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RESEARCH ARTICLE

Effects of patch characteristics and within patch heterogeneity on the accuracy of urban land cover estimates from visual interpretation

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Abstract Landscape ecology links landscape pattern to ecological function. Achieving this goal hinges on accurate depiction and quantification of pattern, which is frequently done by visually interpreting remotely sensed imagery. Therefore, understanding both the accuracy of that interpretation and what influences its accuracy is crucial. In addition, imagery is pixel-based but landscape pattern exists, more realistically, as irregularly shaped patches. Patches may contain only one feature type such as trees, but, in some landscapes, patches may contain several different types of features such as trees and buildings. Using a patch-based approach, this paper investigates two types of variables—whole-patch and within-patch—that are hypothesized to influence the accuracy of visually estimating the cover of features within patches. A highly accurate reference map, obtained from object-based classification, was used to evaluate the accuracy of visual estimates of cover within patches. The effects of the variables on the accuracy of these estimates were tested using logistic regressions and multimodel inferential procedures. Though all variables significantly affected the accuracy, the within-patch configuration of features is the most significant factor. In general, errors of cover estimates are more likely to occur when patches are smaller or have more complex shapes, and features within a patch are (1) more diverse; (2) more fragmented; (3) more complex in shape; and (4) physically less connected. These results provide an important first step towards a quantitative, spatially explicit model for predicting error of cover estimates and determining under what circumstances estimation error is most likely to occur.

Keywords Visual interpretation · Object-based classification · HERCULES · Accuracy · Land cover composition and configuration · Pattern analysis · Spatial heterogeneity · Urban systems

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Introduction

Landscape ecology focuses on understanding the reciprocal link between pattern and process (Turner et al. 2001; Wu and Hobbs 2002). Building this understanding requires accurate quantification of landscape pattern at the grain and extent appropriate for a specific research question (Gustafson 1998; Turner 2005; Shao and Wu 2008). Quantifying

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landscape pattern primarily relies on thematic maps, and these maps are frequently derived from visual interpretation of remotely sensed imagery (Turner et al. 2001; Groom et al. 2006; Iverson 2007). Therefore, pattern quantification, and consequently our ability to apply it to understanding and predicting variation in ecological processes in the landscape, hinges on accurate classification of remotely sensed imagery (Wu and Hobbs 2002; Iverson 2007; Li and Wu 2007; Shao and Wu 2008). Because this is fundamental to advancing research in landscape ecology, it is crucial that we assess what influences the accuracy of these classifications.

Visual interpretation of patterns and land cover features is an approach used both by landscape ecologists and remote sensing specialists. Visual interpretation, frequently referred to as photo-interpretation or manual interpretation, is the process by which human analysts extract information by visually inspecting an image (Lillesand and Kiefer 2004; Richards and Jia 2006). Within the remote sensing literature, visual interpretation has typically been used for digitizing individual landscape features and ground truthing images (Lillesand and Kiefer 2004; Richards and Jia 2006). In landscape ecology, visual interpretation is a well-established method for patch mapping and classification (e.g., Fensham et al. 2002; Allard et al. 2003; Cadenasso et al. 2007; Gill et al. 2008; Heiskanen et al. 2008; Ståhl et al. 2011).

Patches in the landscape can be mapped based on many different criteria such as variation in plant community composition or land use/land cover. Patches can also be delineated based on a contrast in an ecological process, such as rates of denitrification. The appropriate criteria used to delineate patches depend on the specific research question being addressed (Cadenasso et al. 2003). A patch is a spatial unit that has a specific location and dimensionality. Therefore, patches can be quantitatively described by size and shape as well as location relative to other patches (Gustafson 1998). In addition, patches may contain more than one feature. For example, patches delineated using the criteria of land use may all be residential but these patches contain types and amounts of features such as buildings, impervious surfaces, and trees (e.g., Cadenasso et al. 2007; Gill et al. 2008).

Patch mapping and classification commonly consists of two steps: (1) delineating patch boundaries, and (2) deriving attribute values of with-patch features such as percent cover of trees and impervious surfaces (e.g., Allard et al. 2003; Cadenasso et al. 2007; Gill et al. 2008). The variation in delineating boundaries by different interpreters or the same interpreter over time has been extensively assessed (Congalton and Mead 1983; Cherrill and McClean 1995; Ellis et al. 2006). This paper, however, focuses on the accuracy of the second step—visually estimating the cover of features within the patch.

The accuracy of estimating the cover of features within a patch may be affected by the photoscales, land cover types, landscape structure, and the skills of the photo-interpreters (Fensham et al. 2002; Paine and Kiser 2003; Fensham and Fairfax 2007; Zhou et al. 2010). This accuracy has been commonly assessed and calibrated by field measurements (e.g., Fensham and Fairfax 2003; Clehmann et al. 2009) or reference data derived from other approaches (e.g., Zhou et al. 2010). Few studies, however, have quantitatively examined factors that may affect this accuracy (Fensham et al. 2002; Paine and Kiser 2003; Fensham and Fairfax 2007), and we are not aware of any that have investigated how whole-patch characteristics and within-patch characteristics affect the accuracy of visually estimating within-patch cover. We suggest that this accuracy may be influenced by whole-patch characteristics, such as the size and shape of the patch, and within-patch characteristics, such as the composition and configuration of the features (Zhou et al. 2010). Quantitatively understanding the relationship between accuracy of cover estimates and whole-patch and within-patch characteristics can provide insight into potential causes of classification errors and identify under what circumstances classification errors are most likely to occur. In addition, analyses of these relationships provide a potential tool to predict how the magnitude of error is spatially distributed in the landscape. These insights are not available from standard accuracy assessment procedures (Shao et al. 2001; Smith et al. 2002, 2003; Ellis and Wang 2006; Shao and Wu 2008). This paper aims to fill this gap.

