Modeling Current Climate Conditions for Forest Pest Risk Assessment

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Abstract

Current information on broad-scale climatic conditions is essential for assessing potential distribution of forest pests. At present, sophisticated spatial interpolation approaches such as the Parameter-elevation Regressions on Independent Slopes Model (PRISM) are used to create high-resolution climatic data sets. Unfortunately, these data sets are based on 30-year normals and rarely incorporate up-to-date data. Furthermore, because they are constructed on a monthly rather than a daily time step, they do not directly measure simultaneous occurrence of multiple climatic conditions (e.g., days in the past year with appropriate temperature and adequate precipitation). Yet, the actual number of days—especially consecutive days—where multiple conditions are met could be significant for pest dispersal or establishment. For the sudden oak death pathogen (*Phytophthora ramorum*), we used National Oceanic and Atmospheric Administration daily weather station data to create current, national-scale grids depicting co-occurrence of multiple climatic conditions.

For each station, we constructed two count-based variables: the total number of days and the greatest number of consecutive days in a year where the station met several conditions (temperature, rain/fog, relative humidity). We then employed gradient plus inverse distance squared (GIDS) interpolation to generate grids (4-km^2 resolution) of these variables for 5 years (2000-2004). The GIDS technique weights standard inverse distance squared interpolation using coefficients based on geographic location (x, y) and a spatial covariate such as elevation. Using these variables, we determined the GIDS coefficients for each output grid cell via Poisson regression on the 30 closest stations. We also performed model selection to ensure only significant variables contributed to the GIDS coefficients.

We compared the GIDS approach to cokriging and detrended kriging using cross-validation and found similar accuracies among all three interpolation methods. We also compared the output grids to maps assembled from the PRISM data depicting the probability all conditions were met in a given year. As expected, we found differences in areas highlighted as suitable for *P. ramorum* establishment by the two methods. We suggest that using current weather data and calculating the variable of interest directly will provide more practical information for mapping forest pest risk.

Keywords: Climate, forest pests, GIDS, *Phytophthora ramorum*, risk, spatial interpolation.

Introduction

Forest pest risk assessments detail the nature and severity of threats posed to particular forest species and ecosystems by insects, pathogens, or other organisms (Andersen and others 2004a). With respect to nonindigenous forest pests, risk can be categorized or quantified based on a combination of factors: the potential for the pest to become established, the potential for it to spread following introduction, the potential to cause economic damage, or the potential to cause environmental harm (NAFC 2004). A commonly desired product of such assessments is a map depicting the threat posed by introduction or establishment of a forest pest throughout a geographic area of interest (Andersen and others 2004a). These maps can facilitate early detection and response procedures, providing a template for the design of regulatory programs and detection surveys. If a pest has already been established in one part of the geographic area of interest, threat assessment maps are used to help set control priorities for other geographic areas that are at high risk of invasion (Andersen and others 2004b).

Importance and Availability of Climate Information

Forest pest risk maps are typically assembled by combining spatial data from three principal subject areas: host species distribution, pathways of pest movement, and key environmental factors (Bartell and Nair 2004). Climatic attributes such as temperature and moisture strongly shape pest behavior, affecting survival, reproductive rate, and in many cases, the ability to spread at a continental scale. Thus, climatic data provide an important coarse filter for forest pest risk analyses. Regularly gridded climate maps covering the entire geographic area of interest are typically required for analytical purposes. Such maps may be constructed by spatial interpolation of weather station data. These data are readily available for much of the United States, dating back several decades, from the National Oceanic and Atmospheric Administration (NOAA) National Climatic Data Center (NCDC).

Spatial Interpolation of Climatic Variables—
A wide array of spatial interpolation algorithms (e.g., geostatistical, regression, spline, inverse distance weighting) have been used to construct broad spatial-scale climatic data sets from weather station data (Daly 2006, Mardikis and others 2005, Nalder and Wein 1998, Price and others 2000, Xia and others 2000). Most currently accepted methods acknowledge that terrain is a significant factor governing climate at all but the broadest scales, and they use elevation measurements to represent terrain and adjust climatic variable values accordingly (Daly 2006). One well- received interpolation approach is the Parameter-elevation Regressions on Independent Slopes Model (PRISM). Initially developed to generate precipitation maps for the Pacific Northwest (Daly and others 1994), the approach has since been applied to create maps of temperature, relative humidity, snowfall, growing-degree days, and many other variables (Daly and others 2000). In particular, the PRISM approach was applied to generate most of the maps in the recent version of the Climate Atlas of the United States (Plantico and others 2002), as well as similar products for Canada and China (Daly and others 2000). The PRISM approach is a knowledge-based system integrating a local climate-elevation regression with other algorithmic com-ponents: station weighting, topographic facets, coastal proximity, and a two-layer atmosphere (Daly and others 2002). When initially tested on precipitation in the Pacific Northwest, the PRISM approach outperformed other interpolation methods in comparative analyses (Daly and others 1994).

Limitations of Existing Interpolated Climatic Data Sets—
There are several limitations of PRISM-de rived or similar data sets with respect to their use for forest pest risk maps. First, most national-scale climatic data sets are calculated as normals, meaning an average of the variable of interest across a window of time, typically a 30-year period. For example, most data sets in the recent version of the Climate Atlas of the United States are based on inputs from 1961 through1990 (Plantico and others 2002). Current weather data are not incorporated into the maps, so any pest risk map constructed from them will not include current events—and the accompanying variability—that may be relevant to an assessment of immediate risk.

