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HYDROLOGIC MODELING UNCERTAINTY RESULTING FROM LAND COVER MISCLASSIFICATION[1]

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ABSTRACT: A stochastic, spatially explicit method for assessing the impact of land cover classification error on distributed hydrologic modeling is presented. One-hundred land cover realizations were created by systematically altering the North American Landscape Characterization land cover data according to the dataset's misclassification matrix. The matrix indicates the probability of errors of omission in land cover classes and is used to assess the uncertainty in hydrologic runoff simulation resulting from parameter estimation based on land cover. These land cover realizations were used in the GIS-based Automated Geospatial Watershed Assessment tool in conjunction with topography and soils data to generate input to the physically-based Kinematic Runoff and Erosion model. Uncertainties in modeled runoff volumes resulting from these land cover realizations were evaluated in the Upper San Pedro River basin for 40 watersheds ranging in size from 10 to 100 km^2 under two rainfall events of differing magnitudes and intensities. Simulation results show that model sensitivity to classification error varies directly with respect to watershed scale, inversely to rainfall magnitude and are mitigated or magnified by landscape variability depending on landscape composition.

(KEY TERMS: sensitivity; surface water hydrology; remote sensing; simulation; AGWA; KINEROS2.)

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INTRODUCTION

Land cover is a critical watershed characteristic in surface water hydrologic modeling as it directly affects processes governing hydrologic response, specifically evapotranspiration, infiltration, runoff, and erosion. Thus, most hydrologic models use some form of input parameters based on land cover (Spanner *et al.*, 1990, 1994; Nemani *et al.*, 1993). Distributed models, in particular, need specific data on the distribution of land cover within a watershed, and classified remotely sensed imagery has emerged as a standard mapping product for characterizing the spatial distribution of land cover (Singh and Woolhiser, 2002). Given that a hydrologic simulation model is sensitive to land cover, it is hypothesized that simulations results will be erroneous

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if land cover is misclassified. Some level of uncertainty or error will be present in any land cover map as it is difficult to fully account for natural spatial variability and ambiguity in mapping landscape phenomena. Numerous efforts have focused on quantifying spatial error inherent in classified remote sensing imagery (van Genderen and Lock, 1977; Moody and Woodcock, 1994; Wilkinson, 1996; Burrough and McDonnell, 1998; Choudry and Morad, 1998; Skirvin *et al.*, 2000; Bird *et al.*, 2002; Hurd and Civco, 2004).

The accurate depiction of earth surface processes and their responses to land cover, climate, or managerial change has been the goal of research hydrologists for nearly a century. Fully integrated watershed assessment tools for support in land management and hydrologic research are becoming established both in basic and applied research (Moore and Grayson, 1989; Gee *et al.*, 1990; Vieux, 1993; Julien *et al.*, 1995; Johnson and Miller, 1997; Arnold *et al.*, 1998; Storck *et al.*, 1998; DHI, 2000; Miller *et al.*, 2002). Distributed hydrologic models are frequently used for investigating the various interactions among climate, topography, vegetation, and soil as they affect watershed response (Singh and Woolhiser, 2002). Conventional calibration and validation exercises can improve the predictive capabilities of models, but the determination of uncertainty associated with different model inputs is needed to better explain the limitations inherent in the modeling technique.

One of the basic concepts of watershed hydrology is that hydrologic processes are spatially nonuniform and defined by changes in topography, geology, soils, land cover, and landuse. The effects of different watershed configurations of landuse or land cover on streamflow response and water quality have been intensively studied and relatively well understood (National Research Council, 1999; Brooks *et al.*, 2003). Watershed assessment tools, used for watershed management or engineering design, must be able to integrate the spatial information to assess the varying responses from different watershed configurations (National Research Council, 1999; Singh and Woolhiser, 2002).

