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CHARACTERIZING THE LANDSCAPE DYNAMICS OF AN INVASIVE PLANT AND RISK OF INVASION USING REMOTE SENSING

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Abstract. Improved understanding of the spatial dynamics of invasive plant species may lead to more effective land management and reduced future invasion. Here, we identified the spatial extents of nonnative cheatgrass (*Bromus tectorum*) in the north central Great Basin using remotely sensed data from Landsat MSS, TM, and ETM+. We compared cheatgrass extents in 1973 and 2001 to six spatially explicit landscape variables: elevation, aspect, hydrographic channels, cultivation, roads, and power lines. In 2001, Cheatgrass was 10% more likely to be found in elevation ranges from 1400 to 1700 m (although the data suggest a preferential invasion into lower elevations by 2001), 6% more likely on west and northwest facing slopes, and 3% more likely within hydrographic channels. Over this time period, cheatgrass expansion was also closely linked to proximity to land use. In 2001, cheatgrass was 20% more likely to be found within 3 km of cultivation, 13% more likely to be found within 700 m of a road, and 15% more likely to be found within 1 km of a power line. Finally, in 2001 cheatgrass was 26% more likely to be present within 150 m of areas occupied by cheatgrass in 1973. Using these relationships, we created a risk map of future cheatgrass invasion that may aid land management. These results highlight the importance of including land use variables and the extents of current plant invasion in predictions of future risk.

Key words: Bromus tectorum; *cheatgrass; Landsat; plant invasion; remote sensing; risk assessment; spatial modeling*.

Introduction

Invasion by nonnative species is a recognized threat to ecosystems and economies worldwide (Vitousek et al. 1996). In many areas, large scale colonization by nonnative plants is changing nutrient cycling, increasing fire severity, and seriously compromising ecosystem condition and native biological diversity (Vitousek et al. 1996, Mack et al. 2000, Mooney and Cleland 2001). Conservation of native species threatened by ecosystem-transforming invasives relies on intelligent and informed land management. A critical component of effective land management to control plant invasion is identification and active protection of areas at high risk of future invasion (Hobbs and Humphries 1995). Additionally, it is important to identify and minimize land uses that promote invasion, for example emplacement and improvement of roads (Forman and Alexander 1998, Trombulak and Frissell 2000).

Spatial modeling is a promising approach to predicting risk of invasion. Spatially explicit models have been used to predict distributions of invasive species, deforestation, urbanization, and vegetation type (Franklin 1995, Guisan and Zimmermann 2000). Spatial patterns of invasion can be predicted by linking current presence and absence of invasive species to spatially explicit predictor variables, like land use, geomorphology, and topography, using geographic information systems (GIS; Store and Kangas 2001). Land use and land form characteristics related to increased probability of invasive species can then be used to inform conservation and management efforts.

Spatial modeling of invasion by nonnative species has relied on empirical data or expert opinion (Martin et al. 2005) to establish some a priori knowledge of the relationship between occurrence of the invasive species and spatially explicit predictor variables. Successful modeling efforts have demonstrated that establishing such spatial relationships requires extensive field data. For example, Larson et al. (2001) collected data from more than 1300 transects in the Theodore Roosevelt National Park, North Dakota, USA to determine nonnative plant relationships to native plant communities and anthropogenic disturbance. Rouget and Richardson (2003) modeled risk of invasion in the Agulhas Plain, South Africa based on land cover data collected during a six-month field survey. Underwood et al. (2004) identified potential distributions of nonnative plants based on the relationship between those plants and slope, elevation, and plant community structure at 236 plots in Yosemite National Park, California, USA. Not only the sample size requirements but also the spatial extent of many invasions makes collection of field data extremely time consuming and expensive. Additionally, if one aims to understand changing relationships between patterns of invasion and predictor variables over time, data must be collected over many years. If

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FIG. 1. Native sagebrush steppe near Winnemucca, Nevada, USA (left) and cheatgrass monoculture in Antelope Valley, Nevada (right) illustrate the potential land cover change associated with cheatgrass invasion.

predictive models are not based on large sets of spatially extensive data, they may not identify important drivers of invasion and therefore may lead to inaccurate models of future invasion.

Remotely sensed data can improve data-collection capacity and increase the accuracy of predictive spatial models of invasion (Cohen and Goward 2004). Such data have been used to identify recent land cover changes like deforestation (Adams et al. 1995, Mayaux et al. 1998, Riitters et al. 2000) and urbanization (Ridd 1995, Masek et al. 2000, Stefanov et al. 2001). Resulting maps of land cover change cover broad spatial extents, increasing our ability to understand land cover relationships to spatially explicit predictor variables. Remotely sensed variables, like the normalized difference vegetation index (NDVI), which is a measure of photosynthetic "greenness" (Tucker and Sellers 1986), have been used to inform models predicting the occurrence of plant and animal species (Gould 2000, Muldavin et al. 2001, Kerr and Ostrovsky 2003, Gillespie 2005). Among the requirements for application of remotely sensed data to predict and manage the spatial dynamics of an invasive species is the ability to accurately identify distribution patterns of invasive species through time. One example of successful remote detection of invasive species has been the use of Landsat imagery to identify presence of cheatgrass (*Bromus tectorum*) in the Great Basin, USA (Peterson 2005, Bradley and Mustard 2005).

Cheatgrass is an annual grass, native to Eurasia, whose spread into perennial shrub ecosystems has been documented throughout the Great Basin (Mack 1981, 1989, Knapp 1996). A similar ecosystem transformation is occurring in the Mojave and Sonoran Deserts with invasion of red brome (*Bromus rubens*) (Salo 2005). Cheatgrass presence leads to increased fire frequency (Whisenant 1990), due to higher fuel loads in formerly patchy ecosystems. Burned lands typically are quickly colonized by windblown cheatgrass seeds, creating cheatgrass monocultures (Fig. 1; Hull and Pechanec 1947, Billings 1990, Melgoza et al. 1990, Young and Allen 1997). The presence of cheatgrass in rangeland is problematic because the grass senesces in late spring and, unlike native perennial grasses, is unpalatable for livestock through the summer (Currie et al. 1987, Young and Allen 1997). Peterson (2005) demonstrated that cheatgrass can be detected using Landsat TM and ETM+ imagery due to its early growth relative to native shrubs and grasses. Bradley and Mustard (2005) used time series of Landsat TM and ETM+ imagery to identify cheatgrass based on its amplified interannual response to precipitation. Both of these studies showed that phenological differences between invasive cheatgrass and native grasses and shrubs were distinct enough to accurately identify cheatgrass presence (Fig. 2).

Models of risk of cheatgrass presence previously have been created using field data (Gelbard and Belnap 2003) and a priori knowledge of cheatgrass distribution (Suring et al. 2005, Wisdom et al. 2005). Gelbard and Belnap (2003) measured plant communities within 50 m of roads in southern Utah and found that probability of cheatgrass presence increases with level of road improvement (ranging from packed dirt to paved). Gelbard and

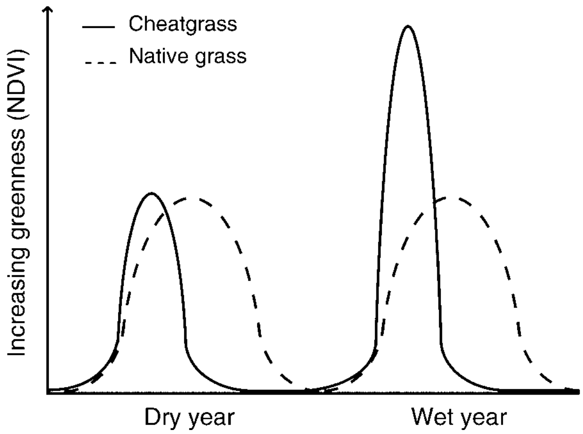

FIG. 2. Schematic representation of differences in cheatgrass phenology that allow for its detection via remote sensing. Cheatgrass germinates earlier and has an amplified interannual response to rainfall compared to native shrubs and grasses. NDVI is the normalized difference vegetation index, a measure of photosynthetic "greenness" (Tucker and Sellers 1986).

Belnap (2003) collected enough field data to draw a compelling inference about the cheatgrass–road relationship across broad spatial extents. However, they did not consider the relationship between cheatgrass and other spatially explicit predictor variables that also may increase the probability of invasion. Suring et al. (2005) created a regional model of probability of cheatgrass invasion in the Great Basin (650 000 km^2) based on aspect, elevation, and soil type. Although this model was built on field studies and expert opinion, the work did not consider whether land use affected probability of invasion. Predictive models of invasion would be strengthened by considering a wider range of possible land uses and topographic variables across extensive spatial areas. Relationships between these potential predictors and cheatgrass occurrence can be identified empirically across broad spatial areas using maps of cheatgrass presence derived from remotely sensed data.