Second, there are related issues of cost and data format. The Climate Atlas contains polygonal maps for a large number of potentially relevant climatic normals but does not include the regularly gridded data from which the maps are derived. These polygonal maps have limited attribute resolution, with the range of the original gridded data typically compressed into nine or fewer classes. Monthly gridded maps of a few variables—precipitation amount, mean minimum temperature, mean maximum temperature, and mean dewpoint—are available for public download from the PRISM group at Oregon State University (http://www.ocs.orst.edu/prism/. [Date accessed unknown]). Notably, these maps are fairly current (finalized maps are available from 1997 through mid-2006), and the database is regularly updated, but it does not include many climatic variables that might be of interest for forest pest risk assessment (e.g., relative humidity, number of days above freezing, or number of days with measurable precipitation). Regularly gridded data of these and other (30-year normal) variables, derived using the PRISM method, are available, but at substantial cost (from the Climate Source: http://www.climatesource.com/. [Date accessed unknown]).

Third, most available climatic spatial data sets, whether derived using PRISM or other methods, are monthly or annual summaries depicting mean or extreme values over the time period. For some forest pests, the short-term, even daily status of multiple weather conditions may be relevant to the pest's growth, persistence, or invasiveness. Fungal pathogens are particularly affected by the interaction of temperature and moisture availability. For example, the pathogen that causes late blight of potato (*Phytophthora infestans*) develops best at cool temperatures during extended periods of wet weather, as do many other *Phytophthora* species (Davidson and others 2002, Harvell and others 2002, Marshall-Farrar and others 1998). The interaction of climatic variables can also be important for some insect pests (Harrington and others 2001, Peacock and others 2006). Nevertheless, although there has been some effort to create maps of daily precipitation and temperature at a broad scale (Hunter and Meentemeyer 2005), there has been little attention paid to the co-occurrence of multiple weather conditions favorable to pest persistence and spread. Daily weather data allow the counting of how often, and for how long, variables meet certain threshold values. Creation of broad-scale maps from data derived in this manner may require a different spatial interpolation approach than that used for continuously distributed variables (van de Kassteele and others 2005).

Objectives

Given the limitations of existing climatic data sets, we explored the use of NCDC daily weather station data for the United States as an alternate source for maps relevant to forest pest risk assessments. We had three basic objectives: (1) spatially interpolate annual counts of the number of days with co-occurrence of multiple climatic variables relevant to the growth and spread of a specific forest pest—the pathogen that causes sudden oak death (*P. ramorum*); (2) identify a spatial interpolation method appropriate for count-based data and compare it to some common geostatistical approaches; and (3) assess the utility of the derived maps for depicting risk.

Case Study Species: *Phytophthora ramorum*

Phytophthora ramorum was first recognized in the United States in 1994 and was likely introduced via international trade of commercial plants (Ivors and others 2006). Since its introduction, the pathogen has infected western live and red oaks in coastal forests of California and Oregon, sometimes causing mortality greater than 40 percent (Garbelotto and others 2001, 2003). In addition, *P. ramorum* infects dozens of commercial shrub host species that can yield large numbers of aerially dispersed spores (Davidson and Shaw 2003, Davidson and others 2002, Tooley and others 2004). Many of these shrubs (e.g., rhododendrons, azaleas, camellias) are sold as nursery stock (Garbelotto and others 2001, Tooley and others 2004). In the past few years, wholesale nurseries on the west coast have unknowingly shipped infected plants to retail and wholesale outlets in roughly 40 States (Stokstad 2004), although surveys have not detected the pathogen in natural forests outside California and Oregon.

A large portion of the Eastern United States is considered at high risk for establishment of *P. ramorum* if it is introduced into forested areas. Much of the concern has to do with climatic conditions believed to be favorable for the pathogen. Growth, sporulation, and infection are all affected by moisture and temperature. Optimal temperatures for *P. ramorum* growth, based on laboratory analysis, appear to be between 64.4 °F and 71.6 °F (Werres and others 2001), but some growth occurs across a wider temperature range (up to at least 80 °F). Peak sporangia formation appears to occur at 59 to 68 °F (Davidson and others 2005). Persistent moisture on foliage is considered critical to spread. Laboratory inoculation trials on California bay laurel (*Umbellularia californica* (Hook. & Arn.) Nutt.), a major source of *P. ramorum* spores in California, suggest 9 to 12 hours of free moisture on leaf surfaces under appropriate temperatures are necessary for significant leaf infection (Garbelotto and others 2003). Further studies suggest that at least 24 to 48 hours of generally wet conditions are necessary for sporulation, with infection requiring additional time (Davidson and Shaw 2003, Davidson and others 2002, Rizzo and Garbelotto 2003). Fog and high relative humidity may be important for spread of aerial *Phytophthora* species within forest stands (Werres 2003), as high air moisture can keep leaf surfaces wet and enable spore production. Nevertheless, despite regular summer fog in California, *P. ramorum* sporulation and infection seem to be restricted to the winter-spring rainy season (Rizzo and others 2005).

