Image Misregistration Error in Change Measurements

Hongqing Wang and Erle C. Ellis

Abstract

Planimetric positional error limits the accuracy of landscape change measurements based on features interpreted from high spatial resolution imagery (≤1 m), and this limitation depends on the magnitude of the positional error, the spatial heterogeneity of landscapes, and the spatial extent of the change detection window (the change detection resolution). For this reason, accuracy assessments of change measurements from feature-based approaches require careful evaluation of the impacts of positional errors across landscapes differing in spatial heterogeneity at different change detection resolutions. We quantified such impacts by computing the false changes produced by spatially shifting and comparing high-resolution ecological maps derived by feature interpretation and ground interpretation of 1 m resolution Ikonos imagery of rural China and 0.3 m resolution aerial photographs of suburban United States. Change detection error increased significantly as positional errors increased, as landscape heterogeneity increased, and as the change detection resolution became finer. Regression-derived relationships between change estimation error and positional error, change detection resolution, and landscape heterogeneity allow calculation of the minimum change detection window size at which it is possible to obtain change measurements of a specified accuracy given any set of feature-based ecological maps and their positional error. Prediction of this "optimal change detection resolution" is critical in producing reliable high-resolution change measurements from feature-based ecological maps.

Introduction

Planimetric positional errors between spatial datasets, or misregistration, can substantially decrease the accuracy of land-use and land-cover (LULC) change measurements and the ecological change estimates derived from them, such as deforestation, carbon sequestration, and biodiversity loss (Switzer, 1975; Townshend *et al.*, 1992; Hunter and Goodchild, 1995; Verbyla and Boles, 2000; Carmel *et al.*, 2001; Plourde and Congalton, 2003; Serra *et al.*, 2003, Wang and Ellis, 2005). Even a small amount of misregistration (e.g., subpixel) markedly reduces the accuracy of LULC change estimates and the degradation of accuracy per unit of misregistration error increases as pixel resolutions become finer (Townshend *et al.*, 1992). With the growing use of automated feature-extraction methods based on high-resolution remote sensing imagery such as Ikonos and QuickBird, the limits of positional errors to the accuracy of change estimates are ever more important (Lee *et al.*, 2003).

Normally, there are two categories of change detection: (a) pixel-based, and (b) feature-based (Congalton, 1997; Stow, 1999). In the pixel-based approach, changes are detected based on changes in the spectral properties of images corresponding to class changes that are detected by selected thresholds of the classes from *training* data on a pixel-to-pixel basis. Pixel-based approaches suffer from (a) unavoidable misclassification errors caused by dependence on spectral dimensionality rather than spatial context to classify images, (b) mixed classes within pixels, and (c) being unable to differentiate between changes in imaging condition, such as surface moisture and shadowing, and those due to important changes in landscapes. Feature-based approaches, on the other hand, involve the extraction of features from imagery by visual interpretation and manual digitizing of features, or by automated methods, which may be combined with direct ground-based observations (groundtruthing) and correction of derived features on a vector basis, thus avoiding many of the problems of pixel-based approaches (e.g., Serra *et al.*, 2003). Though often far more labor intensive than pixel-based approaches, and requiring significant local knowledge, feature-based approaches allow change detection from imagery of many different types, while pixel-based approaches generally require comparison of imagery from the same sensor.

There are few empirical studies on positional error in high-resolution feature-based change estimates, and it is often assumed that when positional accuracy meets mapping requirements, it is not an important factor in change detection accuracy even though this is not so (Swain *et al.*, 1982; Townshend *et al.*, 1992; Husak *et al.*, 1999; Carmel *et al.*, 2001). Most studies of positional error are pixel-based analyses that are not fully comparable with feature-based methods (Congalton, 1997) or use moderate to coarse resolution remote sensing data (≥30 m to 1 km resolution; e.g., Swain *et al.*, 1982, Townshend *et al.*, 1992; Husak *et al.*, 1999; Verbyla and Boles, 2000; Smith *et al.*, 2003) that are generally too coarse to relate LULC changes to many important ecological processes (O'Neill *et al*, 1996; Husak *et al.*, 1999; Ellis *et al.* 2000; Ellis, 2004). For example, small but ecologically significant features

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such as houses (usually <15 m × 15 m), agricultural fields, and small patches of trees are typically dispersed evenly across densely populated rural landscapes in China and other developing nations and in the suburban and urban areas of more developed nations (Ellis, 2004). Even what appear to be large agricultural fields in China are laced with field borders <1 m wide (Ellis *et al.*, 2000).

