean temperature of coldest quarter
BIO12	Annual precipitation
BIO13	Precipitation of wettest month
BIO14	Precipitation of driest month
BIO15	Precipitation seasonality (coefficient of variation)
BIO16	Precipitation of wettest quarter
BIO17	Precipitation of driest quarter
BIO18	Precipitation of warmest quarter
BIO19	Precipitation of coldest quarter

Appendix B. One hundred of the most problematic invasive exotic species identified by BONAP[a] and the number of counties in the northwest (INVADERS database) and the continental US (BONAP database) each is present in per time period.

		INVADERS database				BONAP database	
Scientific name	Common name	1930	1960	1990	2005	2004	2007
Abutilon theophrasti Medik.	Velvetleaf	3	7	38	63	954	1,167
Achillea millefolium L.	Yarrow, common					2,068	
Aegilops cylindrica Host	Goatgrass, jointed		6	17	51	462	480
Ailanthus altissima (P. Mill.) Swingle	Tree-of-heaven	5	10	18	20	720	920
Akebia quinata (Houtt.) Decne.	Chocolate vine					42	60
Albizia julibrissin Durazz.	Silktree					439	552
Alhagi maurorum Medik.	Camelthorn			2	4	43	44
Alliaria petiolata (Bieb.) Cavara & Grande	Mustard, garlic				2	383	591
Allium vineale L.	Garlic, wild		6	10	12	756	817
Amaranthus retroflexus L.	Pigweed, redroot					1,114	
Ambrosia artemisiifolia L.	Ragweed, common					1,777	
Avena fatua L.	Oat, wild	22	33	52	74	433	456
Bromus tectorum L.	Brome, downy	66	122	155	171	1,507	1,677
Bryonia alba L.	Bryony, white			15	24	33	34
Capsella bursa-pastoris (L.) Medik.	Shepherd's-purse	58	88	120	133	1,832	2,038
Cardaria chalapensis (L.) Hand.-Maz.	Whitetop, lens-podded		8	15	23	124	
Cardaria draba (L.) Desv.	Cress, hoary	19	53	105	161	500	532
Carduus nutans L.	Thistle, musk	3	19	55	118	689	965
Centaurea diffusa Lam.	Knapweed, diffuse		22	74	151	264	274
Centaurea solstitialis L.	Starthistle, yellow	11	24	39	82	218	315
Centaurea biebersteinii DC.	Spotted knapweed					830	
Ceratocephala testiculata (Crantz) Bess	Buttercup, bur					194	207

Appendix B. Continued.

Scientific name	Common name	INVADERS database				BONAP database	
		1930	1960	1990	2005	2004	2007
Chenopodium album L.	Lambsquarters, common	58	99	135	149	1,611	
Cirsium arvense (L.) Scop.	Thistle, Canada	28	75	137	185	1,051	1,245
Conium maculatum L.	Poison-hemlock	12	41	81	125	917	1,066
Convolvulus arvensis L.	Bindweed, field	35	82	127	162	1,318	1,536
Crupina vulgaris Cass.	Crupina, common			5	13	16	17
Cynoglossum officinale L.	Houndstongue	12	51	88	108	664	763
Cyperus esculentus L.	Nutsedge, yellow	7	12	17	19	1,197	0
Cyperus rotundus L.	Nutsedge, purple					306	334
Cytisus scoparius (L.) Link	Broom, Scotch	13	23	39	56	209	229
Datura stramonium L.	Jimsonweed					1,012	1,176
Digitaria ischaemum (Schreb.) Schreb. ex Muhl.	Crabgrass, smooth	9	20	26	33	1,104	1,275
Digitaria sanguinalis (L.) Scop.	Crabgrass, large	10	29	45	53	1,359	1,528
Echinochloa crus-galli (L.) Beauv.	Barnyardgrass					1,692	1,835
Eichhornia crassipes (Mart.) Solms	Waterhyacinth					189	202
Elaeagnus angustifolia L.	Russian-olive	2	10	46	60	441	493
Elaeagnus umbellata Thunb.	Autumn-olive		2	3	6	318	533
Eleusine indica (L.) Gaertn.	Goosegrass					1,145	1,310
Erodium cicutarium (L.) L'Hér. ex Ait.	Filaree, redstem	57	82	103	115	679	726
Erucastrum gallicum (Willd.) O.E. Schulz	Mustard, dog	5	6	10	15	218	243
Euphorbia esula L.	Spurge, leafy	6	48	96	151	687	787
Fatoua villosa (Thunb.) Nakai	Mulberryweed					61	87
Galega officinalis L.	Goatsrue				2	16	18
Galeopsis tetrahit L.	Hempnettle, common		9	23	27	167	196
Halogeton glomeratus (Stephen ex Bieb.) C.A. Mey.	Halogeton		10	21	26	99	102
Heracleum mantegazzianum Sommier & Levier	Hogweed, giant			5	7	36	48
Hieracium caespitosum Dumort.	Hawkweed, meadow					420	486
Hydrilla verticillata (L. f.) Royle	Hydrilla					77	107
Hyoscyamus niger L.	Henbane, black	20	43	78	105	181	187
Hypericum perforatum L.	St. Johnswort, common	27	63	93	106	1,082	1,223
Ipomoea purpurea (L.) Roth	Morningglory, tall		4	5	5	678	831
Isatis tinctoria L.	Woad, dyer's		11	30	55	124	132
Lactuca serriola L.	Lettuce, prickly	38	80	117	131	1,539	1,713
Lamium amplexicaule L.	Henbit	15	31	50	64	1,207	1,405
Lamium maculatum L.	Deadnettle, spotted	3	4	7	9	95	119
Lamium purpureum L.	Deadnettle, purple	6	15	36	47	679	861
Lepidium campestre (L.) R. Br.	Pepperweed, field	7	28	52	63	945	1,069
Lepidium latifolium L.	Pepperweed, perennial		8	32	86	216	220
Lespedeza cuneata (Dumont) G. Don	Lespedeza, sericea					702	794
Linaria dalmatica (L.) P. Mill.	Toadflax, Dalmatian	3	30	77	149	324	335
Lonicera japonica Thunb.	Honeysuckle, Japanese					1,013	1,225
Lythrum salicaria L.	Loosestrife, purple		5	34	98	567	929
Melaleuca quinquenervia (Cav.) Blake	Melaleuca					25	20
Microstegium vimineum (Trin.) A. Camus var. *imberbe* (Nees) Honda	Mary's-grass					325	400