The overarching goal of this study, therefore, is to determine whether patch characteristics at two scales—whole-patch and within-patch—influence the accuracy of estimating the relative cover of land cover features inside patches. Specifically, the objectives are to (1) investigate whether whole-patch characteristics, such as patch size and shape, and within-patch characteristics, such the composition and configuration of features, are useful predictors of errors in estimating the cover features within a patch, and (2) examine the relative strength of whole-patch and within-patch characteristics as predictors of errors in estimating the cover of features within a patch.

Methods

Study area

We have delineated and classified land cover patches in the Gwynns Falls watershed of Baltimore, MD, USA as part of the Baltimore Ecosystem Study, a Long Term Ecological Research Program funded by the National Science Foundation (www.beslter.org). The watershed is approximately 17,150 ha, and traverses an urban–suburban–rural gradient from downtown Baltimore City, through suburban and suburbanizing areas, out to the rural/suburban fringe (Fig. 1). Because of this size and range of land cover, the land cover data layer consists of patches that vary in size and shape and that vary in the relative cover of features within them. Therefore, this data layer is well suited for the goals of this research.

Data

Creating a patch layer to assess classification accuracy

A base patch layer was created using the high ecological resolution classification for urban landscapes and environmental systems (HERCULES) land cover classification. This classification was specifically developed for urban landscapes (Cadenasso et al. 2007), and focuses on the biophysical structure, specifically: (1) coarse-textured vegetation—trees and shrubs (CV), (2) fine-textured vegetation—herbs and grasses (FV), (3) bare soil, (4) pavement, (5) buildings, and (6) building typology (Cadenasso et al. 2007). Because the last feature is qualitative, it will not be discussed further. The first five features are allowed to vary independently of each other and a shift in the amount or distribution of one or more features will result in a different patch. The utility of this approach for linking landscape pattern to ecological processes is best illustrated by an example. Using standard land use/land cover classifications, residential areas in the urban landscape would be classified the same and be delineated as one continuous patch. But residential

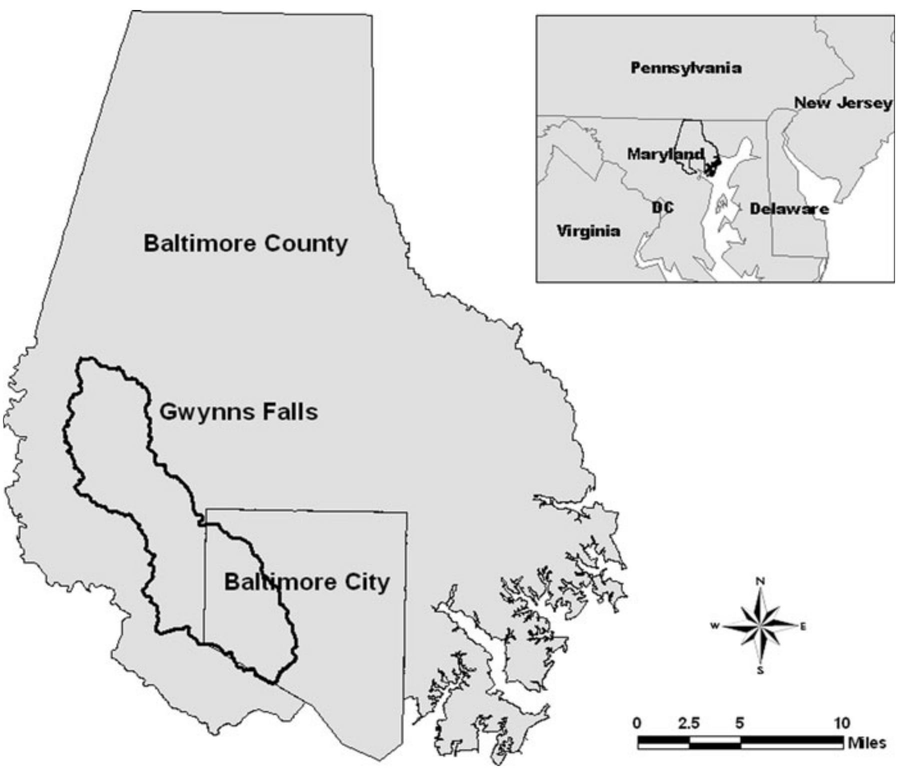

Fig. 1 The Gwynns Falls watershed includes portions of Baltimore City and Baltimore County, MD, USA, and drains into the Chesapeake Bay

Landscape Feature	Cover Category
Build	3
CV	1
FV	2
Pave	1
Bare soil	2

Landscape Feature	Percent	Cover Category
Build	0.16	2
CV	0.03	1
FV	0.24	2
Pave	0.47	3
Bare soil	0.10	2

Landscape Feature	Response Variable
Build	0
CV	1
FV	1
Pave	0
Bare soil	1

Fig. 2 HERCULES patches and within-patch cover of each of the five land cover features. *Left panel* high-resolution image with HERCULES patch boundaries superimposed. *Right panel* land cover classification map with HERCULES patch boundaries superimposed. *Left table* cover categories of the five features estimated by visual interpretation for the patch highlighted in the *right panel*. *Center table*: percent cover of the features obtained for the same highlighted patch by object based classification and the equivalent cover category. *Right table*: binary response variables used to represent whether the cover was correctly estimated by visual interpretation. Value of one indicates a correct categorization and zero indicates an incorrect categorization

blocks can vary considerably in terms of building density or the presence and abundance of trees. This variation may influence ecological processes such as biodiversity or carbon storage. The HERCULES classification captures this heterogeneity in biophysical features and delineates different patches where a shift in tree abundance occurs. Patch boundaries, where possible, are digitized down the middle of a road (Fig. 2).