The influence of positional errors on change detection accuracy should be a function not only of the spatial resolution of the input data (imagery, mapped features) and classification system, but must also depend on the characteristics of the landscape under investigation, especially its spatial heterogeneity (the composition and distribution of patches/classes), and the window size selected for the change detection analysis (i.e., the change detection resolution) that is used for change measurements across the spatial extent of the area of interest (AOI) for change detection. Townshend *et al.* (1992) found that to keep change detection error to <10 percent of the total change measured required significantly smaller registration errors in the more heterogeneous densely vegetated areas than in sparsely vegetated areas with lower heterogeneity. In a highly fragmented Mediterranean agricultural landscape, Serra *et al.* (2003) found that the accuracy of feature-based LULC change measurements based on Landsat imagery could be increased by more than 30 percent using a pixel erosion method that limited the effect of misregistration error, but reduced the effective change detection resolution. Serra *et al.* (2003) also demonstrated that the impacts of positional error increased as landscape fragmentation increased, especially at higher spatial resolutions, because of the abundance of small linear and polygon features.

Feature-based mapping is necessary for long-term change detection because the earliest available remote sensing record is generally black and white aerial photography, and these data are not usually amenable to pixel-based methods. This paper is rooted in our efforts to map and estimate long-term ecological changes in rural China between the 1940s and today based on World-War-II-era (WW2) aerial photographs co-registered to orthorectified 2002 Ikonos imagery at five field sites in China (Ellis, 2004; Wang and Ellis, 2005). Positional error, or misregistration, between our Ikonos imagery and WW2 aerial photographs ranged from 4.4 to 6.2 m by root mean square error (RMSE) and 6.5 m to 9.3 m circular error at 90 percent confidence (CE90). As our Ikonos and WW2 image resolutions allowed feature mapping at ≥1 m resolution, image co-registration error would appear to present a significant limit to the precision of change estimates possible using our data.

Given the goal of reliable high-resolution ecological change estimates in heterogeneous landscapes using feature-based methods, we need to determine the relative amount of change detection error caused by positional error, and the minimum change detection resolution, in order to reduce the impacts of positional error to an acceptable level. By examining the false change error produced by shifting the position of a set of high-resolution ecological maps from landscapes with different characteristics, we can describe and model quantitative relationships between change estimate accuracy and positional error, change detection resolution, and landscape heterogeneity, so that the amount of positional false change error can be estimated and controlled in high-resolution, feature-based ecological change estimates.

Methods

Selection of Ecological Maps

We selected a sample of 20 ecological maps in local UTM projection, each covering a square 500 m × 500 m AOI that were interpreted and groundtruthed based on orthorectified 1 m Ikonos GEO imagery of rural China (n = 19; Space Imaging, Inc., www.spaceimaging.com) and 0.3 m orthorectified aerial photographs of suburban landscapes in Baltimore, Maryland (n = 1; Wang and Ellis, 2005; Ellis, 2004). These landscapes represent typical rural areas in five environmentally distinct regions in China based on terrain, climate, and soils (Ellis, 2004), as well as hilly suburban landscapes in the United States. Landscape features were mapped and classified using a high-resolution ecological classification system revised from that of Ellis *et al.* (2000) that maps a continuous mosaic of fine-resolution "ecotope" land use features with minimum dimension ≥2 m for linear features (field borders, ditches, and roads), ≥5 m for hard polygon features (buildings and water surfaces), and ≥10 m for soft polygon features (agricultural fields and forest patches) (Ellis, 2004). We used our groundtruthed maps rather than simulated landscape maps because we know of no simulation methods that can create realistic maps with the complex patterns of regular and irregular feature shapes and sizes that are typical of densely populated landscapes.

Effects of Positional Errors on Change Detection of Different Landscapes

Planimetric positional errors were simulated for each of the twenty sample maps by moving each map to the Northeast (45°) by increments of 0.1, 0.5, 1, 2, 3, 4, 5, 10, 20, 30, and 50 m (i.e., with dx = dy = 0.0707, 0.35, 0.71, 1.41, 2.12, 2.83, 3.54, 7.07, 14.1, 21.2, and 35.4 m, respectively) using a GIS (ArcInfo® 8.3, Environmental Systems Research Institute with ET Geowizards 8.6 extension, **http://www.ian-ko.com/**). By comparing shifted and original map pairs, the "false change" in feature cover caused by the shift can be estimated, providing a proxy measure of the positional error between maps caused by error in co-registration of different images used for mapping the same AOI at different times. This method is rapid, convenient, and preserves feature topology, but also creates uniform positional error across maps without the anisotropy of positional error that is usually part of image orthorectification error, especially in hilly areas. Prior to shifting, a 50 m border area around each map was removed, leaving a 400 m × 400 m area that was then shifted by the increments listed above. After shifting, original maps were clipped to the extent of each shifted 400 m × 400 m map, creating continuous 400 m × 400 m areas for comparative analysis of false change errors caused by map shifting.

Percent false change for each ecotope class was computed by dividing the area change for each class by the total area in the 400 m × 400 m analysis area. Total false change for the analysis area was then calculated by summing the absolute values of the percent changes for all ecotope classes in the analysis area and dividing by two to normalize the maximum possible false change to 100 percent (the use of absolute values produces a maximum possible error of 200 percent).

