

## **Forecasting Rangeland Condition in Southeastern Idaho using GIS**

Keith T. Weber, GISP. GIS Director, Idaho State University GIS Training and Research Center, 921 S. 8<sup>th</sup> Ave., Stop 8104, Pocatello, Idaho 83209-8104

### **ABSTRACT**

In light of concerns regarding global climate change, biodiversity loss, and desertification, the monitoring and accurate forecasting of land cover change is an important and yet challenging endeavor. The climatic variability observed in semi-arid and arid ecosystems makes accurate predictive models increasingly challenging over even short time periods. This study used Idrisi Land Change Modeler to develop predictive rangeland condition models for 2008 (short-term) and 2012 (long-term) for semi-arid rangelands in southeast Idaho using imagery from 2003 and 2007. The short-term model was validated using imagery acquired in 2008 resulting in poor overall accuracy (0.49). The observed performance may not be indicative of the potential of Idrisi software, however it was concluded that accurately forecasting change in semi-arid ecosystems requires the use of multiple years of input data to correctly establish variance and trend. The predicted rangeland condition model for 2012 will be validated at a later time and its accuracy is expected to be dependent upon the similarity of 2012 precipitation relative to the precipitation patterns of 2003 and 2007.

*KEYWORDS: Predictive modeling, cellular automata, artificial neural networks, precipitation variability*

## **INTRODUCTION**

Rangelands occupy a large portion of the earth's land surface (Huntsinger and Hopkinson 1996, Branson et al. 1981) and are home to many species of plants and animals uniquely adapted to semi-arid ecosystems (IUCN 2006). Semi-arid rangelands, while marginal and frequently undesirable for cultivation, are important areas of livestock production throughout the world. However, due to the very same characteristics that lends them to livestock production (e.g., unreliable and seasonal precipitation, rocky soils, and steep slopes); rangelands tend to be brittle environments (Savory 1999) with increasing concerns for biodiversity loss and desertification. Traditional scientific investigation – and perhaps human nature itself—seeks to solve complex problems by subdividing the problem into manageable pieces and the simple fact that numerous scientific disciplines exists bears out this observation (Funtowicz and Ravetz 2003). In range science, land degradation has typically been attributed to overgrazing with very little scientific inquiry investigating alternative hypothesis or testing this assumption relative to over-rest. Consequent to observed land degradation –regardless of its cause—a classification describing the degree of degradation was needed to facilitate comparison with future assessments used to describe a trend and/or the effect of remediation (Washington-Allen et al., 2006). To facilitate discussion and communication processes such as these required names and in this case, the terms rangeland condition (Bedell 1998) and later, rangeland health (National Research Council 1994) were coined. Regardless of the original intent, applied terms always take on varying “flavors” as they are learned by others and used by others in subsequent communications. In some cases, terms become buzz-words and ultimately lose much of their original intent.

Regardless of the term applied to the process, assessing the degree of land degradation is important. In this study, the term rangeland condition was used with no additional “baggage” intended. To help quantify landscape condition and avoid qualitative assessment, satellite imagery was used. Two condition states were produced, the first at an “early date” and the second at a “later date”. Using these condition states and the change in condition over time, trend is established. Once a trend has been established the possibility to forecast condition into the future is possible assuming all treatment and environmental variables remain along the same trend vector. Herein lies the crux of such a simplistic approach, for it is unlikely that the environmental conditions which helped create the current condition will remain static in the future (precipitation, temperature, and the interaction of these two variables over time). Further, in the face of known degradation, it is equally unlikely that no change in land use or land tenure (Cummins 2009) will be effected as well.

For these reasons, forecasting change is an important and challenging endeavor (NCSE 2005) and numerous techniques have been developed. In general, predictive land use and land cover (LULC) models can be categorized as either 1) an equation-based, 2) statistical 3) matrix-based, 4) system, 5) expert, 6) evolutionary, 7) cellular automata, 8) agent-based, 9) multiple agent-based, or 10) a hybrid model (Parker et al. 2003).

Equation-based models apply mathematical equations or algorithms to arrive at an assumed stable state of equilibrium which is both derived and solved mathematically (Sklar and Costanza 1991; Chuvieco 1993). Statistical models differ from equation-based models in that they tend to rely upon various forms of regression analyses to predict LULC (Ludeke et al 1990). By comparison, matrix-based models use matrix algebra and focus upon transition potentials to arrive at a prediction of future LULC (Sonis et al.