HERCULES patches were digitized on-screen using high-spatial resolution aerial imagery in ArcGIS™ (version 9.2). The imagery was collected in October 1999, has a pixel size of 0.6 m, and is 3-band color-infrared (green: 510–600 nm, red: 600–700 nm, and near-infrared: 800–900 nm). The imagery was orthorectified and meets the National Mapping Accuracy Standards for scale mapping of 1:3,000 (3-m accuracy with 90 % confidence). A total of 2,250 patches were delineated in the watershed, with a mean size of 7.6 ha, and a density of approximately 13/km^2.

Each HERCULES patch, most likely, contains multiple land cover features such as buildings and trees (Fig. 2). We evaluate whether the accuracy of visually estimating the cover of those features within a patch is influenced by whole-patch characteristics—size and shape—and within-patch characteristics—composition and configuration of the features.

Creating the test and reference datasets

Using the HERCULES patch layer for the watershed, the cover of all five features within a patch were estimated using two approaches: (1) visual interpretation, and (2) object-based classification. Through visual interpretation the cover of each feature within a patch was assigned to a cover category: (0) absent, (1)

Table 1 Summary of the accuracies for the reference land cover map obtained from object-based image analysis

	Building	CV	FV	Pavement	Bare soil
User's accuracy (%)	83.6	97.7	94.9	91.9	90.0
Producer's accuracy (%)	94.4	94.4	89.3	88.3	100
Overall accuracy	92.3 %		Kappa statistic	0.899	

present to 10 %, (2) 11–35 %, (3) 36–75 %, and (4) > 75 % (Fig. 2; Cadenasso et al. 2007). This was the test dataset. The object-based classification approach used the software eCognition (Zhou and Troy 2008) to generate the reference dataset containing the cover of features in the patches as a continuous value. The continuous cover values were then assigned into the cover categories described above (Fig. 2). The continuous values were converted to categories so that the two approaches could be compared. The overall accuracy of the object-based classification was 92.3 %, with producer's accuracies ranging from 88.3 to 100 %, and user's accuracies from 83.6 to 97.7 % (Table 1).

The test and reference datasets were compared to assess the accuracy of estimating cover of features within patches based on visual interpretation. Each land cover feature was assigned a one or a zero to indicate whether or not the proportion cover estimates from visual interpretation were in the same category as those generated from the object-based approach. The resulting binary variables were used as response variables in the later logistical regressions.

Whole-patch and within-patch characteristics

Many metrics have been developed to characterize and measure spatial pattern in landscapes (Gustafson 1998; McGarigal et al. 2002). We selected commonly used metrics to describe whole-patch characteristics and the composition and configuration of features within a patch (Fig. 3; Table 2). Whole-patch metrics included: total area, total edge (i.e., perimeter), fractal dimension index, shape index, and perimeter–area ratio. Within-patch metrics included those to describe the composition of the features—percent cover of each feature and the Simpson's diversity index—and those to describe the configuration of features—area, edge, density, shape, connectivity, and proximity of each feature type (Table 2) (Gustafson 1998; McGarigal et al. 2002). Simpson's diversity combines richness (i.e., the number of feature types present) and evenness (i.e., the distribution of area among features). Cohesion index (CI) was used to quantify connectivity among land cover features within a patch (Schumaker 1996). Proximity/isolation was measured by Euclidean nearest neighbor distance (McGarigal et al. 2002). All of the metrics, except for Euclidean nearest neighbor distance, were calculated at both the feature level (e.g., PD_Build, patch density for building) and whole-patch level (e.g., PD_LS, patch density of all five land cover features within a patch) (Table 2). Statistical summaries, including mean and standard deviation, were calculated for metrics of patch size, patch edge, fractal dimension index, shape index, perimeter–area ratio, and Euclidean nearest neighbor distance (Table 2).

Metrics of whole-patch characteristics and within-patch composition and configuration were calculated for each feature separately in ArcGIS^{TM} 9.3 (McGarigal et al. 2002). These metrics were calculated based on the HERCULES patch layer and the reference land cover layer generated from object-based classification (Table 2). These metrics were used as predictor variables in later statistical analyses to examine whether whole-patch and within-patch characteristics affect the accuracy of cover estimates based on visual interpretation.

Statistical analyses

Using logistic regressions, we first examined how variables of whole-patch characteristics could affect cover estimates by visual interpretation. We repeated the analyses using the variables of within-patch composition and configuration. Whether a combination of whole-patch and within-patch variables yielded better predictions than either alone was then investigated. The response variable for each of the five land cover features was binary, with value of one or zero representing the proportion cover estimates from visual interpretation were correct or incorrect. Five models were constructed and compared for each response variable. Those five models have a given dependent variable as a function of: (1) whole-patch

Variables	Value
Metrics of whole-patch characteristics	
PA (ha)	7.28
PERIM (km)	1.24
FRAC	1.03
PARA	0.02
SHAPE	1.15
Metrics of within-patch composition	
Per_Build	0.16
Per_CV	0.03
Per_FV	0.24
Per_Pave	0.47
Per_BS	0.10
SIDI	0.69
Metrics of within-patch configuration	
AMN_Build (m^2)	493.9
EMN_Build (m)	159.5
LPI_Build	1.43
PD_Build	329.6
ED_Build	525.8
PARAMN_Build	0.36
SHAPEMN_Build	1.81
FRACMN_Build	1.19
ENN_MN_Build (m)	35.8
CI_Build	97.6
AMN_LS (m^2)	353.5
EMN_LS (m)	110.6
LPI_LS	43.4
PD_LS	2929.2
ED_LS	3127.8
PARAMN_LS	1.36
SHAPEMN_LS	1.67
FRACMN_LS	1.24
CI_LS	99.42

