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ABSTRACT

Cheat grass (Bromus tectorum) invasibility represents a serious threat to natural ecosystems dominated by sagebrush (Artemisia tridentata). Ecosystem susceptibility to annual grass invasion seems to be driven by specific biophysical conditions. The study was conducted in Rich County, Utah, where cheat grass invasion is not yet an apparent problem, but an imminent invasion might be just a matter of time (temporal scale) to meet spatial variations in environmental conditions (spatial scale). Literature review and expert knowledge were used to define biophysical variables and their respective suitability ranges of where cheat grass takeover might occur. GIS, remote sensing and logistic regression-statistical analyses were employed to estimate probability of cheat grass invasion along environmental gradients. GIS procedures were used to spatially predict areas prone to be invaded by cheat grass under present climatic conditions (model prediction power was 47 percent). Afterwards, simulated climatic change projections (for 2099 year) from the Community Climatic System Model (CCSM-3) were used to model the invasibility risk of cheat grass. The 2099 cheat grass prediction map showed a favorable reduction of around 25 percent in the areas affected by cheat grass invasion, assuming that climate changes occurred as predicted by the CCSM model. The location of highly predisposed areas can be useful to alert managers and define where resources might be allocated to reduce a potential invasion and preserve native rangeland ecosystems.

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RESUMEN

El riesgo de invasión de Bromus tectorum representa una grave amenaza para los ecosistemas naturales dominadas por Artemisia (Artemisia tridentata). La susceptibilidad del ecosistema a la invasión anual de este pasto parece ser impulsada por condiciones biofísicas espaciales. El estudio se realizó en el Condado Rich, estado de Utah, donde la invasión de esta especie no es aún un problema aparente, pero una invasión inminente podría ser sólo una cuestión de tiempo (escala temporal) para satisfacer las variaciones espaciales en las condiciones ambientales (escala espacial). Revisión de literatura y el conocimiento de expertos se utilizaron para definir las variables biofísicas la adaptabilidad del pasto. Análisis SIG y teledetección y un análisis de regresión logística se emplearon para estimar la probabilidad de invasión a lo largo de gradientes ambientales. Procedimientos SIG fueron utilizados para predecir espacialmente las zonas propensas a ser invadidas por dicho pasto, bajo las condiciones climáticas actuales (2009) (la precisión del modelo fue de 47 percent). Posteriormente, proyecciones simuladas del cambio climático (para el año 2099) del Modelo del Sistema de la Comunidad Climática (CCSM-3) se utilizaron para modelar el riesgo invasibilidad del pasto. El mapa del 2099 mostró una reducción de alrededor del 25 percent de las áreas afectadas por Bromus tectorum, asumiendo que los cambios climáticos ocurren como predice el modelo CCSM. La ubicación de las zonas predispuestas a la invasión pueden ser útiles para alertar a los administradores y definir los recursos para reducir una posible invasión y preservar los ecosistemas nativos.

INTRODUCTION

Cheat grass (*Bromus tectorum*) arrived from Europe more than a hundred years ago and now it has spread out all over the western US in more than 11 states (Lloyd 1955, West 1999). It can be found in more than 60 millions acres of public and private lands (Wisdom et al. 2005). In the Great Basin desert, it is estimated that cheat grass already covers around 3.3 million acres (Wisdom et al. 2005). The land management implications of invading cheat grass include the loss of prime wildlife habitat, impact to the regrowth of native vegetation following wildland fire events, soil erosion, loss of rangeland health, and the distribution and expansion of other noxious weeds (Harris 1967, Holechek et al. 1989, Lloyd 1955).