Table 1—Number of NCDC weather stations used in interpolations

Year	Number of stations
2000	4,310
2001	4,258
2002	4,302
2003	4,144
2004	3,926

NCDC = National Climatic Data Center.

Isolated rains during otherwise dry summer months do not appear to facilitate spore production or dispersal (Davidson and others 2002). Ultimately, it is unknown how the pathogen's behavior on the west coast will translate to the Eastern United States, where warm season and cool season precipitation are similar (Akin 1991).

Methods

We downloaded 5 years (2000 to 2004) of daily surface data from the NCDC online climate data clearinghouse (http://cdo.ncdc.noaa.gov/CDO/dataproduct. [Date accessed unknown]). The downloaded data included dozens of climate variables recorded for more than 19,000 stations nationwide. We processed the data to extract four variables: total precipitation, minimum and maximum temperature, and relative humidity. For each station, we tallied (1) the total number of days and (2) the longest number of consecutive days in a given year that met the following conditions: maximum temperature greater than 60 °F, minimum temperature less than 80 °F, and at least a trace amount of precipitation or relative humidity of greater than 85 percent. These threshold values were selected to reflect current knowledge about the climatic conditions favorable for *P. ramorum* survival and spread.

We recorded the latitude, longitude, and elevation values for each weather station from an associated data set. We dropped any stations that fell outside the conterminous United States and any stations with more than 30 days of missing data for any variable in a given year. This filtering process reduced the number of usable stations (Table 1), but still yielded consistent national coverage. For stations missing 1 to 30 days of data, we normalized the total-day and consecutive-day count values by dividing them by the proportion of days in the year for which data were available and then rounding to the closest integer.

Gradient Plus Inverse Distance Squared Interpolation

We interpolated gridded maps of the conterminous United States for both the total-day and consecutive-day variables using a gradient plus inverse distance squared (GIDS) approach. This statistical method was first proposed as a way to interpolate climatic data on a broad spatial scale as input for plant growth models (Nalder and Wein 1998). The GIDS technique combines multiple linear regression with inverse distance weighting interpolation, and like other recently developed interpolation techniques, incorporates elevation as a covariate. For a given unmeasured location k and climatic variable Z, an ordinary least squares regression is performed using the N closest neighboring locations to calculate coefficients (C_x, C_y, and C_e) representing x, y, and elevation gradients: $Z = a + C_x X + C_y Y + C_e E + \varepsilon$, where a is the intercept and ε is error. Then, the basic GIDS formula is

$$Z_k = \frac{\left[\sum_{i=1}^{N} \frac{Z_i + C_x(X_k - X_i + C_y (Y_k - Y_i) + C_e (E_k - E_i)}{d_i^2}\right]}{\sum_{i=1}^{N} \frac{1}{d_i^2}}$$

where Z_k = the predicted value at an unmeasured location k, Z_i = the measured value at location i, X = the x-coordinate for the specified location, Y = the y-coordinate, E_i = the elevation value, and d_i = the distance from measured location i to Z (Nalder and Wein 1998).

Nalder and Wein (1998) compared GIDS with several other methods for interpolating monthly normals of precipitation and temperature in the Canadian boreal forest region. The tested methods included inverse distance squared weighting, nearest neighbor interpolation, ordinary kriging, universal kriging, co-kriging, and detrended kriging. Based on cross-validation using a held-out subset of the data, the GIDS method resulted in the lowest mean absolute errors (MAE), which averaged 0.5 °C for temperature and 3.6 mm, or 11 percent, for monthly precipitation. Price and others (2000) compared the GIDS method with thin-plate moving splines and noted that GIDS, as an inverse distance approach, may have greater occurrence of extreme errors. However, they also noted its transparency and ease of use.

Modification of GIDS for a Count-Based Variable— The ordinary least squares regression implemented in the GIDS approach is intended for continuous, normally distributed variables. Because each of our variables of interest was a count, with large values being rare, we instead performed Poisson regression (Neter and others 1996). For each location of interest, we fitted a Poisson regression model, based on the 30 closest neighboring weather stations, using a maximum likelihood approach. We acknowledged that all three gradient variables (x, y, and elevation) could prove insignificant for a given prediction location and its closest measured neighbors. As a result, we evaluated a sequence of the full and all possible reduced models for statistical significance:

$\log(Z) = a + C_x X + C_y Y + C_e E + \varepsilon,$

$\log(Z) = a + C_x X + C_e E + \varepsilon,$

$\log(Z) = a + C_y Y + C_e E + \varepsilon,$

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$\log(Z) = a + C_x X + \varepsilon,$

$\log(Z) = a + C_y Y + \varepsilon,$

$\log(Z) = a + C_e E + \varepsilon.$

For each prediction location, we tested all seven regression models using the 30 closest stations and identified those models in which all variables were significant. In cases where more than one of the models had all significant variables, we identified the one that yielded the smallest value for Akaike's Information Criterion (AIC). If the best-performing model was not the full Poisson regression model, then the coefficient(s) for any insignificant variable(s) were set to zero in the GIDS equation. If none of the tested models proved to have significant variables, then the GIDS interpolation reverted to inverse distance squared weighting (i.e., all variable coefficients were set to zero).