2007) while system models portray change as a flow from one step to another with various linkages between the steps that allow for interaction or feedback (Sklar and Costanza 1991). Expert models differ from the computationally intensive methods above in that they apply expert knowledge, rules, and probability to achieve a predicted LULC. Whereas expert models frequently apply Bayesian or Dempster-Schaefer theory (Eastman 1999), evolutionary models rely upon artificial neural networks (Mann and Benwell 1996) to make similar predictions of LULC.

Cellular automata models operate over a grid of cells which change over time due to both transition potentials and/or interaction of the focal cell with adjacent cells. Transition potentials are frequently modeled using Markov chain, a stochastic process that determines the future state of a cell based upon the present state of the cell and independent of the past state(s) of the cell (Li and Reynolds 1997). Two criticisms of cellular automata models are 1) they do not model human decisions or human agents (Parker et al. 2003) explicitly and 2) they are unlikely to correctly predict future states as the transition potentials do not account for political or other anthropic forces (Soares-Filho et al. 2002).

Agent-based models focus upon human actions which impact LULC by following a set of rules or behaviors. In contrast to cellular automata, agent-based models may fail to accurately model LULC by overstating the impact due to anthropic forces. One solution to the problems and criticisms of both cellular automata and agent-based modeling is the use of multiple agent-based models which apply cellular automata to predict the biophysical characteristics of a landscape along with agent-based modeling to describe the human decision-making process. In this way, multiple agent-based models may be able to accurately predict future LULC.

The application of LULC change models to semi-arid rangelands is not new. Li and Reynolds (1997) used cellular automata to model rangelands while others have modeled LULC change on rangelands using state-and-transition models (a system-based model) (Westoby et al. 1989; Laycock 1991; Bestelmeyer et al. 2003). Regardless of the specific approach taken, modeling LULC change on semi-arid rangeland is particularly challenging due to the high variability of precipitation and its cascading affects throughout the rangeland ecosystem (IUCN 1989; Khazanov 1994; Niamir-Fuller and Turner 1999). The present study sought to investigate predictive LULC change models for semi-arid rangelands using state-of-the-art software by first creating a short-term prediction of change and then validating that prediction using field observations/ measurements and satellite imagery collected during the time period of prediction. This paper describes the predictive modeling process, validation process, and the implications for future research and range management.

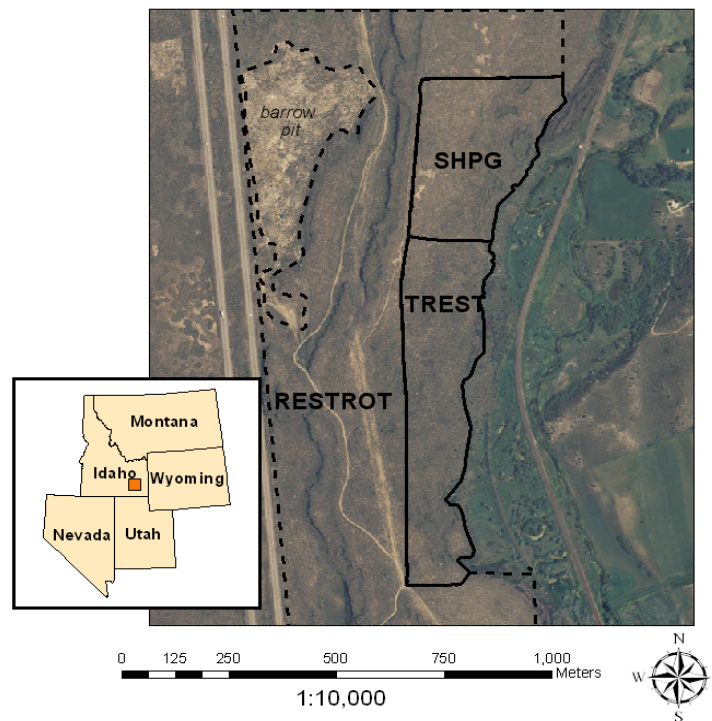
## **MATERIALS AND METHODS**

### *Study Area*

The O'Neal Ecological Reserve is an area of sagebrush-steppe rangelands in southeastern Idaho approximately 30 km southeast of Pocatello, Idaho (42° 42' 25"N 112° 13' 0" W), where many local-scale rangeland studies are being conducted (Figure 1). The O'Neal Ecological Reserve (<http://www.isu.edu/departments/CERE/o'neil.htm>) was donated to the Department of Biological Sciences at Idaho State University by Robin O'Neal. The O'Neal receives < 0.38 m of precipitation annually (primarily in the winter) and is relatively flat with an elevation of approximately 1400 m. The dominant plant species include big sagebrush (*Artemisia tridentata*) with various native and non-native grasses and forbs,