Cheat grass invasibility seems to be driven by genetic conditions, intrinsic to the species, and specific biophysical conditions (Mack and Pyke 1983). Cheat grass has a prolific capacity to produce seeds (Suring et al. 2005). It is able to germinate in the fall or spring, is highly tolerant to recurrent fires and to current grazing practices (Chambers et al. 2007, Pellant 1990). Cheat grass also prepares the site conditions to favor its growth and spread rate. After initial fires, for instance, it increases further risk of subsequent, more frequent fires. This brings serious consequences in terms of loss of wildlife and fish habitat, soil erosion and sedimentation and biodiversity (Bradley and Mustard, 2006). Regarding the biophysical conditions, cheat grass tolerates a wide range of climatic and edaphic conditions (Novak and Mack 2001). Land managers are currently seeking to understand its genetic patterns and preferred biophysical conditions (Bradley et al. 2003).

Invasive species may increase as the climate changes through time (Kriticos et al. 2003). Most the world has already experienced substantial increases in temperature and precipitation as a part of the global climate change scenario (Community Climate System Model project 2010, Morris et al. 2002). Subsequent changes in species distribution, either exotic or native, are expected (Higgins et al. 2003). Managers from federal and state agencies recognize the need of using preventive management to forecast species adaptability and new distributions (Bradley and Mustard 2006).

According to Reichler (2009), Utah will experience a substantial increase in temperature and a decrease in precipitation as a part of the global climate change scenario. Northern Utah is expected to have an approximately 10 percent increase in winter precipitation and a 10 percent decrease in summer precipitation. In general it is expected that this area will receive a uniform warming of ~3°F in winter and ~4°F in summer. According to the same source, other climatic changes will include: less snow pack in winter, earlier snow melt in spring and in summer, warming will increase water demand and therefore there will be less water flowing from watersheds. Changes in current climate regimes will allow some species to expand their range, while others may be restricted to a narrow range, showing so far many sources of uncertainty (Higgings et al. 2003). To our knowledge, no other efforts have been made to assess ecological changes in cheat grass distribution given a hypothetical scenario of global climate change in Northern Utah using a GIS/remote sensing approach.

The proposed research questions for this study were:

> Does cheat grass represent a threat in Rich County, Utah?
>
> If it does, where are the areas prone to be invaded spatially located?
>
> What are the environmental variables that favor cheat grass establishment?
>
> Will there be any change in its spread as a result of an expected climate change?

METHODS

Study Area

The study area was located in Rich County, Utah (figure 1). The area presents an elevation gradient from 1,500 to 2,100 meters above sea level, from East to West. Precipitation places the area in a semi-arid zone, receiving from 200 to 300 mm per year and temperature will usually range between -40 degrees C to 40 degrees C.

The rangelands of Rich County in Northern Utah are largely characterized by having vegetation dominated by sagebrush (*Artemisia* spp.) with associated native and introduced grasses (Shultz 2009), salt desert scrub and pinyon-juniper ecosystems, and other major vegetation types (Washington-Allen et al. 2004). Rich County is best characterized as a higher elevation big sagebrush-steppe / shrubland environment ranging from the pinyon-juniper ecosystems to sub-alpine forests and meadows. These areas have been under commercial agriculture, and grazing for years.

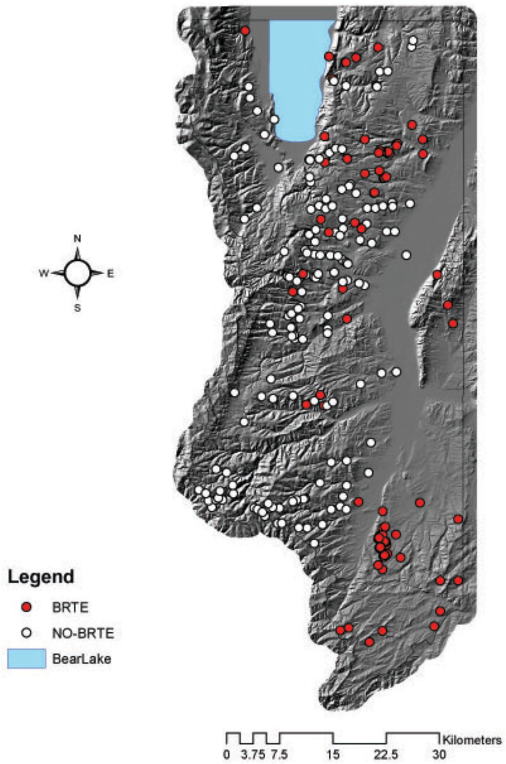

Figure 1. Sampled sites for Cheatgrass (dark color) and Non-cheatgrass sites (white) in Rich Co., UT.