The application of distributed watershed models, that allow for the representation and parameterization of spatially nonuniform of hydrologic processes, has improved our ability to model watershed systems (Singh and Woolhiser, 2002). Kite and Kouwen (1992) compared a lumped parameter hydrological model with a semi-distributed version of the same model where sub-basins were subdivided into land cover types using Landsat images, and found that the semi-distributed model provided better goodness of fit statistics compared with the lumped parameter model. The optimized parameter values found for each land cover type confined the variations in storages and infiltrations expected for each type. Tao and Kouwen (1989) examined the effect of Landsat-derived land cover information for flood forecasting modeling, and found that the distributed model using the Landsat data improved the predicted flood peaks and total runoff at the 10% significance level compared with a lump parameter model. Payraudeau *et al.* (2003) found that land-use types within a distributed model improved modeling results by defining critical threshold levels for runoff generation. Wooldridge and Kalma (2001) found, using a semi-distributed watershed model, that land-surface classification based on a combination of soil depth and land cover type provided the most accurate streamflow predictions during a 10-year validation period. Investigation of the uncertainty associated with the predictions revealed that a simpler classification based solely on land cover actually provided a more robust parameterization of streamflow response. The Wooldridge and Kalma (2001) results illustrated the hydrological importance of distinguishing between forested and nonforested land cover types at the regional-scale.

Remote sensing is commonly used to map landuse and land cover that serve an input into watershed assessment tools and models. Errors associated with image classification may increase uncertainty in modeling results (Rango, 1985; Singh and Woolhiser, 2002). Ragan and Jackson (1980) derived land cover classifications from aerial photographs and Landsat images for the Anacostia River Watershed in Maryland. Using the Soil Conservation Service's curve number model they found runoff differences between the input sources to be insignificant between the two methods. Other researchers have found similar results (Rango *et al.*, 1983; Draper and Rao, 1986). However, other researchers have observed that small classification errors in specific land cover types, especially when related to impervious surfaces, can have a substantial impact on the uncertainty of runoff and water quality modeling results (Stuede and Johnston, 1990; Zhang *et al.*, 2000; Bird *et al.*, 2002; Endreny *et al.*, 2003; Hurd and Civco, 2004).

This study was conducted to evaluate the uncertainty in hydrologic simulations associated with land cover data, created using Landsat imagery, having a known misclassification error. A stochastic methodology is presented to systematically and spatially distribute the misclassification error into land cover maps originally derived from remote sensing images. These altered land cover maps were input into a modified version of the open-source Automated Geospatial Watershed Assessment tool (AGWA; http://www.tucson.ars.ag.gov/agwa) (Miller *et al.*, 2002, 2007), where the land cover data are used to generate parameter input files for the distributed hydrologic model Kinematic Runoff and Erosion Model (KINEROS2) (Smith *et al.*, 1995; Goodrich *et al.*, 2002). KINEROS2 is then used to simulate runoff for each of the land cover realizations. Hydrologic simulations were run at a range of spatial scales and two different rainfall events to evaluate the uncertainty associated with introduced spatial error derived from the land cover error matrix.

KINEROS2 (Smith *et al.*, 1995; Goodrich *et al.*, 2002) is a physically based, event-oriented, distributed hydrologic model. Infiltration-excess overland flow processes are used to generate surface runoff. A watershed is represented as a series of planes and channels, for which the processes of infiltration, interception, runoff, erosion, sediment detachment, transport, and deposition are all explicitly accounted. Runoff is routed using the kinematic wave equations for overland and channel flow. These equations, and those for erosion and sediment transport, are solved using a four-point implicit finite difference method (Smith *et al.*, 1995).

DESCRIPTION OF THE STUDY AREA

Located in southeastern Arizona, the Upper San Pedro Basin encompasses the San Pedro River that flows North from Sonora, Mexico, into Arizona (Figure 1). With a wide variety of topographic, hydrologic, cultural, and political characteristics, the basin represents a unique study area for addressing a range of scientific and management issues. The area is a transition zone between the Chihuahuan and Sonoran deserts and has a highly variable climate with significant biodiversity. Major vegetation components include desert shrub-steppe, riparian, grasslands, agriculture, oak and mesquite woodlands, and pine forests. Elevation within the basin ranges from 900 to 2,900 m and is bounded by relatively steep-fronted mountain ranges. All sites selected for this study were located within the uppermost 7,600 km^2 of the basin, of which approximately 1,800 km^2 is in Mexico. Climate in this region is semi-arid, with the majority of the rainfall associated with high-intensity, convective thunderstorms during the summer monsoon rainfall season (Renard *et al.*, 1993). Detailed rainfall-runoff studies have been performed on the watershed for the past several decades, and the timing and magnitude of rainfall are well established (Osborn *et al.*, 1980; Renard *et al.*, 1993).