Fig. 3 An example of a HERCULES patch (*highlighted*), and the values of the metrics that measure the whole-patch and within-patch characteristics. The building feature is used as an example in the table (*Note*: not all of the configuration metrics for building are listed)

characteristics; (2) within-patch composition; (3) within-patch configuration; (4) within-patch composition + within-patch configuration; and (5) whole-patch characteristics + within-patch composition + within-patch configuration (Table 3). Because there were a large number of predictor variables, and some were highly correlated to each other, we used a forward stepwise variable selection procedure in the logistic regressions to determine which variables to add or drop from the models (Hosmer and Lemeshow 2000). The entry probability was set as 0.05. Consequently, only significant predictor variables were kept in the final models.

In a logistic regression, a response variable that is typically binary (0, 1) is predicted as a function of a series of continuous or categorical predictor variables. Rather than model the binary response variable directly, logistic regression converts the response variable into a logit variable, or the natural log odds of the response occurring. The logistic regression model is given as (Agresti 1996):

$$\begin{aligned} logit(p) &= \ln(p/(1-p)) \\ &= \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k \end{aligned} \tag{1}$$

where ln is the natural logarithm, p is the probability of the proportion cover of a feature within a patch (e.g., buildings) being correctly classified, $p/(1-p)$ is the odds of a specific response occurring, α is the intercept, x_1 through x_k are predictor variables, and β_n is the coefficient of variable x_n.

A positive regression coefficient indicates that the odds of a correct classification increases as the predictor variable increases, while a negative regression coefficient means a decrease in the odds of a

Table 2 Metrics of whole-patch characteristics and within-patch composition and configuration of land cover features

Variable	Description	Mean	SD
Metrics of whole-patch characteristics			
PA	Patch area (m^2)	7.62E4	2.38E5
PERIM	Patch perimeter (m)	1303.88	2189.32
FRAC	Fractal dimension index, measure of shape complexity	1.046	0.044
PARA	Perimeter–area ratio, measure of shape complexity	0.043	0.314
SHAPE	Shape index, measure of shape complexity	1.332	0.532
Metrics of within-patch composition of land cover features			
Per_Build	Percent buildings	0.117	0.120
Per_CV	Percent CV	0.261	0.248
Per_FV	Percent FV	0.306	0.225
Per_Pave	Percent pavement	0.278	0.208
Per_BS	Percent bare soil	0.032	0.122
SIDI	Simpson's diversity index	0.558	0.175
Metrics of within-patch configuration of land cover features			
AMN_Build	Mean patch sizes of all building patches	577.15	1425.69
AMN_LS	Mean of patch sizes of all patches	690.30	675.01
ASD_Build	Standard deviation of patch sizes of all building patches	452.79	1407.93
ASD_LS	Standard deviation of patch sizes of all patches	3073.87	4825.72
EMN_Build	Mean of patch edges of all building patches	110.47	131.80
EMN_LS	Mean of patch edges of all patches	158.95	61.97
ESD_Build	Standard deviation of edges of all building patches	61.35	104.54
ESD_LS	Standard deviation of edges of all patches	434.52	296.33
LPI_Build	Largest patch index for building, calculated at feature level	5.02	8.25
LPI_LS	Largest patch index calculated at landscape level	48.08	21.63
PD_Build	Patch density of buildings, the number of building patches per km^2	338.09	518.72
PD_LS	Patch density, the number patches per km^2	6451.92	1.93E5
ED_Build	Edge density of buildings, the total length of all building patches per hectare	321.21	313.22
ED_LS	Edge density, the total length of all patches per hectare	3131.58	3282.66
PARAMN_Build	Mean of PARA of all building patches	1.50	10.63
PARAMN_LS	Mean of PARA of all patches	2.38	3.22
PARASD_Build	Standard deviation of PARA of all building patches	1.67	11.74
PARASD_LS	Standard deviation of PARA of all patches	5.54	14.79
SHAPEMN_Build	Mean of SHAPE of all building patches	1.54	0.64
SHAPE MN_LS	Mean of SHAPE of all patches	1.99	0.29
SHAPE SD_Build	Standard deviation of SHAPE of all building patches	0.27	0.50
SHAPESD_LS	Standard deviation of SHAPE of all patches	1.07	0.33
FRACMN_Build	Mean of FRAC of all building patches	1.15	0.15
FRACMN_LS	Mean of FRAC of all patches	1.29	0.06
FRACSD_Build	Standard deviation of FRAC of all building patches	0.073	0.11
FRACSD_LS	Standard deviation of FRAC of all patches	0.21	0.05
ENN_MN_Build	Mean of Euclidean nearest neighboring distance, an isolation metric	29.72	30.34
ENN_SD_Build	Standard deviation of Euclidean nearest neighbor distance	9.35	13.80
CI_Build	Patch cohesion index at the feature level for building patches	77.76	37.88

Table 2 continued

Variable	Description	Mean	SD
CI_LS	Patch cohesion index at the landscape level	99.22	0.44

The building feature is used as an example in this table. These metrics were used as predictor variables. For each feature, the predictors of whole-patch characteristics, within-patch composition, and within-patch configuration at the whole patch level were the same as listed in the table, but the predictors of within-patch configuration at the feature level are different. For example, for CV, the patch density of CV (PD_CV), rather than that of Building (PD_Build), was used