Some big sagebrush ecosystems have converted to exotic annual grasslands or to pinyon-juniper dominance, while an equal area has maintained its natural condition (West 1999). Within shrub-steppe, dominant shrub species included Wyoming big sagebrush (*A. t. wyomingensis*), mountain big sagebrush (*A. t. vaseyana*), basin big sage (*A. t. tridentata*), black sage (*A. nova*), antelope bitterbrush (*Purshia tridentata*), snowberry (*Symphoricarpos* spp.), Utah serviceberry (*Amelanchier utahensis*), rubber rabbitbrush (*Ericameria nauseosus*) and yellow rabbitbrush (*Chrysothamnus viscidiflorus*) (Stringham 2010). Perennial forbs and annual grasess are established following mechanical land treatments to alter woody species abundance and continued heavy livestock grazing. With continued impacts from heavy livestock grazing and mechanical removal of native shrubs, the native grass component is markedly decreased. This plant community is characterized by some grazing tolerant herbaceous species, including cheat grass.

Methodology

Current Scenario 2009

Field data were acquired in summer of 2007. Field forms were developed in a Microsoft Access database to record GPS coordinates and photos of field sampling locations. A total of 286 field samples were collected from different sources: 50 percent cheat grass, 50 percent no-cheat grass samples. The 143 samples of non-cheat grass sites were taken mostly from the Southwest GAP Analysis project (Lowry et al. 2005). The cheat grass samples were collected by the main author of this paper (S. Rivera), by the T. Edwards' Lab at USU (Edwards and Howe 2009) and by USU RS/GIS Laboratories (Peterson et al. 2008). These data were used as field-input data in these analyzes. Data layers were produced by clipping raw data layers to a 1 km buffered Rich County boundary, and then scaling by standard deviation. The standard deviations were multiplied by 100 and rounded to the nearest whole number. Spatial data was manipulated using ArcGIS ver 9.2, and environmental data was extracted (drilling) from each layer and the R software was used to study potential relationships, linearity, normality and redundancy among variables.

Table 1 shows all explanatory variables used in this study. Most remote sensing derived data were obtained from a Landsat TM scenes taken in 2006. Data manipulation and analyzes were done mostly using the software Erdas Imagine version 8.5. All layers and data points were arranged in ArcGIS ver 9.2 GIS software. Data overlapping and sampling ("drilling"); the xy points into the layers were used in Arc GIS using the sampling function in the spatial analysis toolbox. The Raster calculator was used to draw the spatial distribution based on the resulting logistic model.

Scenario 2099 (A2)

The climate change A2 scenario is considered the worst case scenario if the current world's policies continue and no special actions are taking to combat global warming or environmental change issues (Morris et al. 2002). Climate change projections have been developed by the Community Climate System Model (CCSM-3) on a Gaussian grid, which is commonly used in scientific modeling (Community Climate System Model project 2010). We selected these GIS layers for northern Utah for total annual precipitation (ppt) and average temperature (ta) for 2099 (Thornton and Wilhelmi 2010). Currently, the datasets can be downloaded in a GIS *shapefile* format, where each point represents a centroid of a corresponding CCSM grid cell (IPCC 2007).

Table 1. List of potential explanatory variables used in this study.