Interpolation Using GIDS— We implemented the Poisson-based GIDS formulation in a script written for R statistical software (R Core Development Team 2006), which we then used to interpolate values for cells covering the conterminous United States. We created a regular grid (with x, y, and elevation values) for the country by resampling an 8100-m^2 resolution digital elevation model (DEM) generated from U.S. Geological Survey data to 4-km^2 cells using a nearest neighbor method. Notably, this is the same spatial resolution used in most of the data sets that are publicly downloadable from the PRISM Group as well as the data sets available for purchase from the Climate Source (see "Limitations of Existing Interpolated Climatic Data Sets"). For each 4-km^2 cell, we determined the 30 closest NCDC weather stations using three-dimensional Euclidean distance measured from the cell's centroid. We rounded the GIDS-predicted value for each grid cell to the nearest integer.

Evaluation

For comparison to the GIDS-derived total-day and consecutive-day count maps, we created gridded maps for 2000 to 2004 using two spatial interpolation methods available through the ArcGIS Geostatistical Analyst extension (Johnston and others 2003). First, we performed cokriging on the count data using elevation as a covariate. Second, we performed detrended kriging, where we removed a second-order trend from the data and then performed ordinary kriging on the residuals. For both methods, we fit a spherical semivariogram model to the input data, calculating the model parameters (nugget, range, and sill) using a weighted least squares approach (Cressie 1993). As with the GIDS maps, we generated a predicted value for each 4-km^2 cell based on the 30 closest NCDC stations, and rounded the predicted value to the nearest integer.

We compared the accuracy of the three methods via station-by-station cross-validation. Using each interpolation method, we derived a predicted total-day and consecutive-day value for each station based on its 30 closest neighbors. We calculated errors by subtracting the actual observed counts for each station from the interpolated values. We then calculated three mean error measures: mean error (ME) indicates bias (positive = over-prediction, negative = underprediction); mean absolute error (MAE) indicates the magnitude of error regardless of sign; and root mean square error (RMSE) is sensitive to outliers and can be used to

Table 2—Interpolation method comparison for total-day variable[a]

	Interpolation Method	2000	2001	2002	2003	2004
Mean	Observed	62.94	61.77	58.77	64.43	70.32
	GIDS[b]	63.44	62.21	59.23	64.93	70.86
	Cokriging	62.97	61.81	58.89	64.64	70.36
	Detrended kriging	62.98	61.79	58.79	64.41	70.37
RMSE	GIDS	13.52	13.13	12.82	13.42	14.27
	Cokriging	13.07	13.07	13.19	14.35	14.00
	Detrended kriging	13.22	12.85	12.52	13.39	14.09
MAE	GIDS	10.39	9.97	9.61	10.14	10.81
	Cokriging	10.10	10.03	9.94	10.92	10.59
	Detrended kriging	10.24	9.82	9.44	10.18	10.66
ME	GIDS	0.508	0.438	0.464	0.500	0.532
	Cokriging	0.033	0.037	0.114	0.216	0.029
	Detrended kriging	0.046	0.018	0.025	-0.018	0.040

[a] Cross-validation results for each interpolation method based on five annual data sets. Errors calculated as observed values minus the predicted values; see text for interpretation of root mean square error (RMSE), mean absolute error (MAE), and mean error (ME).
[b] GID = gradient plus inverse distance squared.

assess the magnitude of extreme errors (Daly 2006, Nalder and Wein 1998).

To provide a basic visual reference, we used 30-year normal PRISM-derived data sets to construct U.S. maps depicting the total number of days and longest string of consecutive days when weather conditions are typically favorable for *P. ramorum*. We started with 12 monthly grids depicting the number of wet days (i.e., the number of days with precipitation) throughout the conterminous United States. For each monthly wet-days grid, we masked out any cells where temperatures did not fall within the 60 to 80 °F range at some time during the month. Using map algebra, we added the 12 monthly grids together to develop a total-day count for each grid cell in our output map. The consecutive-day count map was, by necessity, more approximately constructed. First, we standardized values in each of the masked monthly grids by converting the number of wet days to a proportion (number of wet days / total number of days in the month) and then multiplying this proportion by 30. Then, using map algebra, we recorded the maximum standardized monthly value for each cell in our output map. This approximated the range of values in the GIDS-derived consecutive-day maps. Nonetheless, because we used monthly rather than daily data to build the PRISM-derived maps, any comparison to the GIDS-derived maps must be done with care.

Results

In terms of cross-validation errors, the three spatial interpolation methods performed similarly for both the total-day and consecutive-day count variables (Tables 2 and 3). The GIDS approach, as suggested by the ME values as well as the actual versus the predicted means, tended to over-predict slightly more than the other two techniques. The RMSE results indicate that, for some years, the GIDS approach yielded a few more extreme errors, although GIDS had a lower RMSE than cokriging for the total-day variable in 2002 and 2003, as well as a lower MAE in 2001, 2002, and 2003. In general, error differences among the three were not substantial, with MAE consistently holding at approximately 16 percent of the total-day mean value and 25 percent of the consecutive-day mean value for all three techniques.