In this study, we used Landsat MSS, TM, and ETM+ derived presence/absence maps of cheatgrass in central Nevada, USA at 30–60 m spatial resolution (Peterson 2005, Bradley and Mustard 2005) to establish spatial relationships between cheatgrass occurrence and seven spatially explicit predictor variables: elevation, aspect, and distance to hydrographic channel (topographic lows created by ephemeral water flow), cultivated areas, roads, power lines, and previously invaded areas. By using remotely sensed data, we were able to examine spatial relationships across extensive areas that could not be sampled exhaustively in the field. We compared cheatgrass distributions in 1973 and 2001 to determine how the spatial extent of cheatgrass invasion changed over time. Finally, we predicted risk of future invasion based on current relationships between cheatgrass occurrence and spatially explicit variables. Our work illustrates that integration of remote sensing for land cover identification and spatial modeling can enhance understanding of invasion patterns and potentially improve conservation efforts.

METHODS

Study area

The study area encompasses a 28 000 km^2 portion of northern Nevada imaged by Landsat TM path 32, row 42, which is centered at 118°W, 40°30′ N. In this part of the Great Basin, there has been a high degree of cheatgrass invasion relative to other areas (29% of land cover is invaded vs. 7% of the Great Basin as a whole; Bradley and Mustard 2005) and cheatgrass monocultures are common. The study area contains urban and agricultural lands associated with the towns of Lovelock and Winnemucca, as well as several other distributed agricultural fields. Elevation of the study area ranges from 1100 to 2900 m. Dominant land cover types are salt desert shrub (*Atriplex* spp.) and sagebrush steppe (*Artemesia* spp.). Cheatgrass is the dominant annual in the study area. As a result, phenological differences (Fig. 2) between the annual and native perennials can be used to identify cheatgrass presence (Peterson 2005, Bradley and Mustard 2005).

Cheatgrass detection using remotely sensed data

To identify cheatgrass based on its amplified response to precipitation, we acquired Landsat data from three above average precipitation years (1973, 1988, and 1995) and three below average precipitation years (1974, 1991, and 1992). Acquisition dates of satellite observations were timed to coincide as closely as possible to peak cheatgrass greenness (mid-May). Landsat data were converted to reflectance using non-vegetated, spectrally invariant targets acquired with an ASD FieldSpec spectrometer (Analytical Spectral Devices, Boulder, Colorado, USA) in May, 2003 (Bradley and Mustard 2005). We calculated the normalized difference vegetation index (NDVI) for each of the six observations using the following formula:

$$(\mathrm{NIR} - R)/(\mathrm{NIR} + R)$$

where NIR is reflectance in near-infrared wavelengths and R is reflectance in red wavelengths. NDVI values range from −1 to 1 and are a proxy for photosynthetic greenness of land cover (Tucker and Sellers 1986). For the 1973 and 1974 images, we used MSS bands 2 and 4 to approximate R and NIR. Because of changes in sensor quality and spectral bands, NDVI values measured by MSS and TM are slightly different. However, an estimate of NDVI derived from MSS bands 2 and 4 is a comparable measure of vegetative greenness. Cheatgrass distribution maps were created using the difference between NDVI values of a wet year and a dry year:

$$\mathrm{NDVI_{wet}} - \mathrm{NDVI_{dry}} = \Delta\mathrm{NDVI}.$$

We paired each wet with a dry scene based first on sensor type (MSS vs. TM) and second on time of year to

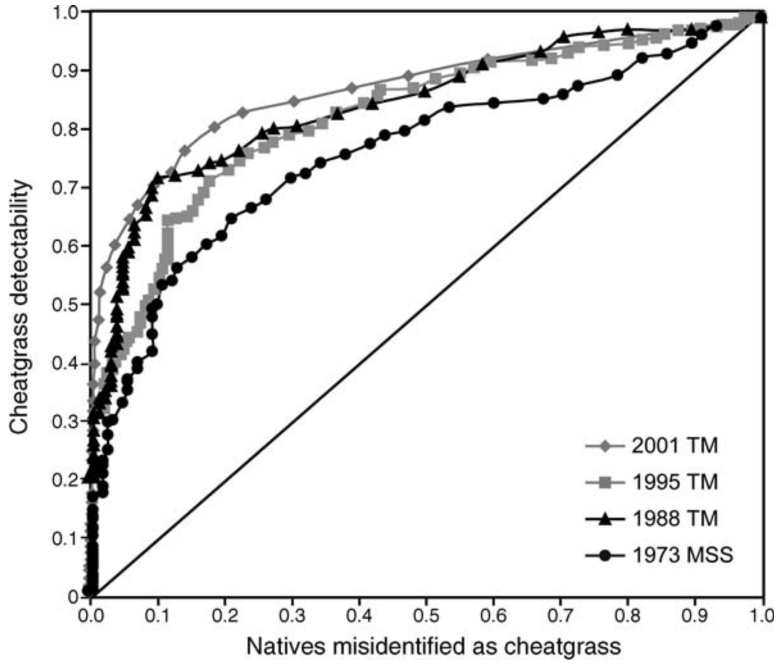

FIG. 3. Receiver operator calibration (ROC) curves of accurately detected cheatgrass vs. native vegetation misidentified as cheatgrass for four time periods, using TM and MSS Landsat data.

create a difference estimate that identified changes due to variability in precipitation. Scene pairs were 1973 and 1974, 1988 and 1992, and 1995 and 1991. Agricultural fields, urban areas, and clouds were excluded from our results.

To identify cheatgrass based on its early season phenology, Peterson (2005) calculated NDVI for Landsat data from 25 April 2001 and 28 June 2001. Urban areas, agricultural fields, and clouds were excluded from the analyses. Peterson (2005) created a cheatgrass occurrence map based on the difference in NDVI between April and June:

$$\mathrm{NDVI}_{\mathrm{April}} - \mathrm{NDVI}_{\mathrm{June}} = \mathrm{dNDVI}.$$

By combining our results with Peterson's, we created a time series of measures of ΔNDVI and dNDVI for the years 1973, 1988, 1995, and 2001. ΔNDVI and dNDVI can be related directly to cheatgrass presence/absence through field validation.

Field validation

In order to define cheatgrass presence/absence from the continuous mapped results, we collected 526 validation points in May 2004, each representative of land cover with respect to cheatgrass and shrubs averaged across an area greater than the 60-m pixel resolution (a 60-m by 60-m square) of Landsat MSS (Bradley and Mustard 2005). Validation points were based on a stratified random sample across ΔNDVI values from 1995 located within 1 km of a road for accessibility. Further details on this methodology can be found in Bradley and Mustard (2005). Cheatgrass was present either as monoculture or as dense cover in shrub interspaces at 289 points and absent at 237 points. Histograms of ΔNDVI (1973, 1988, and 1995) and dNDVI (2001) values were created for locations with and without cheatgrass. Histograms were transformed into receiver operator calibration (ROC) curves to quantify the ability of the remotely sensed maps from 1973, 1988, 1995, and 2001 to correctly identify cheatgrass occurrence in 2004. (Fielding and Bell 1997; Fig. 3). An ROC curve compares detectability (locations correctly mapped as having cheatgrass) with misidentification (locations incorrectly mapped as having cheatgrass). The curve shape is a result of the range of possible thresholds that could be applied to ΔNDVI and dNDVI values to create a presence/absence map. We selected a threshold value for each map that gives the maximum detectability while minimizing false positive misidentification.