Landscape Heterogeneity Metrics

The software FRAGSTATS (McGarigal and Marks, 1995) was used to calculate landscape heterogeneity indices for 400 m × 400 m analysis area maps after converting them to 0.5 m resolution ArcInfo® GRID files. We chose six landscape metrics to characterize heterogeneity: Patch density (PD: a landscape pattern index with high values indicating high spatial heterogeneity), Number of ecotope classes (NCLS: a landscape composition index with higher values corresponding to higher heterogeneity), Simpson's Diversity Index (SIDI: a heterogeneity index based on probability theory), Landscape Shape Index (LSI: a patch shape heterogeneity index that increases as shapes become more irregular, as indicated by edge length), Landscape Division Index (DIVISION: a landscape heterogeneity index that increases as landscapes are more finely subdivided), and Patch Cohesion Index (COHESION: a landscape homogeneity index that increases as patches become more clumped, indicating decreasing spatial heterogeneity).

False Change at Different Change Detection Resolutions

We selected five of the twenty sample maps, varying across the range of landscape heterogeneity metrics measured as above, to investigate relationships between the size of the change detection window (the change detection resolution; no relation with image resolution) and the relative amount of false change error caused by positional error under different landscape conditions. It should be noted that for feature-based methods, the resolution for change detection is flexible within the extent of the change detection AOI, and may be varied from a maximum equal to the spatial extent of the change detection AOI down to minimum even smaller than the pixel size of the input image data, though it is usually set to a resolution many times that of the input image. The optimal minimum resolution for feature-based change measurements is defined as the minimum spatial extent within which the false change error caused by the misregistration of input data (feature-based maps) is insignificant relative to the amount of change that will be measured. The effect of misregistration error is therefore critical in determining the optimal change detection resolution for feature-based mapping because there is always a tradeoff: larger change detection resolutions dilute the precision with which change can be mapped, while finer resolutions produce unreliable change measurements because these are increasingly dominated by false change errors caused by positioning errors.

We measured false change errors at different change measurement resolutions by shifting maps as described previously and then computing the false change error within square sample cells of different sizes ("change detection resolutions": 400, 200, 100, 50, 25, 10, and 5 m) across each 400 m × 400 m analysis area. At each change detection resolution (400, 200, 100, 50, 25, 10, and 5 m), a set of sample cells was selected at random from each of the five maps (n = 3, 6, 9, 10, 11, 11 per map) yielding a sample size of n = 15, 30, 45, 50, 55, 55 for each detection resolution, respectively. The shifted and original maps were then clipped to the sampled cells to calculate the total percent false change within each sample cell by comparing area estimates before and after shifting, using the same method as for the 400 m × 400 m analysis areas.

Regression Models

Multiple linear regression, including interaction (GLM model in SPSS® 11.5 for Windows™ (SPSS, Inc., 2005)) was used to characterize and model relationships between percent false change, positional error (PE), and landscape metrics across the twenty sample AOI maps and between percent false change, change detection resolution (RA), positional error, and the landscape metrics across the sub-sample of five maps described above. We selected two 500 m × 500 m test maps that were not used to derive the regression models described above, one flat (lower heterogeneity, Gaoyi site) and one hilly (higher heterogeneity, Dianbai site), to test the accuracy of our regression models in predicting the change detection error caused by positional error (sites described in Ellis, 2004). Observed percent false change was calculated for test maps across the range of positional errors and change detection resolutions using the same methods described above. Predicted percent false change was calculated by applying the regression models derived above across the standard range of positional errors and change detection resolutions based on analysis of the test maps. Differences between observed and predicted percent false change error were calculated as the RMSE between observed and predicted estimates (Federal Geographic Data Committee, 1998).

Results

Effects of Positional Error on Change Detection in Different Landscapes

Landscape heterogeneity varied considerably across our sample of twenty 500 m × 500 m landscape maps from China and the United States, with especially large variation in patch density (PD), number of classes (NCLS), and landscape shape index (LSI) (Table 1). As expected, false change error was highly positively correlated with positional error across landscapes as demonstrated using simple linear regression (n = 220, r^2 = 0.82, p <0.0001, Figure 1). Moreover, this simple model was able to explain 82 percent of the variation in false change error caused by positional error, with a prediction SE of 1.2 percent, indicating that the model should be useful for predicting false change errors caused by misregistration when measuring changes from

Table 1. Landscape Metrics for Twenty 500 m × 500 m Sample Maps for Rural China (n = 19) and Suburban Maryland, USA (n = 1). PD = Patch Density; NCLS = Number of Classes; LSI = Landscape Shape Index; SIDI = Simpson's Diversity Index; COHESION = Patch Cohesion Index; DIVISION = Landscape Division Index

	Minimum	Maximum	Mean	Standard Deviation	Coefficient of Variation
PD	55	994	396	256	64%
NCLS	6	35	19	10	53%
LSI	3.03	9.5	6.42	1.88	29%
SIDI	0.46	0.93	0.76	0.11	14%
DIVISION	0.49	0.97	0.87	0.12	14%
COHESION	99.2	99.8	99.5	0.18	0.18%