Variable	Explanation
Aspect	Aspect, as computed by ArcMap [-1 = flat]
Elevation	Elevation from the USGS National Elevation Data Set (m).
Normalized Difference Vegetation Index (NDVI)	Reflectance at peak, sampling points selected form non-anthropogenic influence sites, Mean annual NDVI changes over the years for a particular site, a composite of maximum.
Slope curvature	Curvature from r_ned_dem calculated by ArcMap (positive values=convex slope, negative values=concave slope)
Northness	Northing coordinate, NAD83, Zone 12Y UTM coordinates (meters)
Eastness	Easting coordinate, NAD83, Zone 12X UTM coordinates (meters)
Slope	Slope from elevation data set (degrees)
Solar flux index	Annual average solar flux calculated using Zimmerman solar radiation model on r_ned_dem and using Dayment monthly temperature grids (kJ/sq.m/day).
Slope contributing area	log of upslope contributing area calculated using Tarboton "Tau DEM" ArcMap plug-in (ln(m))
Relative humidity	Average annual relative humidity grids calculated from Daymet grids (ranging from 0-100%).
Land form	The 10 landform classes were from 1 to 10: 1) Valley flats, 2) Gently sloping toe slopes, 3) Gently sloping ridges, fans and hills, 4) Nearly level terraces and plateaus, 5) Very moist steep slopes, 6) Moderately moist steep slopes, 7) Moderately dry steep slopes, 8) Very dry steep slopes, 9) Cool aspect scarps, cliffs and canyons, and 10) Hot aspect scarps, cliffs and canyons (Manis et al. 2001).
Temperature	Average annual temperature calculated from Dayment grids (1/100 C).
Precipitation	Sum of annual precipitation grids calculated from Daymet grids (1/100 cm)

Both temperature and precipitation files were downloaded from the CCSM data site (Hoar and Nychka 2008) and then data were clipped using the Rich county shapefile and re-projected. We ran a Kriging interpolation analysis to calculate the temperature layers, the average annual temperatures based on the monthly average temperature. For the precipitation file, a new field was created to calculate the sum of the monthly precipitations to obtain the total annual precipitation. The Kriging method utilized was the Universal method with a linear with linear drift semivariogram model (Gebhardt 2003).

It is important to mention that climate models like these are not like weather forecast models. They do not project specific events at the exact time these events occur (like the 1997 El Niño). The CCSM control runs are designed to show internal model variability, by having fixed external forcing. They are more random and statistical representation of such events rather than actual (Community Climate System Model project 2010).

Sampling

All cheat grass and non-cheat grass events or point data sampling was conducted in all 13 layers variables described in Table 1. The *Sample* spatial analysis function of Arc GIS ver. 9.2 was used to conduct the “drilling” of all layers. The re-sampling algorithm used when re-sampling these raster layers was the nearest neighbor assignment.

Logistic Regression Model

Logistic regression has been used to predict the absence or presence of a particular species (Austin 1985, Dixit and Geevan 2002). A logistic regression model was developed, extracting the information from the “drilling” process in ArcGIS ver. 9.2 using the raster calculator function. The logistic regression model is as follow (equation 1):

$$P = \frac{e^{a + b X}}{1 + e^{a + b X}}$$

OR

$$P = \frac{1}{1 + e^{(\beta 0 + \beta 1 * X1 + \beta 2 * X2 + \ldots + \beta k * Xk)}}$$

Equation 1. Logistic regression model.

Where β0 is a constant and βi are coefficients of the predictor variables. The computed value, P, is a probability between 0 to 1. This logistic model LM (generalized linear model GLM) was used to simulate the present/absence of studied species (Fielding and Bell 1997). The presence of cheat grass was considered a success or 1, and the absence a failure or 0.

Model Accuracy

In thematic mapping from geo-referenced data, the term accuracy is used typically to express the degree of 'correctness' of the predicting model (Foody 2002, Gilbert et al. 2005). Model accuracy assessment was performed in this study to compute the probability of error for the cheat grass prediction map (2009). Samples were "drilled" into the final prediction map to determine which samples fell correctly into the modeled classes (Lowry et al. 2008). In the 2009 prediction map: 50 percent was taken as the cut off number. Below 50 percent was considered as an absence and values higher than 50 percent were considered as presence values. A total of 69 samples (20 percent of all samples) were previously withheld randomly for the accuracy assessment. Procedure involved the use of Arc GIS ver 9.2 and the spatial analysis tool: sampling.