The 1973 map correctly classified cheatgrass occurrence in 54% of the points visited in 2004 with a false positive detection rate of 11%. The 1988 map correctly classified cheatgrass occurrence in 73% of the points visited in 2004 with a false positive detection rate of 10%. The 1995 map correctly classified cheatgrass occurrence in 65% of the points visited in 2004 with a false positive detection rate of 12%. Finally, the 2001 map correctly classified cheatgrass occurrence in 74% of the points visited in 2004 with a false positive detection rate of 14%. Differences in identification power between years can be attributed clouds in some images,

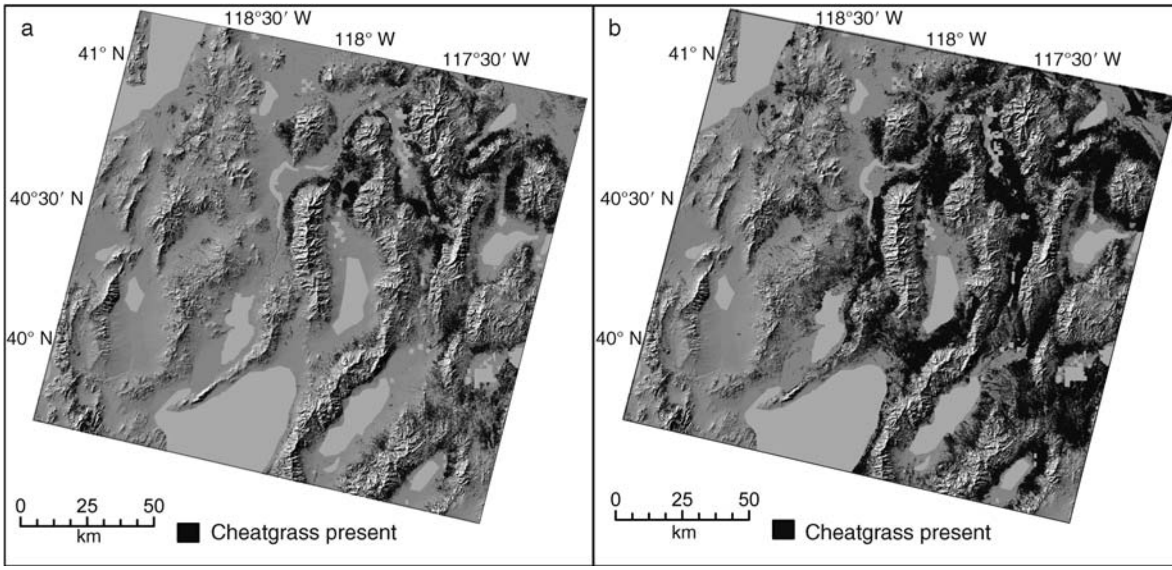

FIG. 4. Cheatgrass presence in (A) 1973 and (B) 2001 based on aggregate maps from 1973, 1988, 1995, and 2001. Alkali flats and cultivated areas (light gray) are excluded. The background image is shaded relief.

variability in image acquisition timing, and different techniques used for cheatgrass detection.

Creation of reduced error maps for 1973 and 2001

In order to reduce false positive error while maximizing our ability to detect cheatgrass, we combined the 1973, 1988, 1995, and 2001 maps to create aggregate cheatgrass occurrence maps for 1973 and 2001. We created a reduced error map of cheatgrass distribution in 1973 based on the assumption that once established, cheatgrass remains present at any given location (pixel) (Billings 1990). Thus, we assumed that a pixel containing cheatgrass in 1973 would contain cheatgrass in subsequent years. To minimize misclassification while maximizing our ability to detect cheatgrass, we categorized cheatgrass as present in a pixel in 1973 only if cheatgrass also was present in at least one of the subsequent years. The 1973 aggregate map correctly classified cheatgrass occurrence in 35% of the points visited in 2004 with a false positive detection rate of 2% (Fig. 4A). It is likely that the low, 35% "accuracy" rate is largely a result of distribution changes between the 1973 map and the 2004 validation.

A reduced error map of cheatgrass distribution in 2001 was based on cheatgrass present in 1973 plus cheatgrass present in either 1988 and 1995, 1988 and 2001, or 1995 and 2001. Thus, if cheatgrass was present in 1973 and/or in any other two scenes then it was considered present in 2001. The 2001 aggregate map correctly classified cheatgrass occurrence in 71% of the points visited in 2004 with a false positive detection rate of 7% (Fig. 4B). Reduced error maps were used to investigate the spatial dynamics of cheatgrass invasion between 1973 and 2001.

Cheatgrass distribution over time

The difference between 1973 cheatgrass presence and 2001 cheatgrass presence was dramatic. The estimated extent of cheatgrass cover more than doubled from 14% cover (3850 km^2) in 1973 to 29% cover (8300 km^2) in 2001. Over that time period cheatgrass both expanded from existing populations and colonized previously unoccupied areas far from existing populations. Our goals were to identify spatially explicit measures of land use and topography that influenced cheatgrass presence in 1973 and to investigate whether those relationships changed between 1973 and 2001.

In our analyses, we assumed that the population of undetected cheatgrass in both 1973 and 2001 was distributed in the same way to the detected cheatgrass. False negatives could be caused by cloud cover at the time of image acquisition, changes in cheatgrass distribution over time, or phenological anomalies. Cloud cover, which was mainly a source of error in the 1995 scene, was reduced by the aggregation of the maps. Although map aggregation improved detection of cheatgrass in cloud covered areas, it limited our ability to detect distribution changes after 1995. However, we expected cheatgrass that colonized the study area between 1973 and 2001 yet remained undetected to follow a similar spatial distribution to the detected cheatgrass. A likely cause of false negatives is a lower than expected degree of growth response to precipitation. This could occur in areas of mixed native shrub/cheatgrass in which cheatgrass occurred as a sparse understory at the time of the remotely sensed image acquisition but increased to dense cover in shrub interspaces prior to collection of validation data in 2004. The remote sensing technique used to identify

TABLE 1. Predictor variables.

Name	Description	Source
Elevation	elevation (m)	USGS (NED)
Aspect	aspect (eight cardinal directions)	USGS (NED)
Distance to channel	distance to any hydrographic channel (m)	2000 census
Distance to cultivation	distance to any cultivated area identified in 1973 or 2001 Landsat imagery (m)	Landsat imagery
Distance to road	distance to any paved or unpaved road (m)	2000 census
Distance to power line	distance to any major utility line (m)	2000 census
Distance to 1973 cheatgrass	distance to cheatgrass present in 1973 (m)	1973 cheatgrass map

Note: NED, National Elevation Data Set.

cheatgrass does not favor detection of some locations over others because sun angle and shading are consistent over time. Therefore it is reasonable to assume that spatial relationships identified here are representative of the total population.

The assumption that identified cheatgrass follows a similar spatial distribution to undetected cheatgrass can be tested using the field validation points. The expected detection rate for any point on the 2001 cheatgrass map is 0.71 based on the field validation (205 cheatgrass points out of 289 were correctly mapped). By stratifying the validation points based on the classified spatially explicit variables (Table 1), we determine whether there is a bias in the mapped result. For example, there were a total of 33 validation points collected on east-facing slopes. Thus, the expected number of correctly mapped points is 23.4 ± 5.1 (mean ± 95% CI). The actual number of correctly mapped points was 25, well within the range of expected values. Fig. 5 shows detection success rate with aspect. All of the measured detection rates are within the 95% confidence interval of the expected detection rates. Further, the pattern shown here (e.g., higher detection rate on northeast slopes and lower detection rates on southeast and south slopes) is not reflected in the modeled relationship between cheatgrass and aspect (see *Results*). Elevation, distance to power lines, and distance to cultivated areas also indicate that there is no significant bias in the mapped results. Potential biases associated with distance to roads and hydrographic channels could not be estimated for lack of validation data distributed across the range of distances. These results suggest that detected and undetected cheatgrass populations follow a similar spatial distribution and, therefore, the spatial relationships derived from mapped data are not affected by significant map bias.

Spatially explicit variables

Spatially explicit variables were assembled from USGS topographic datasets and 2000 United States census in a GIS (Table 1). Distance to cultivated areas was based on cultivated areas visible in the 1973 or 2001 Landsat scenes. Distance to 1973 cheatgrass was created from the remotely sensed aggregate map of cheatgrass present in 1973. Of the variables we measured, elevation, aspect, and the location of hydrographic channels are constant over the time period of our analyses. These three variables were evaluated to examine the strength of the relationship between topography and cheatgrass occurrence. The locations of roads, power lines, and

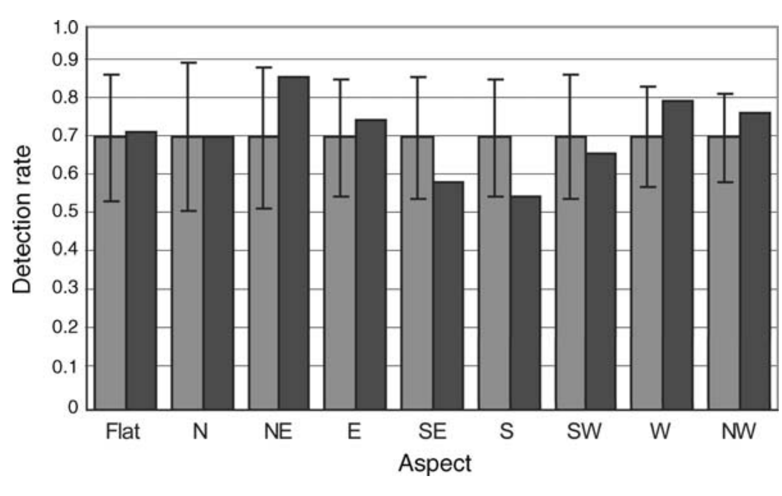

FIG. 5. Detection rate of cheatgrass with changing aspect. Dark gray bars are measured detection rate. Light gray bars are expected detection rate (0.71) based on the total map accuracy. Error bars are the 95% confidence interval of standard deviation for the total number of samples in that aspect class.