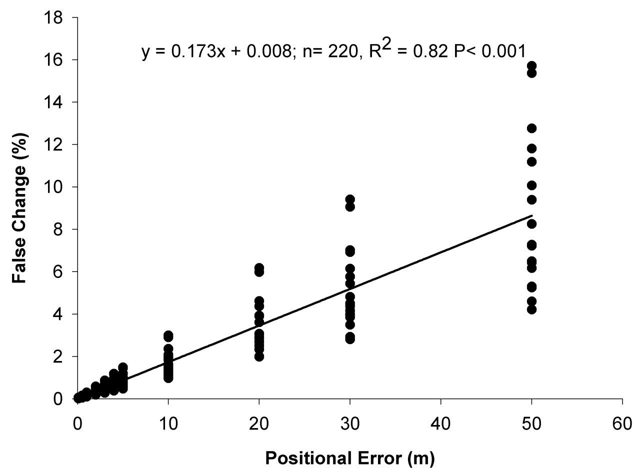

Figure 1. Relationship between percent false change and positional error derived by simple linear regression from a sample of twenty 400 m × 400 m ecological maps with 11 clusters of positional errors (n = 220). Differences in percent false change at same level of positional error are caused by variation in landscape characteristics.

400 m × 400 m ecotope maps of the same area, given their co-registration error. For example, the model (Figure 1) gives an estimated change detection error of approximately 2 percent for a 10 m positional error, a seemingly low level though quite significant when landscape change is small (e.g., a 10 percent change estimate of which 2 percent is erroneous is an error of 20 percent).

There was no statistically significant linear relationship between false change error and any individual landscape metric across the range of positional errors, based on regression on the sample of twenty landscape maps. However, relationships between landscape heterogeneity (indicated by metrics) and false change error appear to have been obscured by the large effect of positional error. When relationships between false change error and individual landscape metrics were tested at each level of positional error, the number of ecotope classes (NCLS) had a significant positive relationship with false change error under all levels of positional error up to 50 m, though the relationship declined as positional error increased, and with the exception of the patch cohesion index (COHESION), no other index was significant when positional error was >0.1 m (Table 2). With positional error ≤30 m, NCLS alone could explain >26 percent of the variation in percent false change, indicating that the number of ecological feature classes within a given area has a significant impact on the potential accuracy of high-resolution change estimates, especially when positional error is small. Although COHESION varied little across landscape samples (Table 1), it could be used to predict up to 20 percent of false change error when positional error was ≤1 m, as it had a significant negative correlation with false change (Table 2).

False Change Versus Change Detection Resolution

Land-use change detection error was significantly related to the resolution of change detection (the "resolution of analysis" = RA), under the influence of positional error (PE) and landscape heterogeneity (Table 3). False change error increased not only with positional error, but also as the RA became finer (Figure 2), demonstrating that higher resolution change estimates are more sensitive to the false change error caused by positional errors. For example, with a positional error of 10 m and NCLS between 5 and 20, change detection error increased from 3 to 6 percent with an RA of 200 m to 10 to 13 percent with an RA of 25 m. False change across change measurement resolutions was also related to all landscape metrics except DIVISION (Table 3), indicating a small but significant increase in change detection error within increasing spatial heterogeneity in landscapes.

Table 4 presents multiple linear regression equations that can be used to predict false change errors based on RA, PE and landscape metrics. These models can explain up to 75 percent of the variation in change detection errors caused

TABLE 2. STATISTICAL SIGNIFICANCE (p) AND r^2 FOR LINEAR REGRESSIONS OF PERCENT FALSE CHANGE (y) ON INDIVIDUAL LANDSCAPE METRICS (x) UNDER DIFFERENT POSITIONAL ERRORS FOR A SAMPLE OF TWENTY 400 M × 400 M MAPS. BOLD TEXT INDICATES STATISTICALLY SIGNIFICANT RELATIONSHIPS ($p < 0.05$, df = 19). NCLS = NUMBER OF CLASSES, PD = PATCH DENSITY, SIDI = SIMPSON'S DIVERSITY INDEX, COHESION = PATCH COHESION INDEX, DIVISION = LANDSCAPE DIVISION INDEX, AND LSI = LANDSCAPE SHAPE INDEX

		Positional Error							
		0.1 m	0.5 m	1 m	5 m	10 m	20 m	30 m	50 m
NCLS	p	**0.001**	**0.005**	**0.010**	**0.020**	**0.022**	**0.018**	**0.022**	0.066
	r^2	**0.466**	**0.365**	**0.314**	**0.266**	**0.260**	**0.272**	**0.258**	0.175
PD	p	**0.024**	0.334	0.340	0.434	0.519	0.567	0.633	0.953
	r^2	**0.254**	0.052	0.051	0.034	0.023	0.019	0.013	0.000
SIDI	p	**0.016**	0.092	0.105	0.136	0.165	0.238	0.367	0.588
	r^2	**0.281**	0.149	0.140	0.119	0.104	0.076	0.045	0.017
COHESION	p	**0.002**	**0.029**	**0.044**	0.067	0.088	0.136	0.207	0.454
	r^2	**0.41**	**0.239**	**0.206**	0.174	0.153	0.119	0.087	0.032
DIVISION	p	0.087	0.380	0.405	0.530	0.596	0.795	0.964	0.598
	r^2	0.154	0.043	0.039	0.022	0.016	0.004	0.000	0.016
LSI	p	**0.005**	0.053	0.067	0.117	0.144	0.179	0.240	0.506
	r^2	**0.366**	0.193	0.175	0.131	0.115	0.098	0.076	0.025