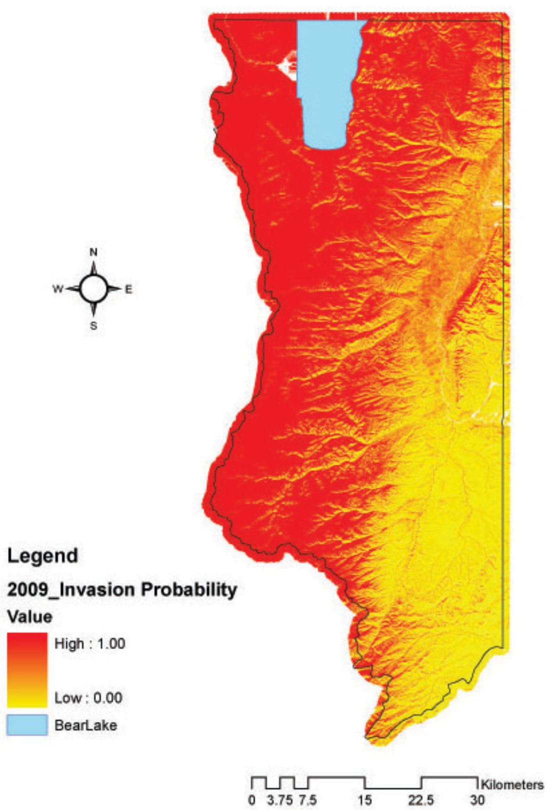

Figure 2. Distribution of 2009-cheat grass and non cheat grass sampling points along the Precipitation 2009 (1/100cm) gradient, Rich County, Utah.

RESULTS AND DISCUSSION

Decrease of Cheat Grass Invaded Areas

Final results showed that there is a decrease of around 20 percent in the 2099 cheat grass invasibility map (figure 2) when compared to the 2009 cheat grass invasibility map. In this case, we observed that the speed of propagation of this invasive species is being restricted by the climatic conditions that are predicted for the 2099-A2 scenario and other studies (Sardinero 2000). In other words, less precipitation, higher temperatures can produce a stress in plant species and reduce the presence of certain species.

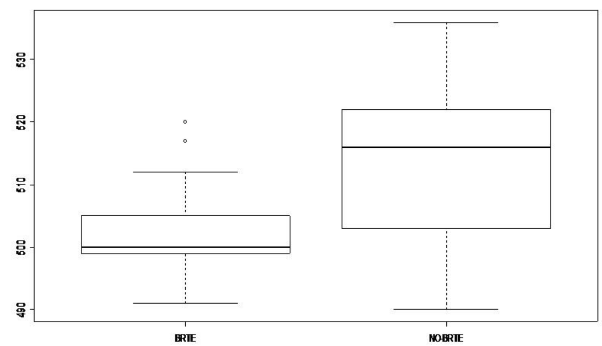

Figure 3. Distribution of 2009-cheat grass and non cheat grass along the NDVI in Rich County, Utah.

Significant Environmental Variables

Final results showed that current (2009) cheat grass distribution in the rangelands in Rich County, may be driven by elevation (α =0.001), solar flux index (α =0.001), relative humidity (α =0.001) and temperature (α =0.001). Slope contributing area also showed some statistical significance (α =0.1) (table 2).

Results of logistic regression analyzes of climate change scenario for cheat grass prediction model in 2099 are shown in Table 3. The highly significant variables were: elevation (α =0.001), solar flux index (α =0.001), temperature 2099 (α =0.001) and precipitation 2099 (α =0.001). The land form category also showed some statistical significance (α =0.1).

In the logistic regression (figure 3), the final model was statistically significant for the following environmental variables: precipitation, temperature, slope contributing area, NDVI and solar radiation. All studied variables and their relationships with the shrub species are described below:

Precipitation: The main driver of presence was humidity at each site. Figure 4 shows that the cheat grass sites receive smaller amounts of precipitation: These sites are generally located at lower elevations.