TABLE 2. Partial table of probabilities of cheatgrass presence relative to binned distance to roads in 2001.

Binned distance to road (m)	Cheatgrass present (no. pixels)	Cheatgrass absent (no. pixels)	ρ†	Study area (%)‡
0–60	707 086	958 165	0.42	6.2
60–120	667 774	944 759	0.41	6.0
120–180	623 637	933 070	0.40	5.8
180–240	519 147	823 313	0.39	5.0
240–300	502 816	844 532	0.37	5.0
300–360	383 397	683 385	0.36	4.0
Discrete class	a	b	$a/(a+b)$	$([a+b]/\text{total area}) \times 100$
Total area	7 929 576	18 914 698	0.29	100

† ρ = no. pixels with cheatgrass present/total no. pixels.
‡ Total area is 28 000 km^2.

cultivated areas were approximately constant, as most of the land use changes in our study system occurred in urban areas, which were excluded from our analysis. Roads, power lines, and cultivated areas were considered to determine whether land use and disturbance were reliable predictors of cheatgrass occurrence.

We excluded from analysis alkali flats, which covered approximately 9% (2400 km^2) of our study area. Alkali flats contain essentially no vegetation. The extent of alkali flats was determined using the Landsat scenes and masked from the analysis. All areas except cultivated, urban, and alkali flats were expected to have a non-zero probability of containing cheatgrass.

Determining spatial dynamics of invasion

We determined the probability of cheatgrass presence as

$$\rho = \frac{\text{no. pixels with cheatgrass present}}{\text{total no. pixels}}.$$

At any given 60-m pixel, cheatgrass can only be present or absent; therefore the total number of pixels equals the sum of cheatgrass present and cheatgrass absent. In order to quantify explanatory and predictive relationships between cheatgrass presence and spatially explicit predictor variables, the predictors must be reclassified, or binned, to create multiple subpopulations. We created more bins (discrete classes) in areas with high expected probabilities of cheatgrass presence (e.g., adjacent to anthropogenic disturbance). We created fewer bins in areas with low expected probabilities of cheatgrass presence (e.g., far from disturbance). For example, road distance was binned into 60-m discrete classes closer to roads (0–60 m, 60–120 m, etc.) with bin size increasing with distance to road. Distances were measured at multiples of 60 m to coincide with Landsat MSS-mapped resolution. We also calculated land area in each discrete class to assess how much land corresponded to each probability of cheatgrass presence. The number of pixels in which cheatgrass was present and absent within each discrete class was summed to determine the probability of cheatgrass presence (Table 2) (Berry 1993). Probabilities of cheatgrass presence and absence within each discrete class in 1973 and 2001 were compared to estimate changes in cheatgrass distribution over that time period.

Modeling risk of future invasion

We created a risk map of future cheatgrass invasion in our study region based on current relationships of cheatgrass occurrence to geography and land use. We assessed relative probability of invasion with multicriteria evaluation (MCE; Schneider and Pontius 2001, Store and Kangas 2001, Store and Jokimaki 2003). In MCE, the relative probabilities of cheatgrass presence associated with each discrete class are summed for all predictor variables (elevation, aspect, distance to roads, etc.) at each pixel. MCE is useful because a range of probabilities exist for each predictor variable, but those probabilities can not be modeled using logistic regression because they are multimodal. Summing probabilities was appropriate in this case because the spatially explicit variables were approximately independent (Table 3). Correlations between distance variables were considered only within distance ranges with increased likelihood of cheatgrass presence (see Results section). Although there was a moderate correlation of 0.34 between distance to cultivation and elevation, correlations between the remaining variables were weak at best. Hence, an additive risk estimate was considered a reasonable indicator of future risk of cheatgrass invasion (Berry 1993, Store and Kangas 2001).

TABLE 3. Pearson correlation matrix of variables.

Parameter	Elevation	Aspect	Distance to channel	Distance to cultivation	Distance to road	Distance to power line
Elevation	1.00					
Aspect	0.11	1.00				
Distance to channel	0.05	0.02	1.00			
Distance to cultivation	0.34	0.06	0.01	1.00		
Distance to road	0.08	0.01	0.05	0.07	1.00	
Distance to power line	0.17	−0.01	−0.01	0.11	0.11	1.00

Notes: Distances included are only those with an increased probability of cheatgrass presence. All correlations are significant at the 99% confidence interval.

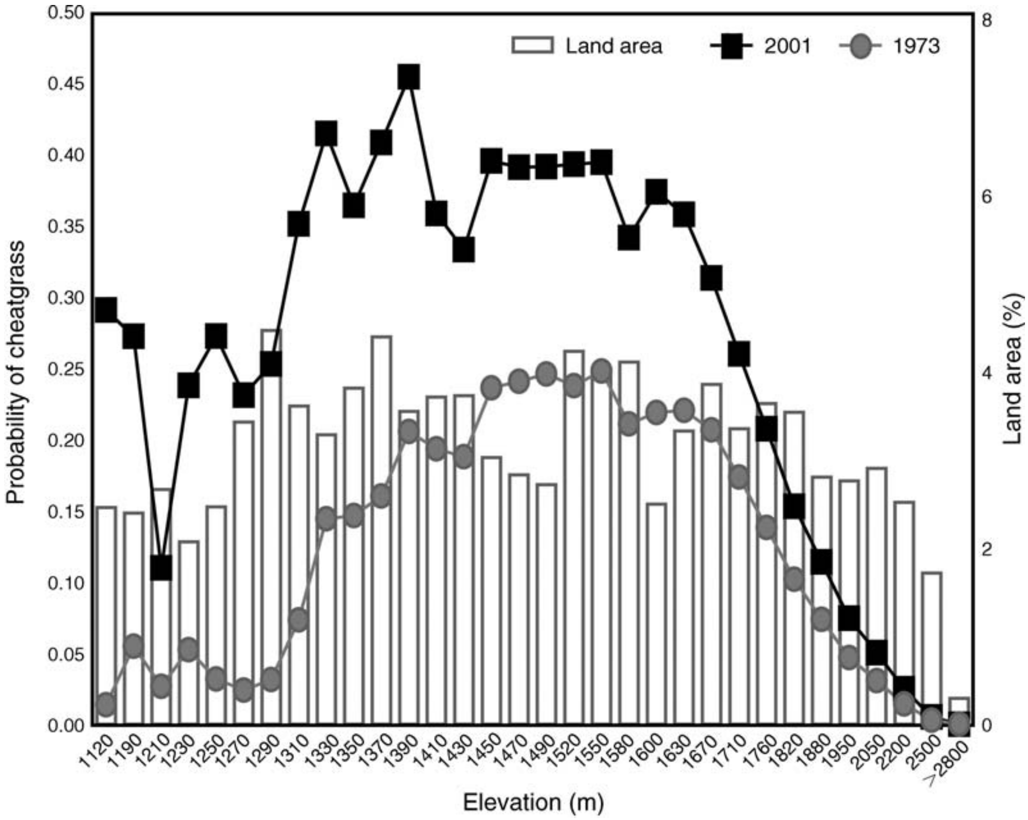

FIG. 6. Total probabilities of cheatgrass presence across elevation classes in 1973 (circles) and 2001 (squares). Bars indicate the relative land area for each elevation class.