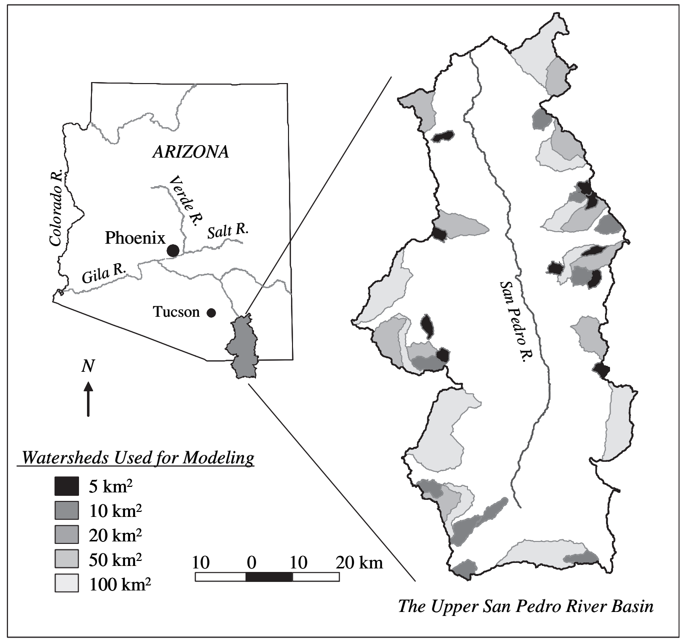

FIGURE 1. Location of the Upper San Pedro River Basin With the 40 Watersheds Used in the Simulation Exercise Highlighted in Shades of Gray According to Their Size Class.

METHODS

A schematic of the research methodology is presented in Figure 2. GIS data for land cover, soils, rainfall, and topography were compiled for the Upper San Pedro River Basin, and a stochastic process was developed to create 100 land cover surfaces with misclassification error redistributed across the landscape. A GIS analysis of the topography within the San Pedro was used to randomly locate 40 watersheds (Figure 1). These watersheds fall within four size classes (10, 20, 50, and 100 km^2), and 10 watersheds within each size class were selected using a random number generator. Each of these watersheds was discretized into upland (overland flow planes) and channel model elements, which were then assigned parameters using AGWA as required by KINEROS2 (Goodrich *et al.*, 2002; Miller *et al.*, 2007) (Figure 2). This process was repeated 100 times for each of the stochastic land cover surfaces for two return-period rainfall events. Simulation results were processed to investigate the uncertainty in runoff.

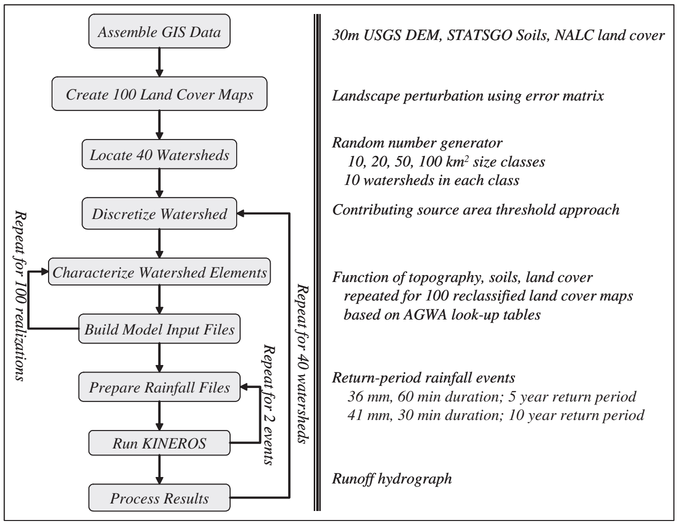

FIGURE 2. Flow Chart Illustrating the Procedures Used to Transform GIS Data Into Hydrologic Parameter Files for Input to KINEROS2.

KINEROS2 Parameterization

The core of the hydrologic modeling was performed using the KINEROS2 model with inputs generated by AGWA, a tool that transforms spatial data into parameter input files for the KINEROS2 hydrologic model, and displays output data from the model runs (Miller *et al.*, 2002). The USDA-ARS Southwest Watershed Research Center, in cooperation with the USEPA Office of Research and Development and the University of Arizona, developed this tool to simplify the construction of model input files. KINEROS2 runs outside of AGWA, and the hydrologic simulations results are imported back into AGWA for visualization using standard GIS techniques. AGWA uses a series of look-up tables and equations, including pedotransfer functions (Rawls *et al.*, 1982; Woolhiser *et al.*, 1990) to perform preliminary parameter estimation (Miller *et al.*, 2007). Soil properties are area- and depth-weighted where necessary to approximate soil conditions for the critical near-surface layer for each channel and upland modeling element. Canopy and vegetation characteristics required by KINEROS2 are approximated based on look-up tables provided by AGWA for vegetation classes in the North American Landscape Characterization (NALC) land cover dataset.