The GIDS-derived maps for the two count variables (Figures 1 and 2) most obviously show a great deal of annual variability. For the consecutive-day variable, the

Table 3—Interpolation method comparison for consecutive-day variable[a]

	Interpolation method	2000	2001	2002	2003	2004
Mean	Observed	5.73	5.72	5.21	6.03	6.25
	GIDS	5.78	5.77	5.25	6.08	6.30
	Cokriging	5.74	5.73	5.21	6.04	6.25
	Detrended kriging	5.73	5.74	5.20	6.03	6.25
RMSE	GIDS[b]	2.14	1.98	1.89	2.15	2.35
	Cokriging	2.10	1.97	1.83	2.14	2.30
	Detrended kriging	2.09	1.98	1.85	2.15	2.30
MAE	GIDS	1.46	1.41	1.28	1.51	1.62
	Cokriging	1.44	1.41	1.24	1.51	1.59
	Detrended kriging	1.45	1.42	1.25	1.51	1.60
ME	GIDS	0.053	0.052	0.039	0.048	0.051
	Cokriging	0.009	0.009	-0.001	0.006	-0.002
	Detrended kriging	0.005	0.018	-0.007	0.003	-0.001

[a] Cross-validation results for each interpolation method based on five annual data sets. Errors calculated as observed values minus the predicted values; see text for interpretation of root mean square error (RMSE), mean absolute error (MAE), and mean error (ME).
[b] GID = gradient plus inverse distance squared.

Eastern United States generally tended to have higher values than the Western United States, with parts of the Appalachian Mountain region and States along the Gulf of Mexico typically exhibiting high values. However, the extent and spatial distribution of the highest-value area fluctuated substantially year to year. The total-day maps exhibited a similar spatial pattern, but more clearly highlighting some relatively high-value areas in the southern and central Rocky Mountains. Perhaps unsurprisingly, the patterns of the GIDS-derived maps were quite different than the patterns depicted in the PRISM-derived maps.

Discussion

Four main points of emphasis emerge from the results. First, for the tested data sets, the interpolation method did not significantly influence the resulting error. There are several possible explanations for this. Foremost, although the GIDS approach may be technically more appropriate than geostatistical approaches for count-based variables, the Poisson model may not have been a good fit for these data, or the data may have been approximately normal enough to remove any advantage of a Poisson-based process over geostatistical approaches. Furthermore, among weighted-average interpolation approaches—a category that includes GIDS—kriging is often the best unbiased predictor for data that are not normally distributed (Johnston and others 2003). Another count-oriented approach—Poisson kriging—has recently emerged in health geography and ecological literature, and this may be a promising future direction for count-based spatial interpolation (Goovaerts 2005, Monestiez and others 2006). In the meantime, GIDS has a number of positive characteristics. It violates fewer assumptions than geostatistical approaches—in particular, the assumption of second-order stationarity (Cressie 1993). Furthermore, the GIDS approach is transparent and easily implemented. To use more complex approaches, particularly PRISM, requires estimation of numerous parameters, so a certain degree of subjectivity is involved. The GIDS approach can easily accommodate covariates besides elevation, and, in fact, could easily be adapted for multiple covariates in order to refine the results. Finally, the GIDS approach has been implemented in R code (R Core Development Team 2006), and as such is an open source resource that may be more readily available than GIS-based interpolation approaches.