including Indian ricegrass (*Oryzopsis hymenoides*) and needle-and-thread (*Stipa comata*). Soils in the O'Neal study area are homogeneous and of the McCarey series-McCarey variant soil association. These shallow, well-drained soils lie over basalt flows and were originally formed from weathered basalt, loess, and silty alluvium (USDA NRCS 1987).

Three treatment pastures exist at the O'Neal Ecological reserve. The first was a simulated holistic planned grazing (SHPG) pasture where cattle graze at high density (66 AU/ 11 ha) for a short period of time (6 days) during the first week of June each year (2006-2008). The second treatment was a rest-rotation (RESTROT) pasture where cattle graze at low density (300 AU/ 1467 ha) for long periods of time (30 days) during the month of May each year. By following this grazing schedule, both production pastures were grazed at as near the same time as was logistically possible. The third treatment was a total rest (TREST) pasture (13 ha) where no livestock grazing has occurred since June 2005.



**Figure 1. The O'Neal Study Area in southeast Idaho is comprised of three treatment pastures, simulated holistic planned grazing (SHPG), rest-rotation (RESTROT), and total rest pastures (TREST).**

While many changes to the landscape are attributable to the environment (e.g., drought) (IUCN 1989) others may be attributable in varying degrees to anthropic forces, or rather, the effect of the human decision-making process (Khazanov 1994, Seligman. and Perevolotsky 1994, Niamir-Fuller and Turner 1999, Hill 2006). For instance, experiments already completed at the O'Neal study area have demonstrated the effect of both the environment (precipitation) and management treatment on soil moisture (Weber and Gokhale 2010). In this case, the SHPG pasture resulted in statistically higher soil moisture levels even when no difference existed in soil association or percent cover of shrubs, grasses, and bare ground. Indeed the only difference between these experimental pastures was the applied treatment and a resulting higher level of litter cover caused by the trampling activity of livestock. It was anticipated that the three treatment pastures will be forecast to diverge over time as a result of differences in land use.

*Satellite Imagery*

To forecast the future condition of a specific rangeland site it is beneficial to know both past and present conditions. To accomplish this, a minimum of two datasets are required: 1) an early land cover or land condition layer (D1) and 2) a later or present land cover/land condition layer (D2). With these data, trend *can* be established however the resulting perfect trend (two data points will be fit by a straight line resulting in an  $R^2$  of 1.00) will be unable to account for the many perturbations between D1 and D2 as no other data are available. Ideally then, additional datasets will be available which describe land cover/condition between D1 and D2. For this specific study, satellite imagery was used to describe land cover/condition at the O’Neal study area.

An understanding of the phenology and vegetation community at the specific rangeland site being modeled (i.e., the O’Neal study area) is also beneficial. With this information, the analyst will be able to select datasets that are phenologically similar (Weber 2001) and thereby less complicated to compare to other datasets and establish a reliable trend. To illustrate, one can imagine being given a photograph taken in spring and comparing that photograph to another –of the same location—taken in late summer. The conclusions deduced from the study of such photographs would lead a person to believe that some dramatic changes have occurred (they have) and to erroneously establish a trend line that when forecast to future dates would lead to gross errors in prediction. To minimize this error, imagery was phenologically synchronized (cf. calendar-date synchronization) as well as logistically possible.

With the above considerations in mind, Landsat 5 TM and Satellite Pour l’Observation de la Terre 5 (SPOT 5) imagery were acquired between the years of 2003 and 2008 for the O’Neal study area (Table 1). All imagery was corrected for atmospheric effects using Idrisi Andes software and the Cos(t) methodology (Chavez 1996).

**Table 1. Satellite imagery acquired to model land cover/condition, forecast, and validate future condtion.**

<b>Year</b>	<b>Date</b>	<b>Satellite platform</b>
2003	August 24	Landsat 5 TM
2004	August 10	Landsat 5 TM
2005	August 13	Landsat 5 TM
2006	September 26	SPOT 5
2007	September 15	SPOT 5
2008	August 18	SPOT 5

*Image Processing*

Using atmospherically corrected imagery, normalized difference vegetation indices (NDVI) (Rouse et al. 1973; Tucker 1979) were calculated for each year. In addition, a moving standard deviation index (MSDI) was calculated for each year (Tanser 1997) using the red band from either Landsat 5 TM or SPOT 5 imagery.