Table 3 Logistic regression models compared for each of the five land cover features

Model number	Model	Description
1	$\alpha + \beta_1 X_1$	Whole-patch characteristics
2	$\alpha + \beta_2 X_2$	Within-patch composition
3	$\alpha + \beta_3 X_3$	Within-patch configuration
4	$\alpha + \beta_2 X_2 + \beta_3 X_3$	Within-patch composition + within-patch configuration
5	$\alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3$	Whole-patch characteristics + within-patch composition + within-patch configuration

For each land cover feature, the response variable was binary, with value of one or zero indicating whether or not the proportion cover estimates from visual interpretation were in the same category as those generated from the object-based approach. X_1 is the vector of whole-patch characteristics variables, X_2 is the vector of within-patch composition variables, X_3 is the vector of within-patch configuration variables, α is the intercept, and each β represents a coefficient vector

correct classification when the predictor variable increases. For continuous predictor variables, the magnitude of β_n is interpreted as the additive effect on the log odds ratio for a unit change in the predictor variable x_n, holding all else constant (Agresti 1996).

Multi-model inferential procedures were used for model comparisons to determine which of the whole-patch or within-patch variables, or some combination, best predicts the variance in each response variable (i.e., correct/incorrect classification of each feature) (Burnham and Anderson 2002). This procedure, which is based on minimization of Akaike's Information Criterion (AIC) (Akaike 1973), selects the model that best explains the data with the fewest parameters. We also calculated the Akaike weight for each model, or the probability of a given model being the best one among a number of candidate models. Akaike weights are especially useful when the difference of AIC values between two models is small (Burnham and Anderson 2002; Wagenmakers and Farrell 2004). Separate comparisons were run for each response variable.

Results

Five models were compared for each response variable, and we present the model parameters, pseudo R^2 value, AIC value, and Akaike weight for each model (Tables 4, 5, 6, 7, 8). The pseudo R^2 value is a measure of the strength of association for regression models containing a categorical dependent variable (Nagelkerke 1991). It is similar to the coefficient of determination, R^2, for linear regression models. For all models within each model group (i.e., the same binary response variable), we ranked each model on the basis of its AIC value. Below, we first present the results from model comparisons for each of the five features. We then discuss the effects of whole-patch characteristics and within-patch composition and configuration of features on the accuracy of cover estimates.

Model comparison: the best model for each land cover feature

Building, coarse-textured vegetation, and bare soil

The best models for these three features are the most complex models which combine variables of whole-patch characteristics, and within-patch composition and configuration (Tables 4, 5, 8). For example, the best model to predict the accuracy of estimating the cover of buildings, Build5, combined a whole-patch characteristic (patch perimeter), within-patch composition

Table 4 Summary results of logistic regression models for the building land cover, including AIC scores, Akaike weights, model ranking and pseudo R^2 values

Model	Explanatory variables/Parameter estimates												AIC	Akaike Weights	Rank	Pseudo R-Square
Build1	SHAPE												2721	0.00%	5	0.006
	0.346															
Build2	Per_Build	Per_Pave	Per_BS	SIDI									2326	0.00%	4	0.236
	-4.650	-1.667	-1.076	-0.3073												
Build3	CI_Build	ED_Build	EMN_Build	FRACMN_Build	CI_LS	AMN_LS	PD_LS						2220	0.00%	3	0.295
	-0.039	-0.001	-0.003	1.539	-0.762	0.001	-1.0E-6									
Build4	Per_CV	Per_Build	Per_FV	CI_Build	EMN_Build	LPI_Build	AMN_LS	CI_LS	FRACSD_LS				2187	4.74%	2	0.313
	1.591	-2.591	1.067	-0.036	-0.001	0.020	0.001	-0.522	2.833							
Build5	PERIM	Per_CV	Per_Build	Per_FV	CI_Build	EMN_Build	LPI_Build	PD_Build	AMN_LS	CI_LS	FRACSD_LS	SHAPEMN_LS	2181	95.26%	1	0.319
	7.8E-5	1.465	-3.236	1.078	-0.037	-0.002	0.026	-3.5E-4	0.001	-0.823	3.059	-0.650				

Only significant predictor variables were kept in the models

Table 5 Summary results of logistic regression models for the coarse textured vegetation land cover, excluding insignificant terms

Model	Explanatory variables/Parameter estimates												AIC	Akaike Weights	Rank	Pseudo R-Square
CV1	PARA	PERIM											2961	0.00%	5	0.031
	-10.22	1.01E-4														
CV2	SIDI	Per_FV	Per_Build										2897	0.00%	4	0.069
	-2.63	-1.12	2.24													
CV3	AMN_CV	ENNMN_CV	PD_CV	ED_CV	ASD_CV	EMN_CV	ASD_LS	LPI_LS	EMN_LS	SHAPEMN_LS			2762	0.05%	3	0.152
	4.04E-4	-0.021	-0.001	-0.001	-5.5E-5	-0.003	9.9E-5	-0.007	-0.003	-0.521						
CV4	Per_CV	Per_Build	ENNMN_CV	ED_CV	ESD_CV	PD_CV	AMN_CV	LPI_CV	ASD_LS	SHAPEMN_LS			2756	1.10%	2	0.155
	3.08	1.83	-0.024	-0.001	-4.62E-4	-0.001	1.41E-4	-0.018	7.3E-5	-0.573						
CV5	PARA	PA	SIDI	Per_Build	Per_CV	Per_Pave	ENNMN_CV	ED_CV	ESD_CV	AMN_CV	PD_CV	ED_LS	2747	98.85%	1	0.162
	-14.055	1E-6	-2.065	2.145	1.818	0.683	-0.024	-0.001	-4.73E-4	1.31E-4	-4.25E-4	2.45E-4				