Land cover data serve as a primary source for estimating various hydrologic parameters in AGWA (Hernandez *et al.*, 2000). Hernandez *et al.* (2000) performed a sensitivity analysis of KINEROS using the AGWA tool, showing that KINEROS is highly sensitive to surface roughness (Manning's n), saturated hydraulic conductivity (K_s), and percent canopy cover, and moderately sensitive to interception depth for small rainfall events. Each of these parameters is either determined expressly from or moderated by land cover and determined by AGWA following a series of look-up tables developed from calibration exercises within the USDA-ARS Walnut Gulch Experimental Watershed (WGEW), and a survey of published reports (Hernandez *et al.*, 2000).

Geospatial Data: Topography, Soils, and Land Cover

The land cover, topographic and soils datasets were assembled as required by AGWA. A USGS Level-2 30-m digital elevation model (DEM) was used to represent topography, a polygonal soils map layer was extracted from the USDA-NRCS State Soil Geographic (STATSGO) Database (USDA NRCS, 2006), and classified NALC data (USEPA, 1993, 2006) were used to describe land cover. The NALC land cover maps were developed from georectified and atmospherically corrected (Lunetta *et al.*, 1998) Landsat TM remotely sensed images. Images used in this study had <30% cloud cover and were atmospherically corrected (Lunetta *et al.*, 1998). The resulting digital land cover maps had 10 classes: Forest, Oak Woodland, Mesquite Woodland, Grassland, Desertscrub, Riparian, Agriculture, Urban, Water, and Barren.

A detailed accuracy assessment of the NALC land cover data was completed by Skirvin *et al.* (2000). In their approach, airborne videography was used to isolate a random sample of 527 points stratified by map class. An error matrix was assembled following Congalton (1991), and Cohen's Kappa and Kendall's Tau-b statistics were used to quantify the producer's, user's and overall classification accuracies (Table 1). User's classification is sometimes referred to as errors of omission, the probability that observed points have been correctly identified. Producer's accuracy (or errors of commission) is the probability that classified data were correctly identified within a given category (Congalton, 1991). Comparisons between observed and classified land cover types produce an overall accuracy score of 71.73%. The Kendall's Tau-B score, a nonparametric correlation ranked test (Zar, 1999) is 0.741 with a standard error of 0.024. The Cohen's Kappa score, a measure of agreement between two classifiers (Cohen, 1960), is 0.646 with a standard

TABLE 1. Error Matrix Detailing Results of the Airborne Video-Based Accuracy Assessment of the 1997 NALC Land Cover Map Based on Results of Skirvin *et al.* (2000).

Predicted Land Cover	**Observed Land Cover**									
	Forest	**Oak Woodland**	**Mesquite Woodland**	**Grassland**	**Desertscrub**	**Riparian**	**Agriculture**	**Urban**	**Barren**	**Total**
Forest	20	4	0	0	0	0	0	0	0	24
Oak woodland	2	50	0	3	0	0	0	0	0	55
Mesquite woodland	0	1	27	13	12	2	0	1	0	56
Grassland	0	8	16	113	21	0	0	1	0	159
Desertscrub	0	4	4	12	115	0	0	2	0	137
Riparian	0	0	0	0	0	21	2	1	0	24
Agriculture	0	0	1	0	15	2	5	1	0	24
Urban	0	0	0	0	0	0	0	24	0	24
Barren	0	0	2	0	19	0	0	0	3	24
Total	22	67	50	141	182	25	7	30	3	527

Note: Results are presented as the number of pixels falling into each class.

error of 0.024. This study focused on the impact of errors of omission, which measure between-class discrimination. These errors occur when a pixel is misidentified as another class. Errors of omission were used in this study as they directly affect the estimation of hydrologic parameters within a given plane. Errors of commission, wherein a pixel is incorrectly classified as belonging to the target class, may compensate for errors of omission in the total producer's accuracy. However, they do not improve the user's accuracy, which is affected by the accuracy of individual pixels and is most important for the overall accuracy of parameter estimation.