All NDVI and MSDI layers were then tested for georectification error and co-registered (Weber 2006; Weber et al. 2008) to one another using 2004 National Agricultural Imagery Program (NAIP) 1 m aerial imagery as the reference layer. First order affine georectification was performed using ESRI ArcGIS software with nearest neighbor resampling. The resulting root mean square error (RMSE) did not exceed

the size of ½ pixels (Weber 2006) and both georectification and co-registration was considered successful with minimal error propagating into subsequent analysis.

All Landsat-derived NDVI and MSDI layers (2003-2005) were resampled using nearest neighbor methodology to 10m spatial resolution to match the resolution of the SPOT-derived layers. While this process unnecessarily inflated the size of the Landsat layers it also allowed for us to retain all data in the SPOT layers used in 2006-2008. Lastly, all layers were windowed to the extent of the O'Neal study area to reduce processing time and confine forecasting results to the three treatment pastures that comprise the study area.

#### *Rangeland Condition Classification*

Annual NDVI and MSDI layers for the O'Neal study area were evaluated to determine a rangeland condition score following Tanser and Palmer (1999). In the present study, a matrix was applied to each NDVI and MSDI layer to re-classify each pixel relative to its land degradation status where NDVI values < 0.44 were considered degraded as were MSDI values > 0.032 (Tanser and Palmer 1999; Jafari et al. 2008). The annual rangeland condition score was determined by evaluating the above degradation status values and pixels were assigned: one (1) where both the NDVI and MSDI models indicated a degraded status, two (2) when the NDVI model indicated degradation but the MSDI model indicated non-degraded (good) condition, three (3) when the MSDI model indicated degradation but the NDVI model indicated good condition, or four (4) when both the NDVI and MSDI models indicated good condition. The resulting rangeland condition layer was used as the input land cover for subsequent forecasting models.

#### *Land Cover Change Forecasting*

Idrisi Andes software was selected to perform LULC forecasting using its land cover change modeler (LCM). The LCM process begins by calculating land cover change analysis using known/past change. To complete this process two image layers are required (i.e., early [2003] and later [2007] layers). The land cover change analysis routine calculates spatial trend which is used later in the forecast process. Next, transition potentials are determined and site and driver variables examined for their explanatory power. Once site and driver variables have been determined, a transitions sub-model is calculated. Using the derived models and input layers a predicted land cover layer is created using a multi-layer perceptron neural network.

The LCM was run twice in this study. First to produce a short-term forecast of change (2008) which was validated using data and imagery collected in 2008 and second to produce a long-term forecast of change (2012).

#### *Validation*

The short-term forecast of change was developed to predict land cover (i.e., rangeland condition score) in 2008. This forecast was validated using NDVI and MSDI layers acquired in 2008 and processed to determine actual rangeland condition score following the process described above. The actual rangeland condition layer was then compared to the forecast rangeland condition layer and an error matrix produced along with the Kappa index of agreement. In addition, a qualitative assessment of the forecasts was made by treatment pasture to better understand the predicted trend of change at the O'Neal study area.

**RESULTS AND DISCUSSION**

Validation of the 2008 forecast model reveals an overall accuracy of 49% (Table 2), producer accuracies ranging from 3% to 72%, and user’s accuracies ranging from 20% to 58%. These results are poor and leave little hope for a successful forecast in 2012. Similar forecast results were observed within each treatment pasture (Table 3a-c) illustrating consistency of the LCM technique as well as its inaccuracy.

**Table 2. 2008 predicted range condition score relative to actual range condition score for the O’Neal study area.**

<b>Range Condition Score</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>Sum of pixels</b>	<b>User's accuracy</b>
<b>1</b>	7284	2664	73	81	10102	0.72
<b>2</b>	4009	8638	10	19	12676	0.68
<b>3</b>	4617	2807	222	589	8235	0.03
<b>4</b>	1468	710	124	173	2475	0.07
<b>Sum of pixels</b>	17378	14819	429	862	33488	
<b>Producer accuracy</b>	0.42	0.58	0.52	0.20	<b>Overall accuracy</b>	0.49