Appendix B. Continued.

Scientific name	Common name	INVADERS database				BONAP database	
		1930	1960	1990	2005	2004	2007
Myriophyllum spicatum L.	Watermilfoil, Eurasian			3	38	260	444
Orobanche minor Sm.	Broomrape, small		2	3	4	36	47
Paulownia tomentosa (Thunb.) Sieb. & Zucc. ex Steud.	Paulownia, royal			2	5	294	349
Peganum harmala L.	Rue, African			4	4	34	34
Plantago lanceolata L.	Plantain, buckhorn	32	61	75	85	1,456	1,637
Polygonum cuspidatum Sieb. & Zucc.	Knotweed, Japanese			40	65	481	622
Polygonum perfoliatum L.	Tearthumb, devil's					20	72
Portulaca oleracea L.	Purslane, common	14	33	66	75	1,073	1,294
Prosopis juliflora (Sw.) DC.	Mesquite					2	1
Pueraria montana var. *lobata* (Willd.) Maesen & S.M. Almeida	Kudzu					477	
Ranunculus repens L.	Buttercup, creeping	22	50	73	76	439	495
Rosa multiflora Thunb. ex Murr.	Rose, multiflora				2	679	944
Rubus armeniacus Focke	Blackberry, Himalaya					141	155
Rumex crispus L.	Dock, curly	52	96	125	143	1,851	2,091
Salsola kali L.	Saltwort, common					149	94
Salvia aethiopis L.	Sage, Mediterranean		4	14	18	27	27
Salvinia molesta Mitchell	Salvinia, giant					11	53
Secale cereale L.	Rye, cereal	5	15	42	51	546	641
Setaria faberi Herrm.	Foxtail, giant					813	994
Setaria viridis (L.) Beauv.	Foxtail, green	39	79	105	119	1,570	1,731
Solanum viarum Dunal	Soda apple, tropical					24	99
Sonchus oleraceus L.	Sowthistle, annual	14	37	54	66	848	1,021
Sorghum halepense (L.) Pers.	Johnsongrass	5	10	19	41	1,238	1,375
Spartina anglica C.E. Hubbard	Cordgrass, common					7	7
Sphaerophysa salsula (Pallas) DC.	Swainsonpea	2	12	17	20	63	63
Stellaria media (L.) Vill.	Chickweed, common	27	66	99	109	1,524	1,711
Taeniatherum caput-medusae (L.) Nevski	Medusahead	5	18	22	38	78	85
Tamarix ramosissima Ledeb.	Saltcedar					203	
Taraxacum officinale G.H. Weber ex Wiggers	Dandelion	42	80	131	142	1,740	1,926
Tragopogon lamottei Rouy						503	576
Tribulus terrestris L.	Puncturevine	4	29	39	77	708	730
Urtica dioica L.	Nettle, stinging					1,211	
Verbascum thapsus L.	Mullein, common	39	71	98	117	1,715	1,918
Vinca minor L.	Periwinkle, common			2	4	468	640
Xanthium spinosum L.	Cocklebur, spiny	11	23	36	38	194	211

[a] BONAP, Biota of North America Program.