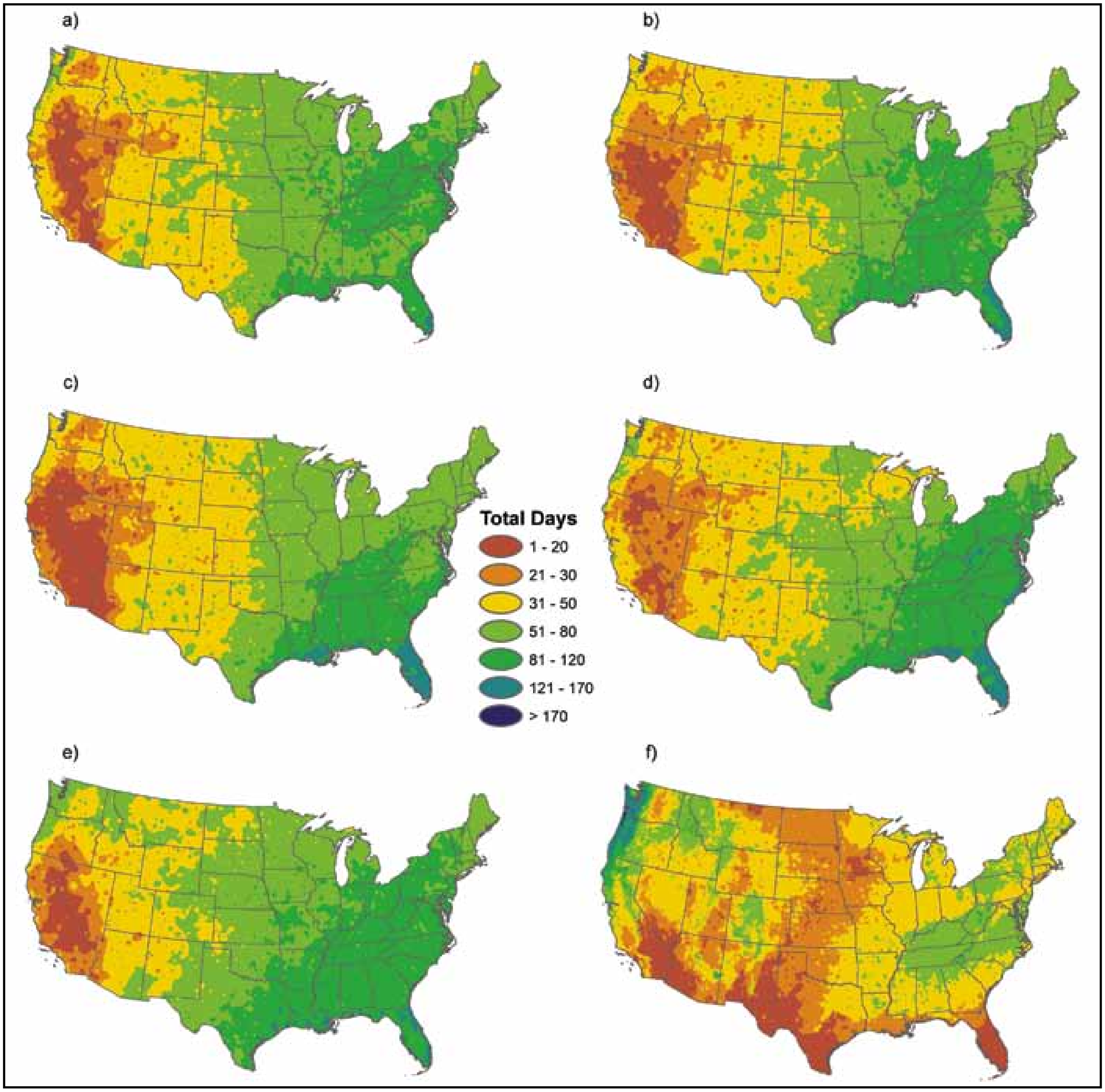

Figure 1—Annual maps of the total number of days with weather conditions favorable for *Phytophthora ramorum*, interpolated using the gradient plus inverse distance squared method: (a) 2000, (b) 2001, (c) 2002, (d) 2003, and (e) 2004; (f) for visual comparison, a total-day map approximated using monthly Parometer-elevation Regressions Independent Slopes Model.

Second, the interpolations of the two-count variables appear to have an acceptable degree of error. The distribution of cross-validation errors for the GIDS interpolations are revealing in this regard. For the consecutive-day variable, across all 5 years, only 25 percent of values were exactly predicted, but nearly two-thirds of predicted values were within 1 day of the observed value. For the total-day variable, only 4 percent of values were exactly predicted, but nearly 50 percent were within 5 days and greater than 75 percent were within 10 days. This should be adequate for