**Table 3. 2008 predicted range condition score relative to actual range condition score for the SHPG treatment pasture (A), RESTROT treatment pasture (B), and TREST pasture (C).**

<b>A. Range Condition</b>						<b>User's accuracy</b>
<b>Score</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>Sum of pixels</b>	
<b>1</b>	281	214	0		495	0.57
<b>2</b>	62	341	0		403	0.85
<b>3</b>	71	92	0		163	0.00
<b>Sum of pixels</b>	414	647	0		1061	
<b>Producer accuracy</b>	0.68	0.53	0.00		<b>Overall accuracy</b>	0.59

<b>B. Range Condition</b>						<b>User's accuracy</b>
<b>Score</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>Sum of pixels</b>	
<b>1</b>	1785	561	0	0	2346	0.76
<b>2</b>	695	4469	0	0	5164	0.87
<b>3</b>	900	402	0	0	1302	0.00
<b>4</b>	62	23	0	0	85	0.00
<b>Sum of pixels</b>	3442	5455	0	0	8897	
<b>Producer accuracy</b>	0.52	0.82	0.00	0.00	<b>Overall accuracy</b>	0.70

<b>C. Range Condition</b>						<b>User's accuracy</b>
<b>Score</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>Sum of pixels</b>	
<b>1</b>	124	107	0		231	0.54
<b>2</b>	48	514	0		562	0.91
<b>3</b>	145	380	0		525	0.00
<b>Sum of pixels</b>	317	1001	0		1318	
<b>Producer accuracy</b>	0.39	0.51	0.00		<b>Overall accuracy</b>	0.48

Closer examination of the existing and forecasted trends by treatment pasture allowed one to qualitatively assess predicted LULC at the O'Neal study area. This examination consisted of the calculation of a running average (cumulative  $\bar{x}$  rangeland condition score was based upon a running average using scores from all previous years and the current year) and computation of resilience (equation 1). The resilience index describes how similar the rangeland condition score for a given year is compared to the cumulative  $\bar{x}$  rangeland condition score.

$$\text{Resilience} = \text{cumulative } \bar{x} \text{ (rangeland condition score)} / \text{current } \bar{x} \text{ (rangeland condition score)} \quad (\text{Eq. 1})$$

Based upon observed rangeland condition scores for 2003, 2007, and 2008, and the 2012 forecast rangeland condition score, the SHPG pasture was determined to be most resilient ( $\bar{x}$  resilience = 0.987 [S.E. = 0.016]) relative to both the RESTROT ( $\bar{x}$  resilience = 0.950 [S.E. = 0.063]) and TREST treatment pastures ( $\bar{x}$  resilience = 0.985 [S.E. = 0.065]).

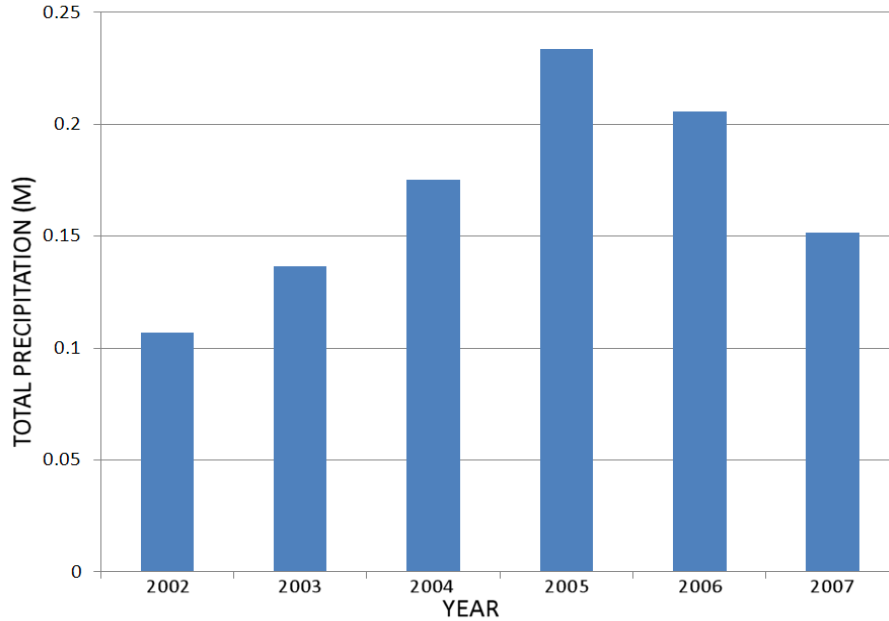
The rangeland condition score for 2012 is forecast to increase for all three treatment pastures. The least improvement is predicted to occur in the SHPG pasture with the greatest improvement predicted to occur in the TREST pasture. Based upon past performance however, it is doubtful if the forecast will be correct. The O'Neal study area will continue to be monitored through the 2012 growing season and comparable satellite imagery will be acquired at that time. The imagery will be processed following the methods used in this paper and the observed rangeland score compared to the forecast rangeland score. Only at that time will one know the accuracy of the forecast model and methodologies described in this paper.