Unit-Area Land Cover Modeling

To illustrate localized impacts of misclassification, a simplified KINEROS2 input file was prepared in which nine upland elements were parameterized according to the landscape characteristics estimated for each of the land cover classes. A unit-area plane with the same dimensions as the NALC GIS data (60 m^2) was input to KINEROS2. Soil parameters were estimated for a sandy loam, the dominant soil type within the study area. The plane slope was set to 4.6%, and rainfall data for a storm with a 30-min duration and 15.7-mm depth served as the input data. Simulated runoff for each land cover class using the generic unit-area plane were compared to demonstrate the relative impact of the type of misclassification error among the various land cover classes.

Error Simulation Model for Land Cover Data

A program was written in Arc Macro Language (ESRI, 1998) to systematically redistribute misclassification errors (Table 1) into the 1997 classified NALC scene to produce 100 realizations of altered land cover data. The stochastic algorithm begins by extracting each of the 10 land cover types from the classified NALC imagery into single-class maps. These data are intersected with random number maps, and individual pixels are transformed into different land cover classes following the errors of omission in Table 1. In this way, 10 new class maps are generated, which are then spatially merged to create a new realization of land cover map with induced error. The total number of cells and proportion of the map area for each land cover class are extracted from the new realization, and the map is accepted or rejected based on the overall similarity to the original map. Each class is allowed to vary within a specified threshold (in this case 1%) from the original map, ensuring that the representation of land cover within all 100 realizations are statistically similar to the others and that neither errors nor land cover classes are over-represented. Each of the 100 realizations retains approximately the same total area in each land cover class (with minor variation in the total number of pixels in each class), but the location of the pixels is highly variable among the maps.

Hydrologic Modeling: Watershed Discretization and Characterization

Each of the 40 watershed outlet points was input in AGWA, which was used to determine the contributing watershed area and to subdivide each watershed into upland and channel planes as required by KINEROS2. AGWA uses a flow accumulation map derived from a DEM to determine the location and extent of stream channels within the basin, and allows for the contributing source area that defines the uppermost headwaters to be adjusted. As the source area is reduced the overall number of channels and plane elements is increased, thereby increasing watershed representation complexity. In this study, the source area was fixed at 1% of the watershed area. One implication of this approach is that as the watershed size increases, the source area also increases; while the number of watershed elements remains relatively constant, the average plane size increases and spatial averaging and smoothing reduces the influence of spatial variation in land cover and soils. Watersheds were subdivided at the same percent contributing source area to maintain a consistent ratio of watershed channel and plane elements among all watersheds. As channels represent significant runoff and sediment sinks as modeled by AGWA, this approach also serves to maintain a more consistent ratio of transmission losses across scale.

Automated watershed parameterization in AGWA takes place on the subdivided watershed, which is intersected with the land cover, soils, and topographic data layers. Algorithms and look-up tables are used to estimate the suite of KINEROS2 hydrologic parameters for each upland element. In this approach, all channels are assumed to be sandy alluvial washes and are assigned identical parameter sets. A majority of watershed elements were not homogenous in soil and cover characteristics; in these cases parameters are area-weighted and the resulting value is used in the final estimation. Thus, large planes tend to approximate regional characteristics, whereas very small planes may be more representative of underlying landscape variability.

Calibration of KINEROS2 on each of the 40 watersheds was not possible due to the lack of runoff gauges. Prior research on the heavily instrumented WGEW was used to provide estimates of model parameters as a function of topographic, soil, and land cover characteristics. Walnut Gulch is assumed to be representative of upland watersheds within the San Pedro. These prior studies (Goodrich, 1991; Syed, 1999) were able to calibrate KINEROS to very high efficiencies depending on scale: correlations coefficients ranged from 0.98 at the sub-hectare scale to 0.86 at the small watershed scale (60 km^2). Syed (1999) found that it was difficult to effectively calibrate KINEROS2 on larger watersheds (>100 km^2) due to low runoff to rainfall ratios at those scales. With increasing watershed size, channel transmission losses reduce the effective discharge per unit area, and calibration becomes increasingly difficult in this influent semi-arid watershed. Watersheds used in this study represent the largest watersheds suitable for modeling with KINEROS2 in the absence of detailed calibration and validation data.