Table 6 Summary results of logistic regression models for the fine textured vegetation land cover, excluding insignificant terms

Model	Explanatory variables/Parameter estimates							AIC	Akaike Weights	Rank	Pseudo R-Square
FV1	PARA							3086	0.00%	5	0.007
	-6.81										
FV2	Per_Build	Per_CV	Per_FV	SIDI				2984	0.00%	4	0.069
	3.567	-0.928	0.893	-0.994							
FV3	AMN_FV	ED_FV	EMN_FV	LPI_LS	EMN_LS			2972	0.00%	3	0.077
	5.22E-4	-0.001	-0.002	-0.019	-0.003						
FV4	Per_CV	Per_Build	SIDI	AMN_FV	EMN_FV	LPI_LS	ASD_LS	2921	62.25%	1	0.107
	-1.264	2.416	-2.176	4.28E-4	-0.003	-0.022	3.0E-5				
FV5	PARA	PERIM	Per_CV	Per_Build	AMN_FV	EMN_FV	ESD_LS	2922	37.75%	2	0.107
	-11.124	1.6E-4	-1.145	1.974	4.2E-4	-0.003	-0.001				

(percent of CV, percent of building, and percent of FV) and within-patch configuration (e.g., connectivity among buildings, building density and shape complex) (Table 4). Approximately 32 % of the variation in the response variable of building cover accuracy was explained by this model.

Fine-textured vegetation

The best model (FV4) for this feature combines variables of within-patch composition and configuration (Table 6). The second best model (FV5) combines variables of whole-patch characteristics and

Table 7 Summary results of logistic regression models for the pavement land cover, excluding insignificant terms

Model	Explanatory variables/Parameter estimates										AIC	Akaike Weights	Rank	Pseudo R-Square
Pave1	PARA	SHAPE									3085	0.00%	5	0.020
	-9.282	0.287												
Pave2	SIDI	Per_BS									2974	0.00%	4	0.083
	-2.953	-1.504												
Pave3	ED_Pave	LPI_Pave	SHAPESD_Pave	CI_Pave	ENNSD_Pave	FRACMN_Pave	CI_LS	ESD_LS			2810	0.00%	3	0.177
	-0.002	0.030	-0.221	-0.024	0.014	1.023	-0.532	-8.65E-4						
Pave4	Per_Pave	Per_BS	Per_Build	SIDI	ED_Pave	PD_Pave	FRACMN_Pave	CI_Pave	FRACSD_LS	FRACMN_LS	2773	50.00%	1	0.199
	3.531	-2.164	1.907	-1.195	-0.003	-5.22E-4	0.894	-0.020	-5.498	3.461				
Pave5	Per_Pave	Per_BS	Per_Build	SIDI	ED_Pave	PD_Pave	FRACMN_Pave	CI_Pave	FRACSD_LS	FRACMN_LS	2773	50.00%	1	0.199
	3.531	-2.164	1.907	-1.195	-0.003	-5.22E-4	0.894	-0.020	-5.498	3.461				

Table 8 Summary results of logistic regression models for the bare soil land cover, excluding insignificant terms

Model	Explanatory variables/Parameter estimates							AIC	Akaike Weights	Rank	Pseudo R-Square
BS1	None of the variables is significant							2206	0.00%	5	0
	N/A										
BS2	Per_Build	Per_CV	Per_Pave	Per_BS	SIDI			2084	0.00%	4	0.091
	2.955	1.427	-1.257	-2.448	-1.34						
BS3	ED_BS	SHAPEMN_BS	ENN_MN_BS	ENN_SD_BS	AMN_BS			2051	0.00%	3	0.113
	-0.002	-0.244	-0.003	-0.012	2.2E-5						
BS4	Per_Pave	Per_FV	ED_BS	SHAPEMN_BS	ENN_MN_BS	ENN_SD_BS		1988	2.93%	2	0.155
	-2.687	-1.361	-0.002	-0.267	-0.003	-0.013					
BS5	PERIM	Per_pave	Per_FV	ED_BS	SHAPEMN_BS	ENN_MN_BS	ENN_SD_BS	1981	97.7%	1	0.161
	1.18E-4	-2.649	-1.270	-0.002	-0.303	-0.003	-0.017				

within-patch composition and configuration. Though AIC and Akaike weights indicate that FV4 is slightly better than FV5, support for FV4 being the best relative to FV5 is weak.

Pavement

The model that best explains pavement (Pave4) combines variables of within-patch composition and configuration (Table 7). After adjusting for the effects of within-patch composition and configuration, no whole-patch characteristic significantly contributes to the explanation of variance in pavement cover estimates (Pave5). Therefore, the model Pave4 was identical to the model Pave5.

The best model for each of the five land cover features provides a better prediction than that by the baseline or intercept-only model (Table 9). The intercept-only model classifies all cases simply by using the most numerous category (i.e., the category 0). For example, the best model for pavement (Pave5) classifies 68.7 % correctly compared to 52.5 % classified correctly by the intercept-only model. For each land cover feature, combining within-patch composition variables with those of within-patch configuration (model group 4) provides better prediction than those models using variables of within-patch composition or configuration alone (model group 2 or 3).

The effects of whole-patch characteristics on the accuracy of cover estimates

Whole-patch characteristics are significant predictors for all five land cover features. Models using patch characteristics alone (i.e., model group 1) provide statistically significant improvement over the intercept-only models, except for bare soil (model BS1, Table 8). However, little variance in estimation accuracy was explained by this model group, suggesting that whole-patch characteristics alone do not provide adequate explanation.