#### *Assessment of Error and Bias*

Idrisi's Land Change Modeler (LCM) software does not appear to produce accurate forecast models within semi-arid rangeland ecosystems. However, the Idrisi Andes release of LCM was fairly new and future versions of the software may produce more reliable models.

LCM appears to place much of its final prediction upon the initial trend of change which is determined by only two data points which are derived from an early image and a later image. The trend line established between any two points will always describe a perfect relationship ( $R^2 = 1.0$ ) and can lead to gross errors within highly variable landscapes.

Semi-arid rangelands represent highly variable landscapes where changes are driven not just by intrinsic factors (e.g., topography and soil type), treatment, and land use decisions, but by environmental factors such as precipitation as well (Khazanov 1994; Niamir-Fuller and Turner 1999). As an example, the affect of increased precipitation on forage biomass can be substantial as evidenced in the semi-arid rangelands of southeast Idaho, where forage biomass measurements averaged 191.3 kg/ha in 2003, 289.7 kg/ha in 2004, and 488.1 kg/ha in 2005 (Sander and Weber 2006; Gregory et al 2008). When one then examines precipitation curves for the O'Neal study area between 2002 through 2007 (Figure 2) large differences are also seen in inter-annual accumulated precipitation. These differences are roughly correlated with forage biomass production and can affect other elements of the landscape as well.



**Figure 2. Accumulated precipitation from 2002 through 2007 at the O'Neal study area.**

The two years selected for use in this study (2003 and 2007) represent fairly similar precipitation years. As a result, detected changes would appear to have been caused by drivers other than the environment (i.e., precipitation). This observation could help explain the poor performance seen in the 2008 forecast and also demonstrates the prominent role of precipitation as a driver variable in LULC in semi-arid ecosystems.

The use of only two data points will not capture the variability in precipitation and resulting forecasts will be no better than a simple random/chance forecast. At a minimum, future forecast models need to include annual input layers instead of only early and later images. In addition, forecast models need to be validated using a short-term prediction before basing any decisions upon longer-term forecasts.

Another source of error which could explain the poor performance of the reported forecast model was the mixed use of Landsat and SPOT imagery. Recent studies suggest that vegetation indices (NDVI) derived from one sensor are not comparable to the same index derived from another sensor (Theau et al. 2010). However, the impact of this error relative to the problems described above is probably minimal although this was not tested. Furthermore, the fact that both NDVI and MSDI layers were reclassified and scored should have helped to marginalize such errors through generalization.

## CONCLUSIONS

Forecasting change in semi-arid ecosystems is challenging due to the important role played by environmental drivers such as precipitation and the highly variable nature of the same. Regardless of the modeling algorithm used (equation-based, statistical, matrix-based, system, expert, evolutionary, cellular automata, agent-based, multiple agent-based, or hybrid) future forecast models will need to take into account annual weather variables and the resulting land cover layers if accurate predictions are expected in semi-arid rangeland ecosystems.

## **ACKNOWLEDGEMENTS**

This study was made possible by a grant from the National Aeronautics and Space Administration Goddard Space Flight Center (NNG06GD82G). ISU would also like to acknowledge the Idaho Delegation for their assistance in obtaining this grant.