Rainfall Input Files

Rainfall data were assembled from long-term records taken on the USDA-ARS WGEW (Osborn *et al.*, 1980), which currently has 89 continuously recording rain gauges. The WGEW lies within the Upper San Pedro River Basin. Return-period rainfall events for a 5-year, 60-min and 10-year, 30-min storms were formulated based on Osborn *et al.* (1980). These events were chosen because they fall within the range of calibration efforts previously mentioned and they typify relatively small and large runoff-producing events in the region. Generally, thunderstorms in the region are characterized as high intensity, convective thunderstorms. However, short duration thunderstorms are typically more intense than storms of longer duration. In this study, the two rainfall events used deliver similar rainfall depths (36 and 41 mm, respectively), but the lesser rainfall total occurred during a more intense storm (0.5 and 1 h, respectively). The rainfall hyetographs were uniformly distributed across the landscape for input to the model. This approach does not represent the spatial distribution of rainfall intensities that naturally occurs in this region, but ensures that the total rainfall on all watersheds is equivalent, thereby reducing uncertainty in the output resulting from rainfall variability.

Evaluation of the Results

Simulated runoff volumes increase with watershed area and are highly variable both within a given watershed and across spatial scales. Thus, model simulation results were normalized according to the average result for a given watershed. Both the range and 95% confidence interval (CI) were normalized for each watershed size class by dividing the range in responses for a given watershed by the mean watershed response. The normalized range for each watershed was determined as

$$r^n = \frac{\mathrm{Max}(Q) - \mathrm{Min}(Q)}{\frac{\sum_{i=1}^{100} Q}{100}}, \tag{1}$$

where r^n is the normalized range, Q is runoff (m^3) for each of 100 simulation runs (n).

The normalized confidence interval (CI^n) for each watershed was determined using

$$\mathrm{CI}^n = \frac{1.96\dfrac{\sqrt{\dfrac{n\sum_{i=1}^{100}Q^2-\left(\sum_{i=1}^{100}Q\right)^2}{n(n-1)}}}{\sqrt{n}}}{\dfrac{\sum_{i=1}^{100}Q}{100}} \tag{2}$$

Global statistics for the minimum (r^n_{min}), average (r^n_{avg}) and maximum (r^n_{min}) normalized range and standard deviation were derived by combining the results from the 10 watersheds within a given size class. The minimum and maximum values represent the smallest and largest values of the range for each of the 10 watersheds in a given size class. These values were calculated using the following equations:

$$r^n_{avg} = \frac{\sum_{h=1}^{10} r^n}{10}; \quad r^n_{max} = \max(r^n); \quad r^n_{min} = \min(r^n) \tag{3}$$

RESULTS

Unit-Area Modeling

The relative importance of misclassification errors found in Table 1 are reflected in the unit-area modeling results (Table 2). Changes in simulation results from a unit area plane are given in Table 2 and show that the type of classification error had a strong effect on simulation results. For example, if an oak woodland is misclassified as mesquite woodland, or vice versa, there is no change in runoff volume. However, if a desertscrub pixel is misclassified as mesquite woodland, simulated runoff increases by 39%. The greatest hydrologic error would be to misclassify a vegetated pixel as urban or vice-versa. However, urban areas are highly distinctive and the probability of misclassifying urban as vegetation is relatively low (see Table 1), thereby reducing the potential for greatly over- or underestimating runoff response. Likewise, there are large hydrologic implications for misclassifying a pixel as riparian, or for misidentifying a riparian target, but the probability of doing so is low. Significant changes in hydrologic response were present throughout the unit-area simulation runs, which emphasizes the sensitivity of KINEROS2 to hydrologic parameters estimated by AGWA.

Watershed-Scale Modeling and Land Cover Uncertainty

There is a strong central tendency in runoff simulations across scales (Table 3) with results generally normally distributed about the mean. The average CI for runoff is consistently low and approaches 1% of the mean value for only the largest of the watersheds. The range in hydrologic response among the 10 watersheds within each size class widens with each increase in watershed area, indicating that greater variability in watershed characteristics and hydrologic response is captured at the larger scales.

The maximum normalized range (r^n_{min}) represents the watershed response within one of the 10 watersheds in a size class that differed most significantly from the global statistics for that size class. A wide spread in the range is an indication that the overall watershed response for watersheds in that class was highly variable.