RESULTS

Relationship between cheatgrass occurrence and elevation

Probabilities of cheatgrass presence across a discrete set of elevation classes are shown in Fig. 6. The large increase in overall probability of cheatgrass presence between 1973 (0.14) and 2001 (0.29) makes it difficult to assess the relative contribution of elevation between the two time periods. In order to compare distribution changes between 1973 and 2001, we subtracted mean probabilities from total probabilities so that departures from 0 indicate a higher or lower probability of cheatgrass presence in a given elevation class relative to the total population. In both 1973 and 2001, elevations from 1400 to 1700 m had a higher probability of cheatgrass presence than other elevations (Fig. 7a). Between 1973 and 2001, probability of cheatgrass presence increased markedly at elevations between 1200 and 1400 m. Between 1973 and 2001, however, cheatgrass did not expand to elevations higher than 1700 m, indicating that cheatgrass expansion over the last three decades has been concentrated at lower elevations. Elevations above 2500 m have approximately 0 probability of containing cheatgrass in both time periods. Relative to all possible elevations, the probability of cheatgrass occurrence in 2001 was 10% higher at elevations from 1300 to 1700 m.

Relationship between cheatgrass occurrence and aspect

In both 1973 and 2001, cheatgrass was more likely to be present on west and northwest facing slopes (Fig. 7b). The relationship between west and northwest facing slopes and cheatgrass presence was stronger in 2001 than in 1973. In both 1973 and 2001, cheatgrass was less likely to be present in flat areas. However, probability of cheatgrass presence in flat areas increased substantially between 1973 and 2001, indicating that the distribution of cheatgrass has expanded on flat slopes as well as west and northwest facing slopes. Relative to all aspects, the probability of cheatgrass occurrence in 2001 was 6% higher at on west and northwest facing slopes.

Relationship between cheatgrass occurrence and hydrographic channels

In both 1973 and 2001, probability of cheatgrass presence was highest within 120 m of hydrographic channels (Fig. 7c). Between 1973 and 2001 the relationship between channels and cheatgrass pres-

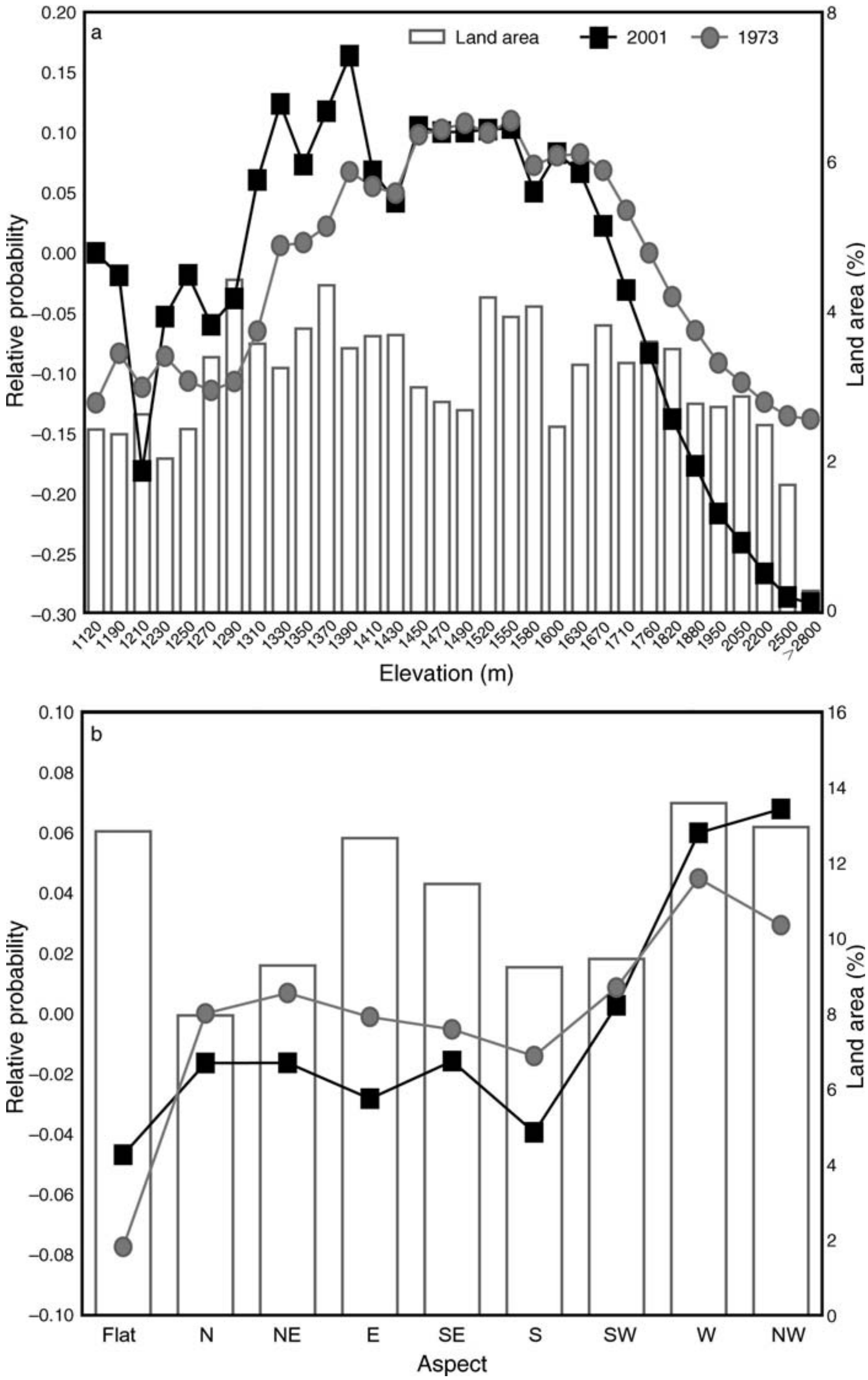

FIG. 7. Relative probabilities of cheatgrass presence with (a) elevation, (b) aspect, and (c) distance to hydrographic channel, and relative land area for each class. Relative probability is created by subtracting mean overall probability of cheatgrass presence for each year (0.14 in 1973 and 0.29 in 2001) such that departures from 0 indicate increased or decreased risk of cheatgrass within each binned interval.

ence strengthened slightly. A comparison of cheatgrass spatial distributions in 1973 and 2001 (Fig. 8) showed that while some expansion occurred along hydrographic channels, extensive new populations also appeared in areas that were not colonized in 1973. The probability of cheatgrass occurrence in 2001 was 3% higher within 120 m of a hydrographic channel.

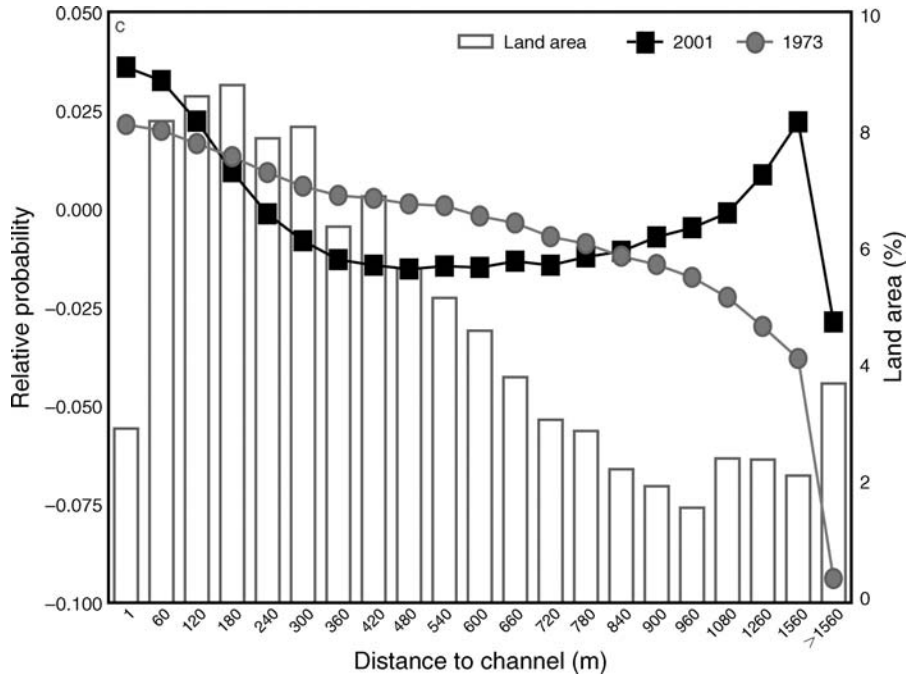

FIG. 7. Continued.