## **LITERATURE CITED**

- Bedell, T. E. 1998. Glossary of Terms using in Range Management. 4<sup>th</sup> ed. Society for Range Management. 32 pp.
- Bestelmeyer, B. T., J. R. Brown, K. M. Havstad, R. Alexander, G. Chavez, and J. E. Herrick. 2003. Development and Use of State-and-Transition Models for Rangelands. *Journal of Range Management*. 56:114-126
- Branson, F.A., G.F. Gifford, K.G. Renard, and R.F. Hadley. 1981. Evaporation and Transpiration. Pages 179-200 in E.H. Reid (Ed.). *Rangeland hydrology*. Range Sci. Ser. 1. 2nd ed. Soc. for Range Management, Denver, CO.
- Chavez, P.S. 1996. Image-based Atmospheric Corrections Revisited and Improved. *Photogrammetric Engineering and Remote Sensing*, 62:1025-1036
- Chuvieco, E. 1993. Integration of Linear Programming and GIS for Land-use Modeling. *International Journal of Geographical Information Systems* 7 (1): 71-83
- Cummins, B. *Bear Country: Predation, Politics, and the Changing Face of Pyrenean Pastoralism*. Carolina Academic Press, 355 pp.
- Eastman, R. 1999. *Guide to GIS and Image Processing*. Clark University, Worcester, MA
- Funtowicz, S. and J. Ravetz. 2003. Post-Normal Science. *International Society for Ecological Economics*. pgs. 1-10
- Gregory, J., L. Sander, and K. T. Weber. 2008. Range Vegetation Assessment in the Big Desert, Upper Snake River Plain, Idaho 2005. Pages 3-8 in K. T. Weber (Ed.), *Final Report: Impact of Temporal Landcover Changes in Southeastern Idaho Rangelands (NNG05GB05G)*. 354pp.
- Hill, J. B. 2006. *Human Ecology in the Wadi Al-Hasa*. University of Arizona Press. 194pp.
- Huntsinger, L. and P. Hopkinson. 1996. Viewpoint: Sustaining Rangeland Landscapes: A Social and Ecological Process. *Journal of Range Management* 49:167-173
- IUCN 1989. *Rainfall in the Sahel*. IIED Issues, Paper no. 10, IIED, London
- IUCN 2006. *International Union for Conservation of Nature and Natural Resources. Red List of Threatened Species*. URL: <http://www.iucnredlist.org/search/search-basic> visited 1-November-2006

- Jafari, R., M. M. Lewis, and B. Ostendorf. 2008. An Image-based Diversity Index for Assessing Land Degradation in an Arid Environment in South Australia. *Journal of Arid Environments*. 72(7):1282-1293
- Khazanov, A. M. 1994. *Nomads and the Outside World* (2<sup>nd</sup> ed.). University of Wisconsin Press. 382 pp.
- Laycock, W. A., 1991. Stable States and Thresholds of Range Condition on North American Rangelands: A Viewpoint. *Journal of Range Management* 44(5):427-433
- Li, H., and J. F. Reynolds. 1997. Modeling Effects of Spatial Pattern, Drought, and Grazing on Rates of Rangeland Degradation: A Combined Markov and Cellular Automaton Approach. Pages 211-230 in D. A. Quattrochi and M. F. Goodchild (Eds.) *Scale in Remote Sensing and GIS*. Lewis Publishers, New York
- Ludeke, A. K., R. C. Maggio, and L. M. Reid. 1990. An Analysis of Anthropogenic Deforestation using Logistic Regression and GIS. *Journal of Environmental Management* 31: 247-259
- Mann, S., and G. Benwell. 1996. The Integration of Ecological, Neural, and Spatial Modelling for Monitoring and Prediction for Semi-arid Landscapes. *Computers and Geosciences* 22 (9): 1003-1012
- National Research Council. 1994. *Rangeland Health: New Methods to Classify, Inventory, and Monitor Rangelands*. National Academy Press, 180 pp.
- National Council for Science and the Environment. 2005. *Forecasting Environmental Changes: A Report of the Fifth National Conference on Science, Policy, and the Environment* (C. M. Schiffries, ed.). 100 pp.
- Niamir-Fuller, M., and M. D. Turner. 1999. A Review of Recent Literature on Pastoralism and Transhumance in Africa. Pages 18-46 in M. Niamir-Fuller (ed.), *Managing Mobility in African Rangelands: The Legitimization of Transhumance*. FAO publications. 314 pp.
- Parker, D. C., S. M. Manson, M. A. Janssen, M. J. Hoffmann, P. Deadman. 2003. Multi-Agent Systems for the Simulation of Land-Use and Land-Cover Change: A Review. *Annals of the Association of American Geographers*, 93(2): 314 – 337
- Rouse, J.W., Jr., R.H. Haas, J.A. Schell, and D.W. Deering. 1973. Monitoring the Vernal Advancement and Retrogradation (Green Wave Effect) of Natural Vegetation. Prog. Rep. RSC 1978-1, Remote Sensing Center, Texas A&M Univ., College Station, 93pp. (NTIS No. E73-106393)
- Sander, L. and K. T. Weber. 2006. Range Vegetation Assessment in the Big Desert, Upper Snake River Plain, Idaho. Pages 85-90 in K. T. Weber (Ed.), *Final Report: Detection, Prediction, Impact, and Management of Invasive Plants using GIS*. 196pp.
- Savory, A. 1999. *Holistic management: A New Framework for Decision Making*. Island Press. 616 pp.