TABLE 3. SIMPLE LINEAR REGRESSION MODELS FOR ESTIMATING FALSE CHANGE (Y) BASED ON CHANGE DETECTION RESOLUTION (RA), POSITIONAL ERROR (PE) AND INDICES OF LANDSCAPE HETEROGENEITY. REGRESSION COEFFICIENT (m) AND STANDARD ERROR (SE), STATISTICAL SIGNIFICANCE (p VALUE), AND r^2 ARE PRESENTED WITH STATISTICALLY SIGNIFICANT VALUES ($p < 0.05$) IN BOLD. NCLS = NUMBER OF CLASSES, PD = PATCH DENSITY, SIDI = SIMPSON'S DIVERSITY INDEX, COHESION = PATCH COHESION INDEX, DIVISION = LANDSCAPE DIVISION INDEX, AND LSI = LANDSCAPE SHAPE INDEX

	400 m Resolution Only[1]				All Resolutions[2]			
Predictors	Coefficient	SE	p	r^2	Coefficient	SE	p	r^2
RA					−0.052	0.0055	**0.001**	**0.13**
PE	0.173	0.005	**0.001**	**0.820**	0.79	0.043	**0.001**	**0.47**
NCLS	0.035	0.019	0.073	0.015	0.27	0.064	**0.009**	**0.024**
PD	0.0005	0.001	0.75	0.001	0.015	0.004	**0.014**	**0.022**
SIDI	1.96	1.8	0.42	0.003	21	6.5	**0.046**	**0.014**
COHESION	−1.17	1.1	0.29	0.005	−16	4.4	**0.022**	**0.019**
DIVISION	−0.06	1.7	0.97	0.000	19	17	0.28	0.004
LSI	0.099	0.11	0.36	0.004	1.4	0.062	**0.039**	**0.015**

[1]n = 20, df = 219.
[2]Resolutions = 200, 100, 50, 25, 10, and 5 m; n = 5, df = 279.

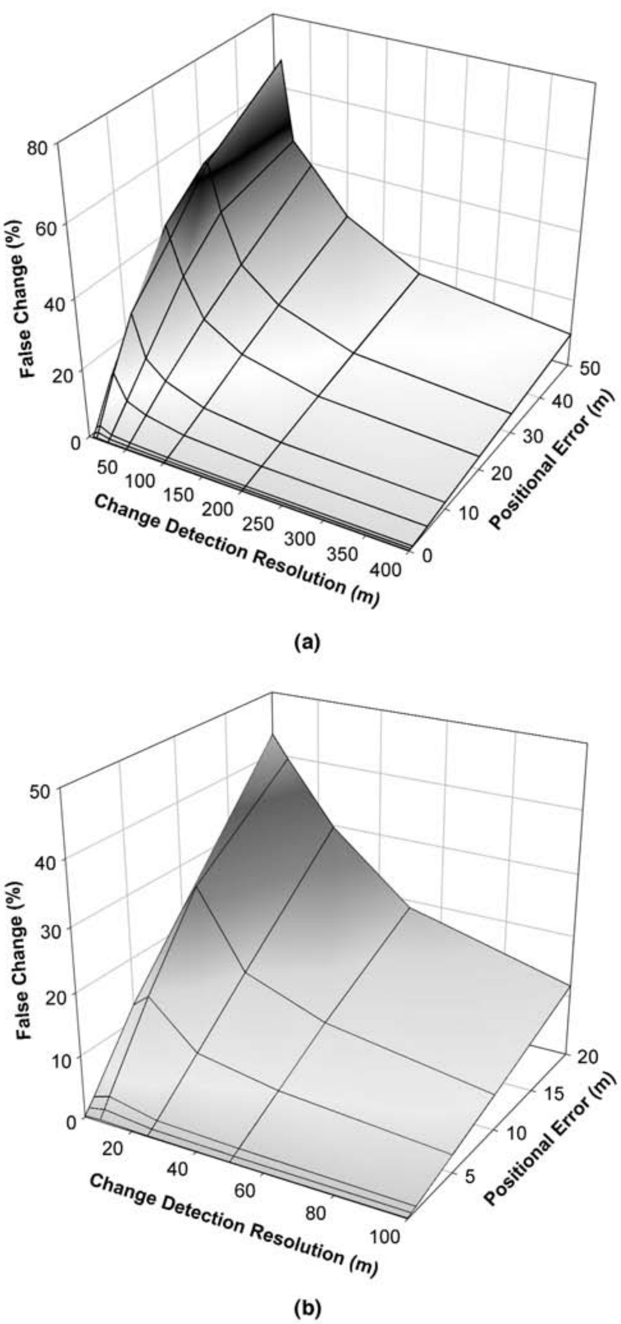

Figure 2. 3-D plots showing the relationship between percent false change (mean of five maps), positional error (PE), and the resolution of change detection (RA) from an analysis of five maps with different landscape characteristics in China: (a) illustrates relationships across the full range of data used for the models, and (b) illustrates relationships for the range of variables commonly observed in feature-based change measurement.