Among the five indicators of whole-patch characteristics, perimeter–area ratio (*PARA*) and perimeter (*PERIM*) are the most significant. *PARA* was a significant predictor for CV and FV when adjusting for the effects of variables of within-patch composition

Table 9 Classification table for the best models and baseline or intercept-only models summarized by land cover features

Landscape feature	Model	Observed	Predicted		Percent correct (%)	Overall percent correct (%)
			1	0		
Building	Best	1	1,413	176	88.9	73.6
		0	417	244	36.9	
	Intercept-only	1	1,589	0	100	70.6
		0	662	0	0	
CV	Best	1	1,156	219	64.0	64.8
		0	572	303	72.9	
	Intercept-only	1	1,375	0	100	61.1
		0	875	0	0	
FV	Best	1	935	310	75.1	61.6
		0	555	450	44.8	
	Intercept-only	1	1,245	0	100	55.3
		0	1,005	0	0	
Pavement	Best	1	683	385	64.0	68.7
		0	320	862	72.9	
	Intercept-only	1	0	1,068	0	52.5
		0	0	1,182	100	
Bare soil	Best	1	1,769	48	97.4	81.4
		0	371	62	14.3	
	Intercept-only	1	1,817	0	100	80.8
		0	433	0	0	

The columns are the two predicted values of the dependent, while the rows are the two observed (actual) values of the dependent. One means that the cover of the feature was correctly estimated, while zero represents misclassification. The values on the diagonal of the two columns under 'predicted' (e.g., 1413 and 244, marked in grey) are the number of cases correctly classified by the models. The column "percent correct" is the percentage of cases correctly classified for a specific category (i.e., 1 or 0), while the "overall percent correct" is the total percentage of cases correctly classified

and configuration (CV5 and FV5). The negative coefficients of *PARA* indicated that the odds of a correct estimation decrease with the increase of patch *PARA*. Patch perimeter (*PERIM*) was a significant predictor for building, FV, and bare soil, when the effects of variables of within-patch composition and configuration were adjusted (Build5, FV5, and BS5). The positive parameters of *PERIM* in the three best models indicated that the odds of a correct estimation for those three features increase with the increase of *PERIM*.

The effects of within-patch composition on the accuracy of cover estimates

Variables of within-patch composition are better predictors of estimation accuracy than those of whole-patch characteristics for all of the five land cover features. Among the six variables of within-patch composition, the cover of buildings (*Per_Build*) and the Simpson's diversity index (*SIDI*) are the most significant metrics predicting the accuracy. *SIDI* was significant in all five models, but *SIDI* was only significant for pavement when the effects of whole-patch characteristics and within-patch configuration were adjusted. The general effects of *SIDI* were consistent for all five land cover features meaning that the odds of correctly estimating cover decrease with the increase of the diversity of land cover features. However, the estimated coefficients, or the magnitudes of the impacts of *SIDI,* varied broadly among features.

Proportion cover of buildings within the patch (*Per_Build*) significantly affected the prediction of accuracy for all of the land cover features except for bare soil. It remained significant in all the best models for FV, CV, pavement and building features, when effects of whole-patch characteristics and within-patch configuration were adjusted. The effects of *Per_Build* on the accuracy, however, varied by feature. While the negative coefficient of *Per_Build* indicated that the increase of building cover within a patch decreased the odds of a correct estimation for building cover, the positive coefficients of *Per_Build* for CV, FV and pavement indicated that the odds of a correct estimation for those land cover features increased with the increase of building cover within a patch.

The effects of within-patch configuration on the accuracy of cover estimates

Models using variables of configuration (model group 3) are superior to those using composition variables alone (model group 2), as well as models only using variables of whole-patch characteristics (model group 1). Configuration metrics, both at the feature level and the whole-patch level, affected the accuracy of cover estimates (e.g., cohesion index at both levels, *CI_Build* and *CI_LS* in model Build3, Table 4). The significance of configuration variables varied broadly among features, with only a very few variables being significant for all or most of the five land cover features. Significant variables included edge density, mean patch size, and mean edge length, all at the feature level. While the significance of configuration variables varied by features, the effects of the same configuration variable were generally consistent across all land cover features. For example, in the model group using only within-patch configuration variables as predictors (model group 3), variables of edge density (e.g., *ED_Build*) were significant for all of the five land cover features, and had consistent negative effects on the accuracy. This suggests that for each of the five features, the odds of the cover of that feature being correctly estimated decreased with an increase of edge density.

Discussion

The results indicate that, though the accuracy of visually estimating the cover of features within patches is significantly affected by both whole-patch characteristics and within-patch composition and configuration of features, within-patch configuration is the most significant factor. In addition, within-patch composition is a better predictor than whole-patch characteristics. Most frequently, however, a combination of whole-patch and within-patch characteristics provides the best prediction of accuracy of cover estimates. The relative importance of whole-patch characteristics, and within-patch composition and configuration on the accuracy of cover estimates will be discussed in order of increasing importance.

Whole-patch characteristics

Characteristics, such as perimeter and perimeter–area ratio, are useful predictors of accuracy of cover estimates through visual interpretation, even after the effects of within-patch composition and configuration were adjusted. The statistical importance of these whole-patch variables indicates that some of the variability in the accuracy of cover estimates that is not explained by within-patch composition and configuration can be attributed to whole-patch characteristics. A very small proportion of the variance in the accuracy of cover estimates, however, can be explained by whole-patch characteristics alone. Our results suggest errors in cover estimates are more likely to occur for smaller patches with more complex shapes, which have larger perimeter to area ratios. This is similar to previous research that digitized individual landscape features and found that misclassification was more likely to occur for smaller features with higher perimeter to area ratios (Ellis and Wang 2006).