Relationship between cheatgrass occurrence and cultivation

In 1973 and 2001, probability of cheatgrass presence was strongly related to distance to cultivated areas. Between 1973 and 2001, probability of cheatgrass presence increased by more than 10% in areas within 3 km of cultivation (Fig. 9a). Interestingly, probability of cheatgrass presence was not highest directly adjacent to cultivated areas, but instead peaked at 2–3 km distance.

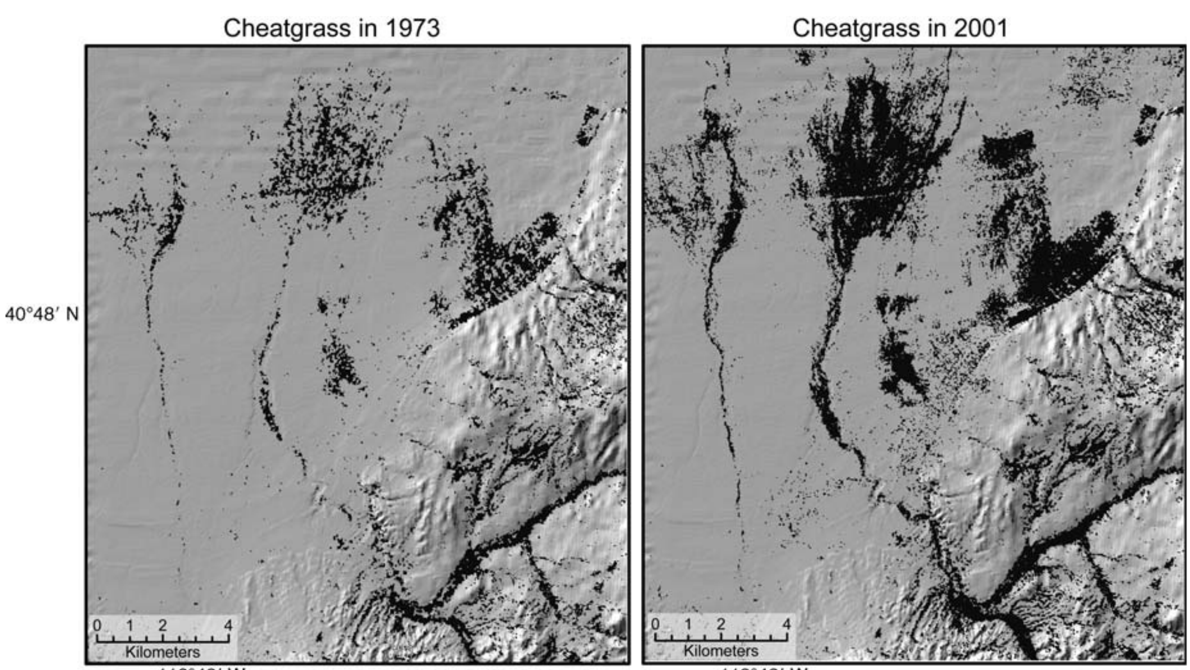

FIG. 8. Cheatgrass presence in 1973 and 2001 shows invasion along major channels. Outside of channels, cheatgrass expands away from populations existing in 1973. The background image is shaded relief.

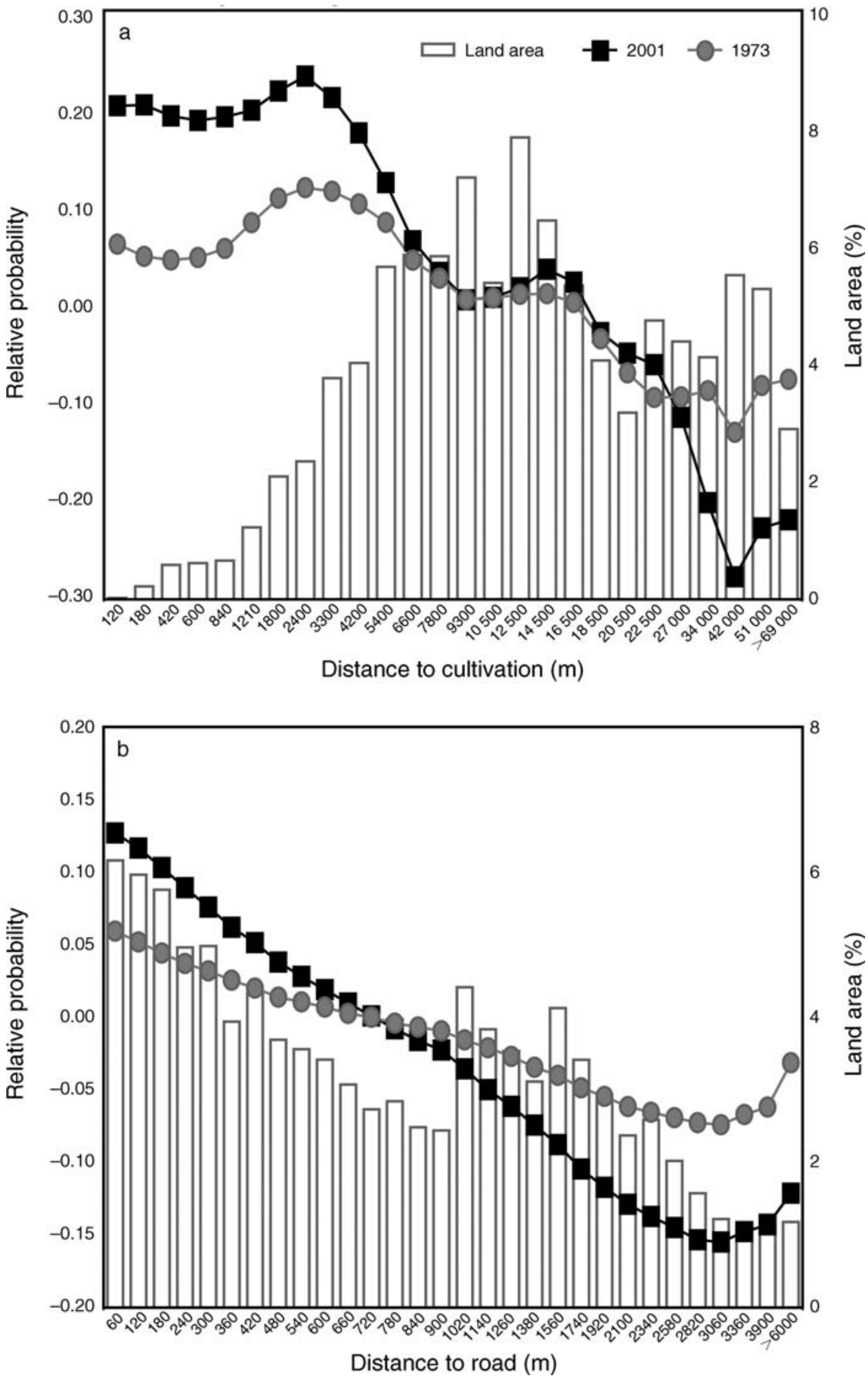

FIG. 9. Relative probabilities of cheatgrass presence with (a) distance to cultivated area, (b) distance to road, and (c) distance to power line and relative land area for each class.

When viewed spatially, cheatgrass initially occurred in foothills proximal to cultivation in 1973, but by 2001 had fully invaded the valley and surrounded cultivated lands (Fig. 10). The probability of cheatgrass occurrence in 2001 was 20% higher within 3 km of a cultivated area.