Seligman, N. G., and A. Perevolotsky. 1994. Has Intensive Grazing by Domestic Livestock Degraded the Old World Mediterranean Rangelands? Pages 93-104 in M. Arianoutsou and R. H. Groves (eds.), *Plant-Animal Interactions in Mediterranean-Type Ecosystems*. Kluwer Academic publishers, 182 pp.

Sklar, F. H., and R. Costanza. 1991. The Development of Dynamic Spatial Models for Landscape Ecology: A Review and Prognosis. Pp. 239-288 in M. G. Tuner and R. H. Gardner (Eds.) *Quantitative Methods in Landscape Ecology*. Springer-Verlag, New York

Soares-Filho, B. S., G. C. Cerquera, C. L. Pennachin. 2002. *DINAMICA- A Stochastic Cellular Automata Model Designed to Simulate the Landscape Dynamics in an Amazonian Colonization Frontier*

Sonis, M., M. Shoshany, and N. Goldshlager. 2007. Landscape Changes in the Israeli Carmel Area: An Application of Matrix Land-use Analysis. Pages 61-82 in E. Koomen et al. (Eds.), *Modelling Land-Use Change*. Springer.

Tanser, F. C. 1997. *The Application of a Landscape Diversity Index using Remote Sensing and Geographical Information Systems to Identify Degradation Patterns in the Great Fish River Valley, Eastern Cape Province, South Africa*. M. Sc. Thesis. Rhodes University, Grahamstown. 167 pp.

Tanser, F. C. and A. R. Palmer. 1999. *The Application of a Remotely-sensed Diversity Index to Monitor Degradation Patterns in a Semi-arid, Heterogeneous, South African Landscape*. *Journal of Arid Environments*. 43:477-484

Theau, J., T. S. Sankey, and K. T. Weber. 2010. Multi-sensor Analyses of Vegetation Indices in a Semi-arid Environment. Pages 89-102. In K. T. Weber and K. Davis (Eds.) *Final Report: Forecasting Rangeland Condition with GIS in Southeastern Idaho*. 189 pp.

Tucker, C.J. 1979. *Red and Photographic Infrared Linear Combinations for Monitoring Vegetation*. *Remote Sensing of Environment*, 8, 127-150

USDA NRCS. 1987. *Soil Survey of Bannock County Area, Idaho*. 347 pp.

Washington-Allen, R. A., N. E. West, R. D. Ramsey, and R. A. Efroymson. 2006. *A Protocol for Retrospective Remote Sensing-Based Ecological Monitoring of Rangelands*. *Rangeland Ecology and Management* 59(1):19-29

Weber, K. T. 2001. *A Method to Incorporate Phenology into Land Cover Change Analysis*. *Journal of Range Management* 54(2):A1-A7

Weber, K.T. 2006. *Challenges of Integrating Geospatial Technologies into Rangeland Research and Management*. *Rangeland Ecology & Management*, 59(1): 38-43

Weber, K. T., J. Theau, and K. Serr. 2008. *Effect of Co-registration Error on Patchy Target Detection using High-resolution Imagery*. *Remote Sensing of the Environment*. 112(3):845-850

Weber, K. T. and B. S. Gokhale. 2010. Effect of Grazing Treatment on Soil Moisture in Semi-Arid Rangelands. Pages 161-174 in K. T. Weber and K. Davis (Eds.) Final Report: Forecasting Rangeland Condition with GIS in Southeastern Idaho. 189 pp.

Westoby, M., B. Walker, and I. Noy-Meir. 1989. Opportunistic Management for Rangelands not at Equilibrium. *J. Range Manage.* 42:266-274

**Recommended citation style:**

Weber, K.T., 2010. Forecasting Rangeland Condition in Southeastern Idaho using GIS. Pages 177-189 in K. T. Weber and K. Davis (Eds.), Final Report: Forecasting Rangeland Condition with GIS in Southeastern Idaho (NNG06GD82G). 189 pp.

*Notes*

*Notes*