by positional error and have a standard error of prediction in the 10 percent range (Table 4). This moderate level of prediction accuracy indicates the presence of other possible predictors and complex interactions among PE, RA, and landscape heterogeneity in producing false change error. Nevertheless, these equations facilitate computation of the minimum change detection resolution with a specified acceptable maximum percent false change error using ecotope maps for a given AOI, as long as the positional error is known.

Validation of Regression Models

Predicted false change errors from multiple regression models were tested against observations using two maps, one for a flat AOI (Gaoyi) and one for a hilly AOI (Dianbai) (Figure 3). RMSE of predictions ranged from 8.2 to 10 percent and from 7.0 to 8.1 percent for Dianbai and Gaoyi, respectively (Figures 3a and 3c) based on predictions from PE between 0.1 and 50 m and RA between 5 and 200 m. RMSE of predictions was reduced significantly, to 2.1 to 2.6 percent and 3.9 to 4.8 percent for Dianbai and Gaoyi, respectively, when PE was limited between 5 and 50 m, and RA was between 25 and 200 m (Figures 3b and 3d). The analysis demonstrates also, that models that include landscape metrics yielded prediction accuracies 2 to 5 percent higher than those without them.

Discussion

Our analysis successfully characterized relationships between positional error and change detection error in the context of change estimates using quantitative comparison of high-resolution feature-based ecological maps. In general, higher change detection errors were associated with higher positional error, higher landscape heterogeneity, and finer change detection resolutions. The regression models in Table 4 describe empirical relationships between positional error, change detection resolution, and landscape heterogeneity indices that can be applied to predict false change errors when comparing landscape maps derived from ecotope feature mapping and classification methods (Ellis, 2004). These empirical models were validated using two highly dissimilar landscape samples that were not part of the model derivation, demonstrating RMSEs for false change error predictions between 2 percent and 5 percent, when positional errors were between 5 m and 50 m and change detection resolution was between 25 m and 200 m (Figure 3). Given that image co-registration errors for orthorectified high-resolution image pairs usually range from 1 m to 10 m (Wang and Ellis, 2005), and that maps are readily made for extents up to and greater than 1000 m $\times$ 1000 m (Ellis, 2004), these models are generally useful for estimating false change across the range of typical ecotope mapping conditions. Moreover, these equations make it possible to compute the optimal change detection resolution using a specific pair of ecotope maps, given their coregistration error and the maximum acceptable percentage of false change error desired by the investigator. For example, if we wish to estimate the minimum change detection resolution with a false change error $\leq$5 percent using maps with a co-registration error of 10 m and 20 feature classes, the NCLS-based regression model in Table 4 indicates that the minimum change detection resolution should be $>$237 m.

Our analysis demonstrated, though the effect was small, that false change prediction models that include landscape heterogeneity indicators are more accurate than those without them (Table 4). Therefore, whenever these metrics are available, they should be used. The landscape heterogeneity indicator most strongly linked to feature-based map change estimate error was the number of mapped feature classes, in accord with the results of Verbyla and Boles (2000) who found that false change caused by positional error increased as the number of classes increased using pixel-based change estimates at a variety of spatial resolutions of image data. The relatively small improvement gained by including landscape

Table 4. Multiple Linear Regression Models for Estimating False Change Error (fc, in %), from Resolution of Change Analysis (RA), Positional Error (pe) and Landscape Metrics (lm) Based on Analysis of Five Landscape Maps Using the Equation: $FC = a \times RA + b \times PE + c \times RA \times PE + d \times LM + e \times PE \times LM + f$. Regression Coefficients (a, b, c, d, e, f) ± 1 Standard Error (SE), Adjusted r^2 and Prediction SE for FC are Given in the Table. All Models Have $n = 280$ and $p < 0.001$. Landscape Metrics are ncls = Number of Classes, pd = Patch Density, sidi = Simpson's Diversity Index, cohesion = Patch Cohesion Index, and lsi = Landscape Shape Index