Relationship between cheatgrass occurrence and roads

In both 1973 and 2001, probability of cheatgrass presence was higher within 700 m of roads, with the highest probability found directly adjacent to roads (Fig. 9b). Between 1973 and 2001, probability of

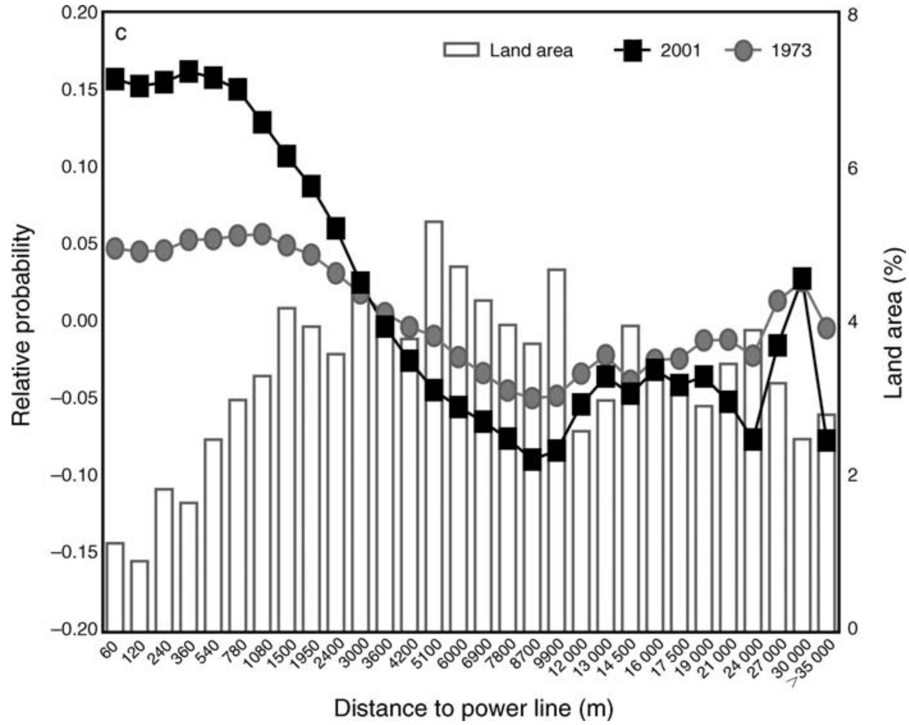

FIG. 9. Continued.

cheatgrass presence adjacent to roads increased by up to 7%. The probability of cheatgrass occurrence in 2001 was as much as 13% higher within 700 m of a road.

Relationship between cheatgrass occurrence and power lines

In both 1973 and 2001, cheatgrass was more likely to be found within 1 km of a power line, and had an increased probability of presence up to 4 km from power lines (Fig. 9c). Between 1973 and 2001, the probability of cheatgrass presence within 1 km of a power line increased by more than 10%. Cheatgrass had similar probabilities of presence at all distances within 1 km of power lines in both 1973 and 2001. The probability of cheatgrass occurrence in 2001 was more than 15% higher within 1 km of a power line.

Cheatgrass presence over time

To examine spatial relationships of cheatgrass presence over time, we considered only those locations in which cheatgrass was present in 2001 but not in 1973. The probability of cheatgrass presence in a location from which it was absent in 1973 was 0.15. In 2001, cheatgrass was up to 26% more likely to be present within 150 m of its location in 1973 (Fig. 11). Proximity to cheatgrass in 1973 was a more influential predictor of cheatgrass presence in 2001 than any other variable we examined. Over the 30 years, cheatgrass was highly likely to expand outward from existing occurrences and to distance of 150 m (Figs. 8, 10).

Risk map

Risk of future cheatgrass invasion was determined using multi-criteria evaluation (MCE) (Schneider and Pontius 2001, Store and Kangas 2001, Store and Jokimaki 2003), which sums the relative probabilities of cheatgrass presence associated with each discrete class for all spatially explicit variables. The highest risk of future invasion occurred adjacent to edges of current invasion, as well as near cultivated areas, power lines, and roads (Fig. 12). Cheatgrass appears unlikely to invade areas at high elevation or at great distance from land use.

DISCUSSION

Management implications

Between 1973 and 2001, the probability of cheatgrass presence increased substantially across the study area, but the topographic and land use characteristics of areas most likely to be colonized had many similarities. Probability of cheatgrass presence was highest between 1400 and 1700 m elevation, on west and northwest facing slopes, and in areas close to disturbance features like roads, power lines, and agricultural fields. In all cases, the strength of specific relationships between predictor variables and probability of cheatgrass occurrence increased between 1973 and 2001. These results suggest that cheatgrass invasion patterns have remained consistent over time, and therefore patterns of past occurrence can be used to predict future risk of invasion.

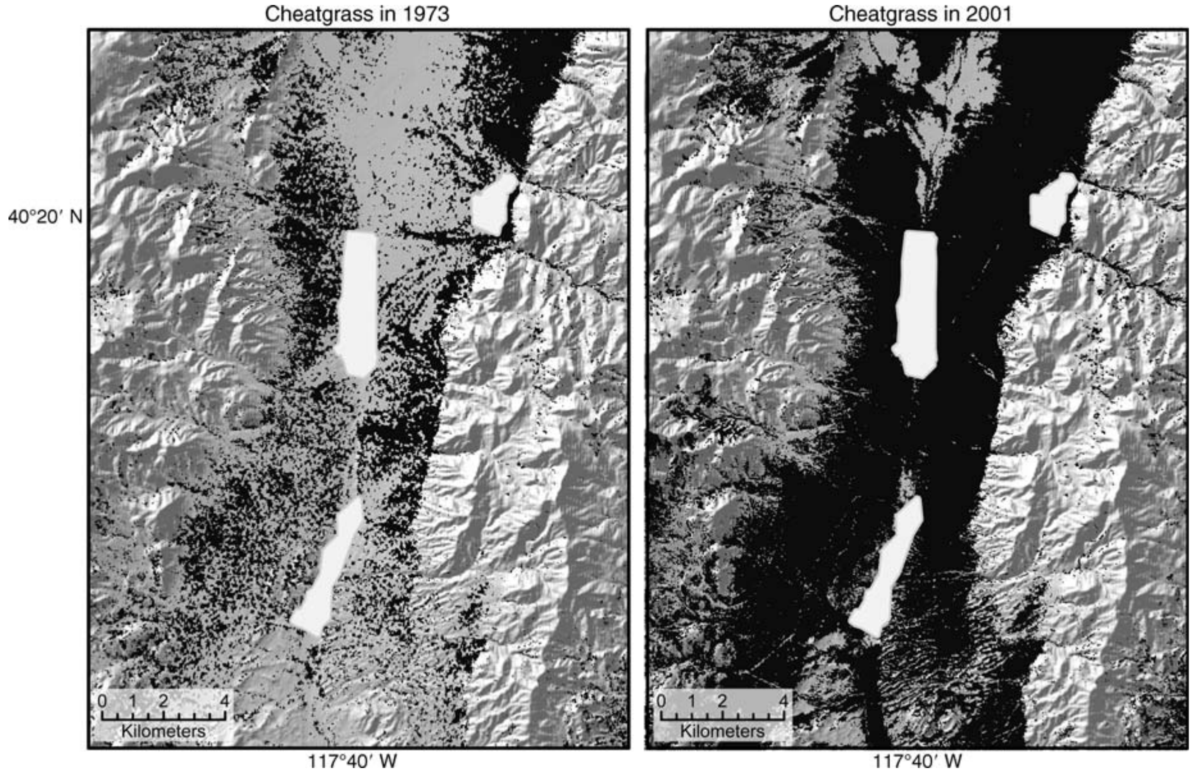

FIG. 10. Cheatgrass presence in 1973 and 2001 shows that initial populations proximal to cultivated areas (light gray) invade to surround cultivated areas by 2001. The background image is shaded relief.

Cheatgrass invasion poses a risk to the economic value and sustainable use of rangelands as well as increasing fire frequency and thereby reducing native biological diversity (Mack 1989, Whisenant 1990). It is vital to consider how current and future land use alternatives might affect the dispersal of cheatgrass seeds and colonization of cheatgrass in high risk areas. Our work suggests that risk is elevated by human land use, and that high risk areas occur adjacent to currently invaded areas. Therefore, active management to treat and reseed cheatgrass monoculture (Ponzetti 1997) should consider proximity to uninvaded, high risk areas to prevent future seed dispersal and colonization. Current presence of cheatgrass can also be used to identify isolated invasions, or foci, which are considered a high priority for management (Moody and Mack 1988, Hobbs and Humphries 1995).

Topographic effects

Elevations between 1400 and 1700 m had an increased probability of cheatgrass presence. However, the probability of cheatgrass presence below 1400 m increased between 1973 and 2001, indicating that cheatgrass has tended to invade lower elevations. Young and Tipton (1990) observed cheatgrass invasion into low elevation desert shrub communities beginning in the 1980s. Initial invasion occurred primarily in higher elevation sagebrush steppe, but later invasion was not limited to those higher elevations. Our results are consistent. Although cheatgrass presence expanded at lower elevations, the relative probability of cheatgrass presence at high elevations above 1700 m declined, indicating that high elevations are at relatively low risk of invasion. However, the ability of cheatgrass to invade lower elevations may suggest that the species can adapt to a range of environmental conditions and expand accordingly.