Even in those cases where a wide range in watershed response was observed, the CI remained relatively

TABLE 2. Percent Change in KINEROS2 Simulated Runoff Volume (m^3) Resulting From Misclassification of a Uniform 60-m Resolution Grid Cell.

	Misclassified Land Cover								
Predicted Land Cover	**Forest**	**Oak Woodland**	**Mesquite Woodland**	**Grassland**	**Desertscrub**	**Riparian**	**Agriculture**	**Urban**	**Barren**
Forest	**0**	98	98	38	43	−42	76	343	248
Oak woodland	−49	**0**	0	−30	−28	−71	−11	124	76
Mesquite woodland	−49	0	**0**	−30	−28	−71	−11	124	76
Grassland	−28	43	43	**0**	3	−58	27	220	152
Desertscrub	−30	39	39	−3	**0**	−59	23	210	144
Riparian	73	242	242	139	147	**0**	203	664	501
Agriculture	−43	13	13	−21	−19	−67	**0**	152	98
Urban	−77	−55	−55	−69	−68	−68	−60	**0**	−21
Barren	−71	−43	−43	−60	−59	−83	−50	27	**0**

Note: Land cover in the "predicted" class were systematically changed to those in the "misclassified" class.

TABLE 3. Normalized KINEROS2 Simulation Results for Runoff Volume as a Function of Watershed Size and Rainfall Depth.

	5-Year Rainfall Event (36 mm)				10-Year Rainfall Event (41 mm)			
Normalized runoff	**10 km^2**	**20 km^2**	**50 km^2**	**100 km^2**	**10 km^2**	**20 km^2**	**50 km^2**	**100 km^2**
Average runoff (m^3 × 10^5)	0.782	1.02	2.17	2.38	2.28	4.09	9.66	17.2
r^n_{avg}	0.793	1.22	1.36	5.17	0.28	0.34	0.36	0.51
r^n_{min}	0.489	0.660	0.832	0.970	0.19	0.24	0.19	0.19
r^n_{max}	1.43	3.88	2.57	25.49	0.47	0.77	0.51	0.91
CI^n_{avg}	0.028	0.044	0.048	0.272	0.01	0.01	0.01	0.02
CI^n_{min}	0.017	0.028	0.033	0.037	0.01	0.01	0.01	0.01
CI^n_{max}	0.048	0.156	0.109	1.70	0.01	0.03	0.02	0.03

Note: Results are based on 100 simulations for each watershed with 10 watersheds in each size class. normalized results are expressed as a percent of the mean runoff response for the watershed where r^n_{avg} = average normalized range, r^n_{min} = minimum normalized range, r^n_{max} = maximum normalized range, CI^n_{avg} = average normalized 95% CI, CI^n_{min} = minimum normalized 95% CI, and CI^n_{max} = maximum normalized 95% CI.

small (data not shown). This is an indication that the distribution associated with the 100 simulations is still tightly constrained around the mean, even though there may be outliers in which the introduction of misclassified data significantly impacted the simulated hydrologic response. Conversely, the normalized minimum range and CI are representative of results in which a given watershed was insensitive to introduced spatial error. In those cases, where the normalized range or CI are within 1% of the mean, there is effectively no distinction among all the simulation realizations for that watershed.

Impact of Rainfall

The range and CI are narrowed with increased rainfall intensity and magnitude, and the variability in runoff volume was small across the range of watershed scales for the 10-year rainfall event. Although a strong association between watershed scale and the variability in runoff volume is evident for the 5-year rainfall event (36 mm), no such clear trends are apparent when the larger magnitude 10-year rainfall event (41 mm) was used.

DISCUSSION

In AGWA, land cover modifies the estimated value of K_s using a direct relationship to canopy cover. KINEROS simulations are strongly affected by both K_s and rainfall intensity. Errors in classification that tend to increase the estimated canopy cover, such as from desertscrub to agriculture (Table 2) will result in slightly elevated values of K_s, resulting in decreased runoff. Increases to Manning's roughness are generally associated with increasing vegetative density and canopy cover (Shen and Julien, 1993), which further increases the opportunity for infiltration thereby decreasing overland flow and runoff volume.