Landscape Metric	a	b	c	d	e	f	r^2	SE
None	−0.0118 ± 0.0063	1.11 ± 0.050	−0.0028 ± 0.0003	—	—	3.50 ± 1.10	0.70	10.6
NCLS	−0.0118 ± 0.0058	0.754 ± 0.080	−0.0028 ± 0.0003	0.024 ± 0.070	0.0170 ± 0.003	3.00 ± 1.77	0.75	9.71
PD	−0.0118 ± 0.0058	0.756 ± 0.082	−0.0028 ± 0.0003	0.0009 ± 0.004	0.0010 ± 0.0002	3.16 ± 1.81	0.75	9.79
SIDI	−0.0118 ± 0.0060	−0.0451 ± 0.254	−0.0028 ± 0.0003	−0.972 ± 7.176	1.49 ± 0.324	4.25 ± 5.63	0.74	10.0
COHESION	−0.0118 ± 0.0061	—	−0.0028 ± 0.0003	−16.2 ± 3.73	0.0112 ± 0.0005	1610 ± 371	0.72	10.3
LSI	−0.0118 ± 0.0060	0.545 ± 0.146	−0.0028 ± 0.0003	0.137 ± 0.455	0.0836 ± 0.0206	2.58 ± 3.23	0.73	10.1

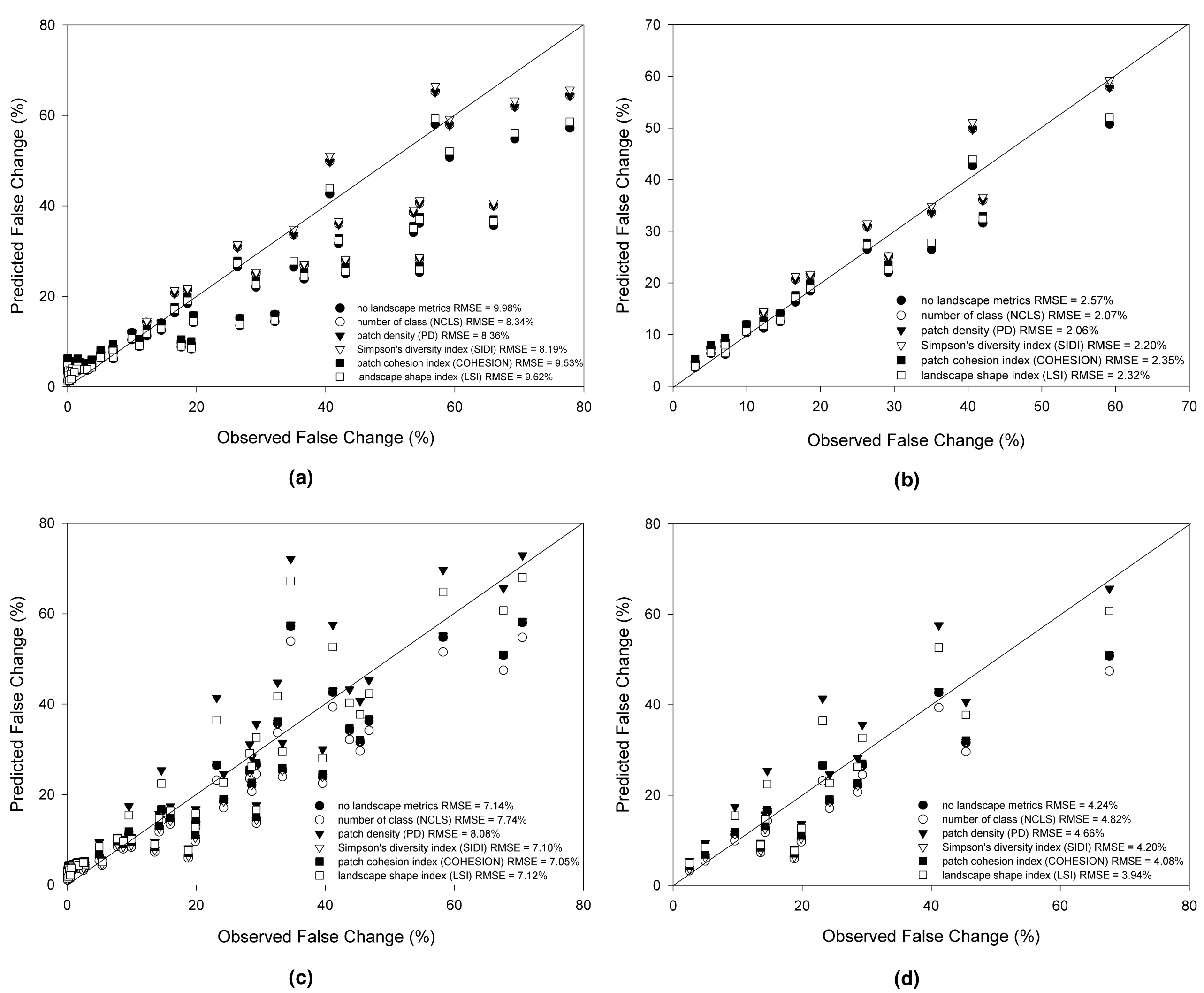

Figure 3. Comparison between observed and predicted change detection errors using multiple linear regression models at a hilly (Dianbai) and a flat site (Gaoyi): (a) and (c) illustrate expected versus observed false change error for positional errors (PE) between 0.1 m and 50 m and change detection resolution (RA) between 5 m and 200 m for Dianbai and Gaoyi, respectively. (b) and (d) are the same as (a) and (c), but with PE between 5 m and 50 m and RA between 25 m and 200 m.

metrics indicates that interactions between change detection error and landscape pattern are complex, so that higher landscape heterogeneity need not necessarily lead to higher errors in change estimates. We also observed that the impact of positional error on change detection error increased as the change detection resolution became finer (detection window size becomes smaller), a result that parallels those from pixel-based approaches (Townshend *et al.*, 1992).