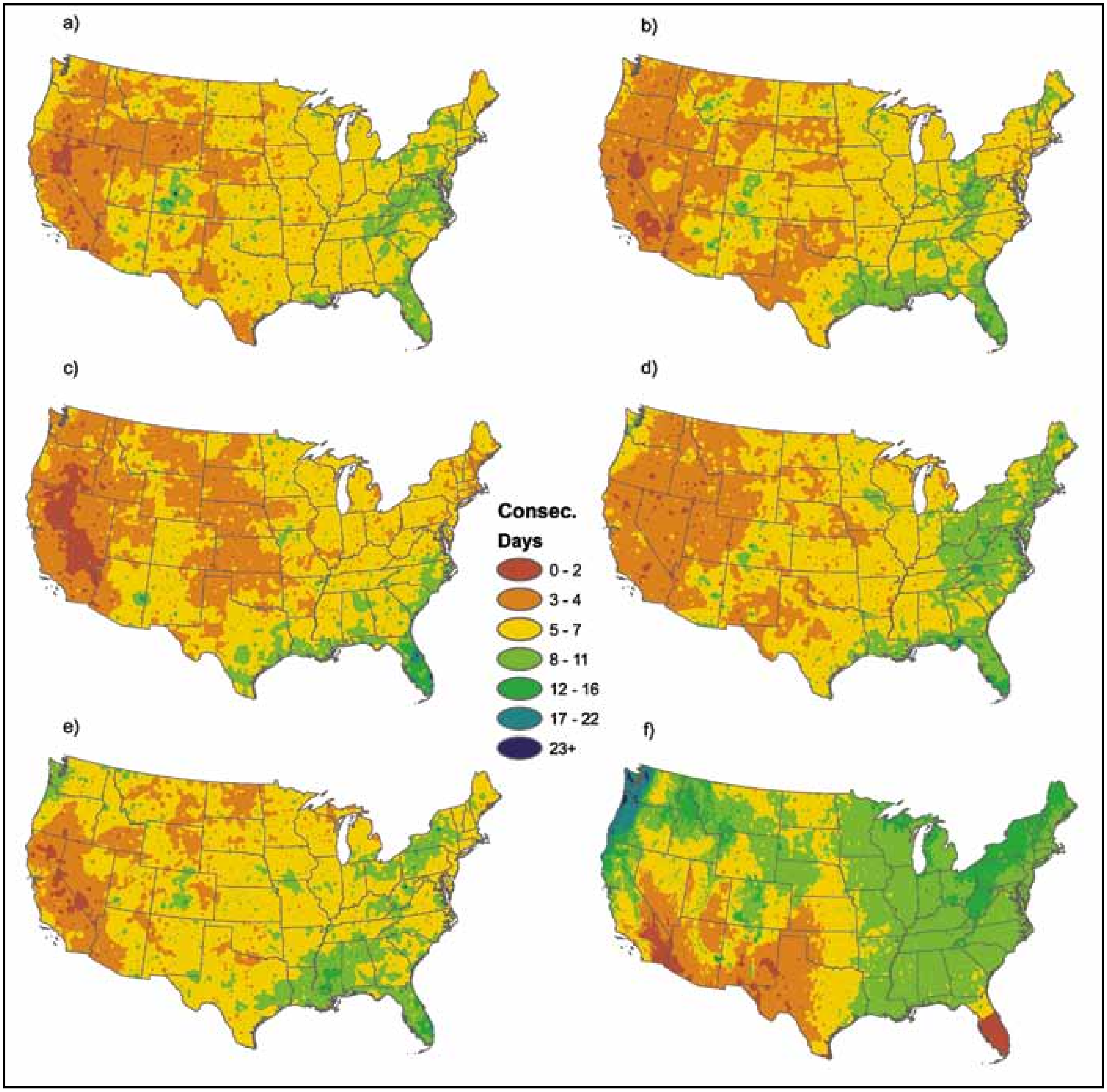

Figure 2—Annual maps of the longest string of consecutive days with weather conditions favorable for *Phytophthora ramorum*, interpolated using the graident plus inverse distance squared method: (a) 2000, (b) 2001, (c) 2002, (d) 2003, and (e) 2004; (f) for visual comparison, a total-day map approximated using monthly Parometer-elevation Rrgressions Independent Slopes Model

broad-scale ranking of areas according to their relative risk based on climatic and weather conditions.

The third and perhaps more important point is that the information provided by the constructed annual count maps is substantially different from results that can be captured using monthly climatic data sets based on 30-year normals. For *P. ramorum* and other currently emerging threats, it may be advantageous to identify areas that have exhibited favorable conditions in a given year and determine whether, for example, the pathogen was positively detected at any nurseries in those areas during that time period. In fact, this suggests a need for a regularly updated database, and the GIDS method may be one way to generate a regularly updated data set from the NCDC data. Recent annual maps can be used in conjunction with 30-year normal data to create a strong picture of current risk.

Fourth, if the count-based variables we calculated are reasonable representations of the level of favorable climatic conditions for *P. ramorum*, then this suggests that large portions of the Eastern United States—perhaps more than originally estimated—have periods during each year where they may be especially susceptible to infection. Because climate and weather may not be severely limiting factors, detailed analyses of potential pathways and potential host species distribution may be in order for much of the Eastern United States.

Literature Cited

Akin, W.E. 1991. Global patterns: climate, vegetation, and soils. Norman, OK: University of Oklahoma Press. 370 p.

Andersen, M.A.; Adams, H.; Hope, B.; Powell, M. 2004a. Risk analysis for invasive species: general framework and research needs. Risk Analysis. 24(4): 893–900.

Andersen, M.A.; Adams, H.; Hope, B.; Powell, M. 2004b. Risk assessment for invasive species. Risk Analysis. 24(4): 787–793.

Bartell, S.M.; Nair, S.K. 2004. Establishment risks for invasive species. Risk Analysis. 24(4): 833–845.

Cressie, N.A.C. 1993. Statistics for spatial data. Rev. ed. New York: John Wiley. 900 p.

Daly, C. 2006. Guidelines for assessing the suitability of spatial climate data sets. International Journal of Climatology. 26: 707–721.

Daly, C.; Gibson, W.P.; Taylor, G.H. [and others]. 2002. A knowledge-based approach to the statistical mapping of climate. Climate Research. 22: 99–113.

Daly, C.; Neilson, R.P.; Phillips, D.L. 1994. A statistical-topographic model for mapping climatological precipitation over mountainous terrain. Journal of Applied Meteorology. 33: 140–158.

Daly, C.; Taylor, G.H.; Gibson, W.P. [and others]. 2000. High-quality spatial climate data sets for the United States and beyond. Transactions of the American Society of Agricultural Engineers. 43(6): 1957–1962.

Davidson, J.M.; Rizzo, D.M.; Garbelotto, M.; Tjosvold, S. 2002. *Phytophthora ramorum* and sudden oak death in California: II. Transmission and survival. In: Standiford, R.B.; McCreary, D.; Purcell, K.L., eds. Fifth symposium on oak woodlands: oaks in California's changing landscape. Albany, CA: U.S. Department of Agriculture, Forest Service, Pacific Southwest Research Station: 741–749.

Davidson, J.M.; Shaw, C.G. 2003. Pathways of movement for *Phytophthora ramorum*, the causal agent of sudden oak death. In: Sudden oak death online symposium. The American Phytopathological Society. http://www.apsnet.org/online/proceedings/SOD/Papers/Shaw_Davidson/default.htm. [Date accessed unknown].

Davidson, J.M.; Wickland, A.C.; Patterson, H.A. [and others]. 2005. Transmission of *Phytophthora ramorum* in mixed-evergreen forest in California. Phytopathology. 95: 587–596.

Garbelotto, M.; Davidson, J.M.; Ivors, K. [and others]. 2003. Non-oak native plants are main hosts for sudden oak death pathogen in California. California Agriculture. 57(1): 18–23.

Garbelotto, M.; Svihra, P.; Rizzo, D.M. 2001. Sudden oak death syndrome fells 3 oak species. California Agriculture. 55(1): 16–19.