NDVI: The Normalized Difference Vegetation Index is an indicator of the amount of greenness reflected by the vegetation. Figure 5 shows that the cheat grass sites had lower greenness values when compared with the other plant species.

Relative humidity: Is a measure of atmospheric moisture availability at each site. Figure 3 shows that cheat grass sampling sites showed a lower relative humidity compared with the other types of vegetation.

Elevation: Cheat grass samples were found at lower altitudes between 2,000 and 2,100 meters above sea level, whereas other species were generally found at higher elevations (figure 6).

Table 2. Results of logistic regression analyzes of climate change scenario for the 2009-cheat grass prediction model.

Variable	Statistical significance
Aspect	
Elevation	*** (α =0.001)
Slope curvature	
Northness	
Eastness	
Slope	
Solar flux index	*** (α = 0.001)
Slope contributing area	. (α = 0.1)
Land form	
Relative humidity	*** (α = 0.001)
Temperature 2009	*** (α = 0.001)
Precipitation 2009	

These results are very consistent with the literature findings that cheat grass invasibility varies across elevation gradients and appears to be closely related to temperature at higher elevations and soil water availability at lower elevations (Chambers et al. 2007). In addition, the environmental variables identified as significant were consistent with qualitative requirements of the cheat grass's habitat characteristics. This agreement makes this study comparable to other studies of predicting the invasion of exotic weeds (Collingham 2000). By knowing this, a high agreement between environmental variables, values and species requirements may increase the power of forecasting potential invasions as described by Gilbert (2005).

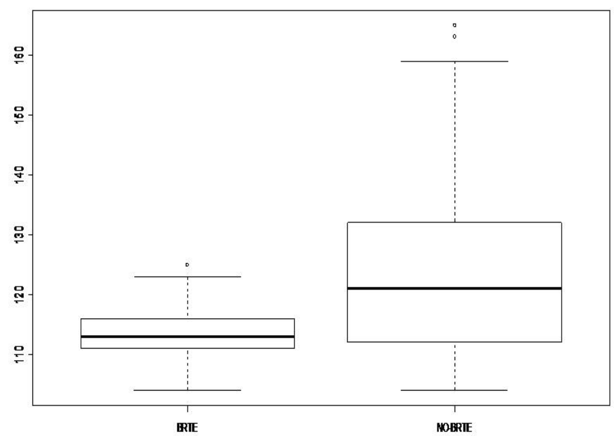

Figure 4. Distribution of 2009-cheat grass and non cheat grass along the Relative Humidity in Rich County, Utah.

Model Validation

The overall accuracy for the 2009 cheat grass distribution model was 31 percent; 46.9 percent for the cheat grass (BRTE) sites and 16.7 percent for the non cheat grass (NO-BRTE) sites (table 4: the confusion matrix and the overall classification accuracy). This indicates that from all withheld sites 47 percent of the cheat grass sites fell correctly into that class in the predicted model. The second analyzed class; non cheat grass species had only 17 percent accuracy. In general, the model performed better at predicting the cheat grass sites. The model also identified a clear and logical distribution pattern along the environmental gradients of elevation, temperature and precipitation. A visual validation was also performed using expert knowledge and field observations. Final distribution was corroborated by experts (Shultz 2010, personal communication) that agreed that final distribution satisfies observed natural distribution tendencies.

The 2099 prediction model could not be validated, since there is no current tool to conduct a validation into a future land cover model.

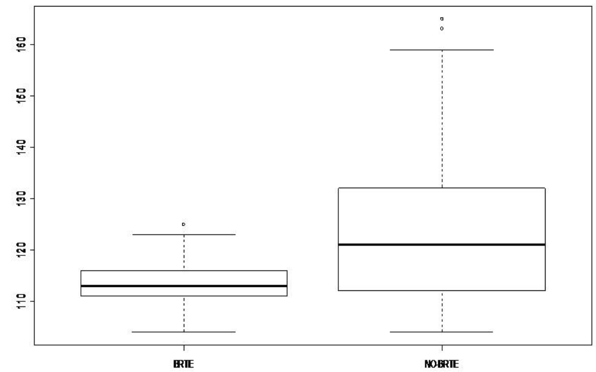

Figure 5. Distribution of 2009-cheat grass and non cheat grass along the elevation (meters) gradient in Rich County, Utah.