High-resolution ecological maps tend toward more feature classes and smaller features than those based on coarser imagery, making change estimates based on these data especially vulnerable to the impacts of positional error. It is therefore critical to quantify and reduce the impacts of false change errors due to positional error in this context. It is possible to reduce positional error by choosing adequate and well-distributed GCPS for image orthorectification and co-registration (Townshend *et al.*, 1992; Wang and Ellis, 2005). Reducing the number of mapped feature classes also reduces the impacts of positional error, but not always in consistent ways, and usually with a corresponding reduction in information about the features. Finally, the resolution for change estimates should be reasonably selected. Though high quality image orthorectification is always valuable and simple classification systems may prove adequate, our analysis demonstrates that the accuracy of feature-based change estimates can be improved simply by reducing their change detection resolution. To achieve this, the empirical models presented in Table 4 can be used to select a change detection resolution with a given level of false change error from ecotope maps with known misregistration error, and then to predict the false change error cause by this positional error at the selected change detection resolution.

In this study we assumed that positional error between maps was uniformly distributed as a constant across maps; to model positional error, we simply shifted entire maps. For small areas, this assumption is reasonable. For example, the positional errors within 500 m $\times$ 500 m image samples from raw versus orthorectified Ikonos GEO imagery were relatively uniform in magnitude (average of 15 m) and direction across 100 km^2 of a hilly site in China (Yiyang site; Wang and Ellis, 2005). We therefore assert that our empirical models for false change error prediction are reliable for estimating change detection errors within smaller areas ($<$1 km^2) of similarly prepared imagery. However, for larger areas, such as entire 100 km^2 Ikonos scenes, positional errors after geometric processing or orthorectification are random and anisotropic (Verbyla and Boles, 2000), so that positional error models for entire processed images and maps at this scale should include random and anisotropic variability. Moreover, misregistration errors calculated by comparing a limited number of GCPs across an image represent positional errors across, but not within, imagery and maps. It is therefore impractical to measure and predict the effect of positional error and landscape heterogeneity on false change errors across large areas. For this reason, it is more reliable to measure changes within smaller subsets of larger areas, as these have more uniformly distributed positional errors, and to measure changes and predict errors from these smaller samples using our empirical models, which may then be summarized across larger areas.

As a final caveat, it should be noted that many other factors besides positional error limit the accuracy of feature-based ecological change measurements, including classification errors, feature detection errors, and feature digitizing errors. In many cases, these other types of errors may have far greater impacts on the accuracy of change measurements than do positional errors. Nevertheless, the effects of positional errors on the accuracy of feature-based change measurements are most likely unrelated to these other types of errors, and are essentially predictable and avoidable. The empirical relationships and methodology we present here provide a reliable basis for the prediction and avoidance of positional errors in change measurements from feature-based maps derived from subsets of larger images, where positioning errors are more regular and predictable. The current methodology should also prove useful when investigating the relative importance of positional errors compared with other types of errors in feature-based change measurements, an important topic for future research.

Conclusions

This study successfully characterized the impacts of positional error on the accuracy of landscape change estimates based on feature interpretation from orthorectified high-resolution imagery of highly fragmented rural landscapes in China and the suburban United States. False change error caused by positional error increased significantly as the magnitude of positional error increased and as landscapes became more heterogeneous. Finer change detection resolutions also proved to be more prone to false change error than lower detection resolutions at a given level of positional error. Given that the change detection resolution for feature-based change measurements may be set to any spatial extent, from an entire AOI to a window smaller than the pixels of the input image, it is useful to estimate the minimum change detection resolution within which the false change errors caused by image misregistration are insignificant relative to the true changes that must be observed. We demonstrate that this optimal minimum change detection resolution is predictable, and provide empirical models for predicting false change error based on positional error and the number of classes within standardized ecological maps. These models support the computation of optimal change measurement resolutions with false change errors below a specified threshold based on the misregistration error of paired maps, with or without the use of landscape heterogeneity indicators for the maps. The regression models may also be used to map predicted false change errors across landscape maps at any selected change detection resolution. These empirical models assume systematic positional errors, but may be applied to larger areas with random or anisotropic positional errors by dividing larger areas into smaller subsets that have more systematic error. Given the increasing use of feature-based methods in high resolution remote sensing, the application of our empirical approach to modeling measurement errors as they interact with heterogeneous landscapes across spatial scales should prove useful for applications beyond our feature-based change detection application.

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