Goovaerts, P. 2005. Geostatistical analysis of disease data: estimation of cancer mortality risk from empirical frequencies using Poisson kriging. International Journal of Health Geographics. 4: 31.1–31.33.

Harrington, R.; Fleming, R.A.; Woiwod, I.P. 2001. Climate change impacts on insect management and conservation in temperate regions: Can they be predicted? Agricultural and Forest Entomology. 3: 233–240.

Harvell, C.D.; Mitchell, C.E.; Ward, J.R. [and others]. 2002. Climate warming and disease risks for terrestrial and marine biota. Science. 296: 2158–2162.

Hunter, R.D.; Meentemeyer, R.K. 2005. Climatologically aided mapping of daily precipitation and temperature. Journal of Applied Meteorology. 44: 1501–1510.

Ivors, K.; Garbelotto, M.; Vries, I.D.E. [and others]. 2006. Microsatellite markers identify three lineages of *Phytophthora ramorum* in U.S. nurseries, yet single lineages in U.S. forest and European nursery populations. Molecular Ecology. 15: 1493–1505.

Johnston, K.; Ver Hoef, J.M.; Krivoruchko, K.; Lucas, N. 2003. ArcGIS 9: Using ArcGIS Geostatistical Analyst. Redlands, CA: Environmental Systems Research Institute. 300 p.

Mardikis, M.G.; Kalivas, D.P.; Kollias, V.J. 2005. Comparison of interpolation methods for the prediction of reference evapotranspiration—an application in Greece. Water Resources Management. 19: 251–278.

Marshall-Farrar, K.D.; McGrath, M.; James, R.V.; Stevenson, W.R. 1998. Characterization of Phytophthora infestans in Wisconsin from 1993 to 1995. Plant Disease. 82: 434–436.

Monestiez, P.; Dubroca, L.; Bonnin, E. [and others]. 2006. Geostatistical modelling of spatial distribution of *Balaenoptera physalus* in the Northwestern Mediterranean Sea from sparse count data and heterogeneous observation efforts. Ecological Modelling. 193: 615–628.

Nalder, I.A.; Wein, R.W. 1998. Spatial interpolation of climatic normals: test of a new method in the Canadian boreal forest. Agricultural and Forest Meteorology. 92: 211–225.

Neter, J.; Kutner, M.H.; Nachtsheim, C.J.; Wasserman, W. 1996. Applied linear statistical models. 4th ed. Boston: WCB/McGraw-Hill. 1408 p.

North American Forest Commission [NAFC]. 2004. EXFOR: The Exotic Forest Pest Information System for North America participant's guidelines. In: Downing, M., coord.; O'Brien, J.G., tech. coord. Insect and Disease Study Group. http://www.spfnic.fs.fed.us/exfor/docs/guidelines.pdf.

Peacock, L.; Worner, S.; Sedcole, R. 2006. Climate variables and their role in site discrimination of invasive insect species distributions. Environmental Entomology. 35(4): 958–963.

Plantico, M.; Goss, L.; Hammer, G. [and others]. 2002. The climate atlas of the United States. Ver. 2.0 [CD-ROM]. Asheville, NC: National Oceanic and Atmospheric Administration, National Climatic Data Center.

Price, D.T.; McKenney, D.W.; Nalder, I.A. [and others]. 2000. A comparison of two statistical methods for spatial interpolation of Canadian monthly mean climate data. Agricultural and Forest Meteorology. 101: 81–94.

Rizzo, D.M.; Garbelotto, M. 2003. Sudden oak death: endangering California and Oregon forest ecosystems. Frontiers in Ecology and Environment. 1(5): 197–204.

Rizzo, D.M.; Garbelotto, M.; Hansen, E.M. 2005. *Phytophthora ramorum*: integrative research and management of an emerging pathogen in California and Oregon forests. Annual Review of Phytopathology. 43: 309–335.

Stokstad, E. 2004. Nurseries may have shipped sudden oak death pathogen nationwide. Science. 303(5666): 1959.

R Development Core Team. 2006. R: a language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing. http://www.R-project.org. [Date accessed unknown].

Tooley, P.W.; Kyde, K.L.; Englander, L. 2004. Susceptibility of selected ericaceous ornamental host species to *Phytophthora ramorum*. Plant Disease. 88: 993–999.

van de Kassteele, J.; Dekkers, A.L.M.; Stein, A.; Velders, G.J.M. 2005. Model-based geostatistical interpolation of the annual number of ozone exceedance days in the Netherlands. Stochastic Environmental Research and Risk Assessment. 19: 173–183.

Werres, S. 2003. Forest and other ecosystems and plant hosts in Europe. In: Sudden oak death online symposium. The American Phytopathological Society. http://www.apsnet.org/online/proceedings/SOD/Papers/Werres/default.htm. [Date accessed unknown].

Werres, S.; Marwitz, R.; Man In't Veld, W.A. [and others]. 2001. *Phytophthora ramorum* sp. nov., a new pathogen on Rhododendron and Viburnum. Mycological Research. 105(10): 1155–1165.

Xia, Y.; Winterhalter, M.; Fabian, P. 2000. Interpolation of daily global solar radiation with thin plate smoothing splines. Theoretical and Applied Climatology. 66: 109–115.

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