Results from the stochastic exercise using 100 variations in land cover were reclassified according to the error matrix of Table 1, which show that the impact of such error on hydrologic simulation is relatively mild for the watersheds in this study (Table 3). Furthermore, rainfall characteristics strongly mitigate the uncertainty associated with simulated runoff. There is an inverse relationship between watershed size and uncertainty for a given rainfall event. The sensitivity of hydrologic response was found to be directly related to the analysis scale. Both the normalized range and the 95% CI became larger as the watershed class size is increased. Furthermore, in all cases the range and CI are dampened with increased rainfall.

Outputs from the 100 simulation runs for each watershed effectively depict the relative impact of land cover on model output. Results given in Table 3 show the general effects on results as a function of scale and rainfall, but this technique can be applied on an individual watershed basis. Results may be presented as a distribution of simulation results that are reflective of the underlying uncertainty resulting from misclassification within the targeted watershed.

The San Pedro River basin is predominately a desertscrub-grasslands community with abundant mesquite woodlands, and it would be expected that the greatest number of misclassified pixels would fall in these categories. As shown in Table 1, there is a high percent error among the most dominant land cover types. Taken together, these observations indicate that the majority of errors are among land cover types that behave relatively similar to one another in a simulation environment (Table 2). Results from this study are inextricably linked to model sensitivity to climatic and land cover conditions. Models that are more sensitive to land cover parameters, such as

SWAT (Arnold *et al.*, 1998), would evince a different range of uncertainty resulting from misclassification error. Likewise, the range in uncertainty is heavily influenced by rainfall patterns and runoff response, and these results are confined in discussion to the semi-arid landscape of SE Arizona and the pattern and magnitude of rainfall used in the analysis.

Given that the locations of the outlets of the 10 watersheds within each size class were randomly generated, they contained a wide variety of land cover and topographic distributions throughout the study area. However, watersheds within a given class size tend to have many features in common. For example, smaller watersheds tend to be located near the headwaters, which are most often in more densely vegetated hilly or mountainous terrain in the San Pedro basin. Thus, smaller watersheds tend to be steeper and often occur on shallow, gravelly soils. Land cover characteristics are also clustered within the San Pedro basin. For example, agriculture occurs only on the valley floor, and watersheds of the scale included in the analysis do not extend fully down the valley. Larger watersheds also include headwater regions, but they extend farther down the mountain fronts and incorporate some characteristics of the lower valley. Thus, a landscape and land cover bias exists in the watershed scale analysis; the larger watersheds are more likely to be representative of the regional characteristics than smaller watersheds that may contain relatively anomalous land cover and soil characteristics.

Large watersheds are more likely to contain a greater range in watershed characteristics simply due to the fact that they cover a larger area. Larger watersheds appear to exhibit a greater degree of error and uncertainty in the estimation of model parameters due to the increased number of misclassified pixels within their boundaries. A comparison of the watersheds that exhibited the greatest and least range in runoff response showed that large watersheds exhibited greater uncertainty in runoff prediction when a greater range in land cover types was present. At the smaller scales, the influence was greatest when urban or riparian cover classes were present.

CONCLUSIONS

Automated watershed modeling approaches that rely on available GIS data, such as AGWA, should account for the uncertainty in modeling results that result from spatial errors inherent in the base datasets. In this case, the land cover data serve as a primary source for model parameters. Uncertainty is propagated through the model as a function of spatial averaging of the data and the probability of the occurrence of error within the watershed boundary. Distributed watershed modeling in ungauged watersheds does not allow for the calibration or validation of simulation results. In such instances, model simulations cannot be constrained through parameter determination, and results should be presented in conjunction with uncertainty estimates as presented in this study.

In the semi-arid setting of this project AGWA-based KINEROS2 modeling did not show a high degree of uncertainty due to quantified land cover error. However, the corollary argument is also true: uncertainty in land cover classification leads to simulation uncertainty for all scales of watersheds when less intense rainfall events are used to drive the model, with the greatest degree of uncertainty associated with large watersheds. These results are inherently model- and location-specific. The impact of misclassification error may be relatively severe if the degree of error presented in the misclassification matrix is relatively high among classes with a highly variant response to rainfall, which is not present in the NALC data for the San Pedro. Applications of this technique using different runoff simulation models, such as SWAT, that have the potential to be more directly responsive to land cover change have suggested future directions for this research. The stochastic algorithm presented here is model-independent and provides a mechanism for evaluating model, rainfall, and location-specific impacts of land cover error on runoff simulation.

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