Table 3. Results of logistic regression analyzes of climate change scenario for the 2099-cheat grass prediction model.

Variable	Statistical significance
Aspect	
Elevation	*** (α =0.001)
Normalized Difference Vegetation Index (NDVI)	n/a
Slope curvature	
Northness	
Eastness	
Slope	
Solar flux index	*** (α = 0.001)
Slope contributing area	
Land form	. (α = 0.1)
Relative humidity	n/a
Temperature 2099	*** (α = 0.001)
Precipitation 2099	*** (α = 0.001)

CONCLUSIONS

Our data indicate that the main driving factors on cheat grass invasion under present conditions are: elevation, temperature, precipitation, NDVI, and relative humidity (figure 7). We can also conclude that under the expected changes in climatic conditions cheat grass establishment will be favored, agreeing literature on analyzing cheat grass propagation and expansion in the Intermountain West, over the past several decades (Bradley et al. 2003, Chambers et al. 2007).

Our data also indicate that the main driving factors on cheat grass invasion under the climate change conditions of scenario A-2, 2099 are: elevation, temperature, precipitation, and relative humidity. In general, again wetter and warmer climatic conditions favor cheat grass establishment, confirming the finding of previous studies (Young and Clements 2007) and personal observations (Shultz 2009) which characterized cheat grass as an opportunistic species.

Table 4. Error matrix of the 2009- cheat grass prediction model and reference data.

Predicted Data	Reference data	
	BRTE	NO-BRTE
BRTE	46.9%	83.3%
NO-BRTE	63.1%	16.7%
% per specie	46.9%	16.7

Overall classification = 31%

It is important to mention that this modeling only predicts cheat grass invasibility based on future climatic condition and does not take into account the probable increase of fires or any changes in management strategies, especially grazing, whose combined effect could potentially trigger a cheat grass spread. The combined effect of fire and grazing, which implies the reduction in of native species, has been identified as significant factors for the growth and reproduction of cheat grass (Chambers et al. 2007).

This study demonstrates the effective use of GIS and remote sensing tools to describe and predict potentially spatial changes in vegetation at the landscape level. Older modeling prediction techniques provided little spatial information of where plant species distribution could be expected to be located in heterogeneous landscapes. GIS and Remote Sensing techniques combined with statistical analyzes, offer a promising tool to place plant distributions along environmental gradients, and thus providing important knowledge of where management efforts might be efficiently directed to mitigate the negative aspects of such possible vegetation change.

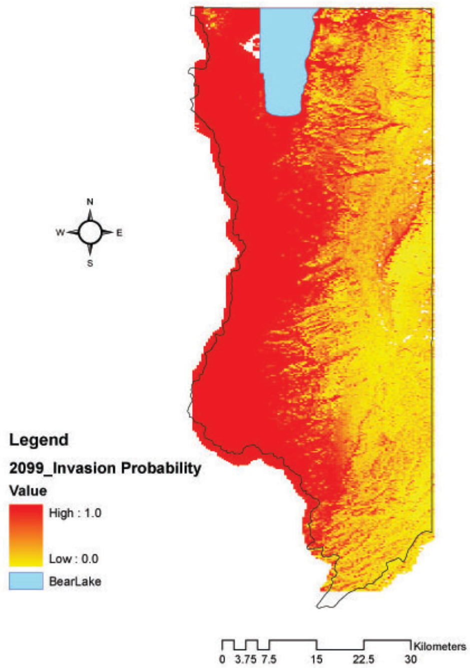

Figure 6. Map of the 2099-cheat grass invasibility model in Rich County, Utah.

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