Contrary to previous work (Billings 1990), we found higher probabilities of cheatgrass presence on west and northwest facing slopes. Billings (1990) found decreased probability of cheatgrass on a south facing slope, and concluded that cheatgrass was poorly adapted to relatively high solar radiation. Across extensive areas, however, we did not detect a north–south gradient of cheatgrass presence. Instead, increased probability of cheatgrass presence on west and northwest slopes may be linked to seed dispersal facilitated by prevailing wind direction (west to east) and rain shadow effects.

Topographic lows created by hydrographic channels, as well as soil types associated with channels, may create favorable micro sites for cheatgrass germination. It is possible that seed dispersal in channels is aided by ephemeral water flow. Channels may also trap wind blown seeds. The influence of channels was low compared to other topographic factors and anthropogenic disturbance, but we may have underestimated probabilities because the width of some cheatgrass-filled

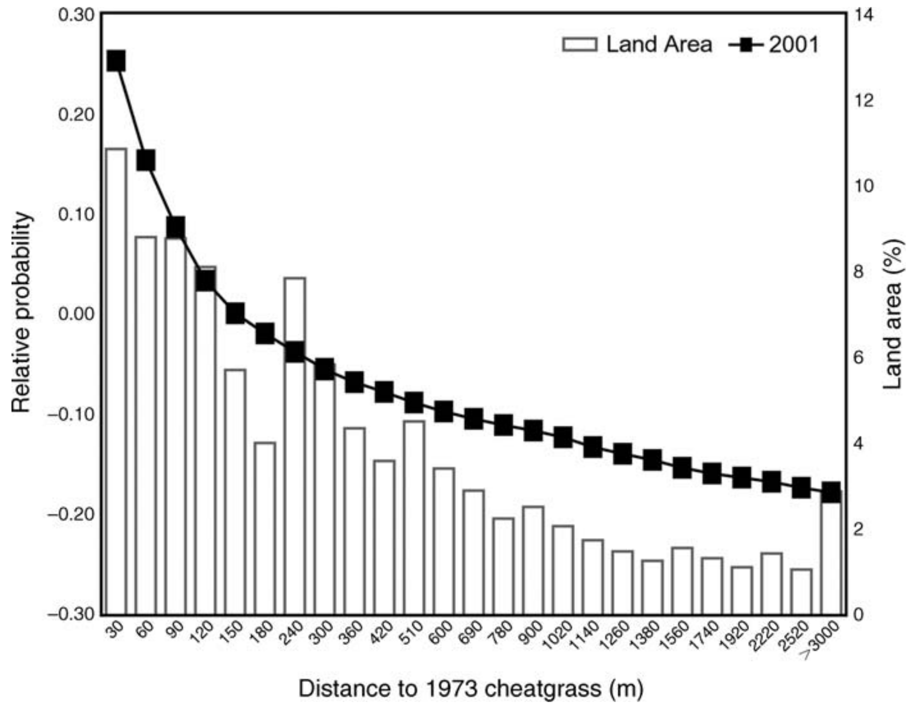

FIG. 11. Relationship between probability of cheatgrass presence in 2001 and distance to cheatgrass present in 1973, with relative land area for each distance class.

channels is too narrow to be detected at the 60 m spatial resolution of Landsat.

Land use effects

The strong relationship between cheatgrass presence and anthropogenic disturbance features such as cultivated areas, roads, and power lines indicates that current invasion reflects past disturbance. Rangelands surrounding cultivated areas are highly susceptible to invasion. Invasion of cheatgrass does not appear to be related directly to agricultural practices, as probabilities of cheatgrass presence were greatest 2–3 km from agriculture. Although previous work has shown that colonization rates of invasive species tend to increase near abandoned agricultural fields (Elmore et al. 2003) as well as within active agricultural fields (Rydrych 1974)**,** the pattern shown here suggests that cheatgrass has expanded toward cultivation rather than away from it. In 1973, cheatgrass was present in foothills surrounding several agricultural fields. By 2001, cheatgrass had colonized the lower-elevation areas surrounding the agricultural fields (Fig. 10). The high incidence of cheatgrass is not likely a result of invasion away from cultivation; however, probability of cheatgrass invasion may be enhanced by grazing and other land uses proximal to human habitation.

Lands adjacent to roads have a high probability of cheatgrass presence. Many studies have linked the presence of invasive species to disturbance caused by roads (Forman and Alexander 1998, Trombulak and Frissell 2000) and suggested mechanisms for invasion including alteration of ecosystem condition adjacent to roads and facilitation of seed dispersal through human (vehicle) and animal vectors. Gelbard and Belnap (2003) showed a positive relationship between roads and cheatgrass, with cheatgrass occurrence increasing with

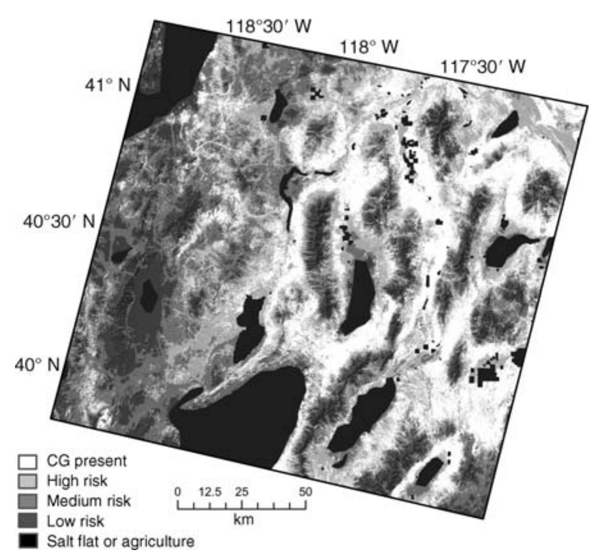

FIG. 12. Risk of future invasion by cheatgrass. Lighter gray areas have a higher probability of cheatgrass presence in the future. White areas contained cheatgrass (CG) in 2001. Black areas are salt flats, urban land, and agriculture.

level of road improvement. In our study, cheatgrass had an increased likelihood of presence up to 700 m from any road. This distance is much greater than typical roadside verge disturbance in the area. Cheatgrass that initially invaded areas directly adjacent to roads may have dispersed over time up to 700 m. Dispersal away from roads may have occurred over a century, as most roads were built for late 1800s mining operations. However, the strengthening of the relationship of cheatgrass presence to roads between 1973 and 2001 suggests that roads continue to facilitate invasion. This strengthening relationship is likely caused by a combination of dispersal away from and along roads invaded in 1973 as well as new invasion fronts along roads disturbed by road improvement and/or increased traffic between 1973 and 2001.

Although power lines are a relatively recent addition to the landscape, their influence on colonization by cheatgrass appears to be even stronger than that of roads. The stronger relationship between cheatgrass presence with recent disturbance (power lines) relative to historic disturbance (roads) indicates that future emplacement of either roads or power lines would very likely result in cheatgrass invasion. The zone of influence of power lines, up to 1 km, is comparable to that of roads. However, dispersal has had much less time to occur from areas directly adjacent to power lines. The emplacement of power lines may create a larger and wider ranging disturbance than road building. The strong relationship of cheatgrass to power lines also suggests that invasion is highly likely in locations where a disturbance occurs near established cheatgrass populations. Regardless of the invasion mechanism, it is clear that human activities in the form of cultivation, road building, and power line emplacement contribute substantially to cheatgrass occurrence.

Distribution changes over time

The best indicator of future invasion of cheatgrass found in this study was proximity to current populations of cheatgrass. Areas within 150 m of cheatgrass in 1973 were up to 26% more likely to contain cheatgrass in 2001 than areas further from cheatgrass. A distance of 150 m seems quite modest for this time period, however, approximately 40% of land area within the study area existed within 150 m of cheatgrass presence in 1973. Invasion as a result of diffusion away from existing populations may have been limited to 150 m because cheatgrass was already occupying the most favorable habitats by 1973 (Mack 1981). Our results imply that disturbance features may increase risk of invasion, but areas close to seed banks will be the first to develop dense cheatgrass populations. This result indicates that while other geographical and land use variables are important for prediction of cheatgrass presence, knowledge of current cheatgrass distribution is critical for prediction of future risk of invasion.

Conclusion

This study demonstrates how empirical relationships between an invasive species, topography, and land use can be established with the aid of remote sensing. An understanding of these empirical relationships and how they change over time is critical for accurate predictions of future risk. Improved risk maps based on spatial relationships, like the ones presented here, contribute to the scientific information base for land management and conservation efforts. Spatial analyses utilizing remotely sensed information about invasive species cover are a much needed link between plot level field studies and landscape scale modeling efforts to better understand and minimize invasion of nonnative species.

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