Within-patch composition

Composition of land cover features within a patch is a better predictor of accuracy through visual interpretation than whole-patch characteristics. Both the proportion abundance of each land cover feature and the diversity of features within a patch significantly affect the accuracy of cover estimates. The most important composition variable in predicting this accuracy is the percent cover of buildings. As the percent cover of buildings increases, the accuracy of estimating building cover decreases, but the accuracy of estimating coarse-textured vegetation (CV), fine-textured vegetation (FV), and pavement increases. Our results suggest that errors in estimating cover are more likely to occur when within-patch composition is more diverse. This is consistent with findings from previous studies that visual estimates of woody crown cover from aerial photography may be influenced by land type (Fensham et al. 2002; Fensham and Fairfax 2007), and that the accuracy of digital land cover classification tends to decrease with the increase of diversity in land cover features (Smith et al. 2003).

Effects of the relative cover of different land cover features on the accuracy of estimating the cover of those features vary by feature types. For example, errors in estimating cover of CV are more likely to occur as the relative amount of CV within a patch decreases. Errors in estimating building cover, however, are more likely to occur with higher building cover. This difference may suggest that interpreters perceive and react to patterns of built (i.e., building) and non-built (e.g. CV) components in different ways.

Within-patch configuration

Within-patch configuration is the most significant predictor of accuracy of cover estimates through visual interpretation. A large number of variables contribute to this significance. While the significance and magnitudes of effects of the variables vary broadly among different types of land cover features, the effects were generally consistent. Our results suggest that errors of cover estimates are more likely to occur when land cover features within a patch are (1) more fragmented (e.g., higher patch density, higher edge density, smaller averaged patch size, and smaller largest patch index); (2) more complex in shape (e.g., patches are more irregular, with larger values of shape index), and (3) physically less connected (e.g., larger averaged nearest neighbor distance). These results may be due to how interpreters perceive and react to landscape patterns by applying many of the Gestalt-laws simultaneously during the process of visual interpretation (Antrop and Van Eetvelde 2000). For example, interpreters generally reduce the complexity of pattern they observe by transforming irregular shapes into geometric shapes and grouping them according to similarity and proximity (Antrop and Van Eetvelde 2000). Consequently, this simplification and interpretation may lead to the decrease in accurately estimating cover, with the increase in complexity of features configuration within a patch. Because the urban landscape is strikingly heterogeneous, with complex fine-scale spatial patterning of individual features such as buildings, driveways and lawns, visual interpretation may not be an effective way to accurately estimate cover of land cover features within a patch (Zhou et al. 2010). This limitation suggests that other approaches, for example object-based image analysis, that can accurately estimate cover of features within a patch are desirable (Benz et al. 2004; Zhou and Troy 2008; Blaschke 2010).

Whole-patch and within-patch characteristics are important predictors of the accuracy of cover estimates based on visual interpretation. The relatively low pseudo R^2 values of the regression models, however, suggest that models using variables of whole-patch and within-patch characteristics as predictors alone are incomplete, and more factors should be considered for better predictions on the accuracy of cover estimates. For example, shadows that frequently occur in high-spatial resolution imagery might contribute significantly to errors in cover estimates (Fensham et al. 2002; Zhou et al. 2009). Therefore, the application of radiometric enhancement (or restoration) methods for shadow removal may alleviate the shadow problem, and thus improve the accuracy of cover estimates (Zhou et al. 2009).

It is important to note that the accuracy of estimating the cover of features within a patch may be affected by the spatial resolution of imagery. For example, previous studies indicated that the exaggeration of crown cover was scale dependent, decreasing with the increase of scale of photography (Fensham and Fairfax 2002; Fensham et al. 2002). In this study, we only used the 0.6 m aerial imagery. Therefore, cross-scale (i.e., multiple spatial resolution) evaluation is recommended in future studies. In addition, it should be noted that there are classification errors associated with the reference land cover map. Therefore, some of the “errors” occurring in the visually interpreted classification map were in fact due to errors in the reference map.

Summary and conclusions

Pattern analysis of landscapes is frequently conducted in an effort to link pattern to ecological processes. As a consequence, the accuracy of that pattern analysis is critical (Wu and Hobbs 2002; Iverson 2007). Knowledge of the magnitude of the errors in pattern analysis, and the factors that affect the generation of errors, is needed (Li and Wu 2007; Shao and Wu 2008). This research examines the quantitative relationships of whole-patch characteristics and within-patch composition and configuration of land cover features with the accuracy of estimating, by visual interpretation, the cover of those features. The results indicate that, though all factors significantly affected the accuracy of cover estimates, within-patch configuration of the features is the most significant. Most frequently, however, a combination of indicators of whole-patch and within-patch characteristics provides the best prediction of accuracy of cover estimates. In general, errors of cover estimates based on visual interpretation are more likely to occur when patches are smaller or have more complex shapes, and land cover features within a patch are (1) more diverse; (2) more fragmented; (3) more complex in shape; and (4) physically less connected.

Though we used a land cover layer created by a new classification, HERCULES, for this analysis, the approach and results are applicable for any analysis using thematic maps based on visual estimation of land cover features to describe landscape pattern. Our results provide insights into increasing understanding of the link between the accuracy of thematic maps based on visual interpretation and the heterogeneity of land cover features. In addition, the logistic regression models provide a useful, predictive tool for determining under what circumstances estimation error is most likely to occur. This provides an important first step towards a quantitative, spatially explicit model for error prediction of cover estimates based on visual interpretation.

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