

An Experimental Assessment of Minimum Mapping Unit Size

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Abstract—Land-cover (LC) maps derived from remotely sensed data are often presented using a minimum mapping unit (MMU) to characterize a particular landscape theme of interest. The choice of an MMU that is appropriate for the projected use of a classification is an important consideration. The objective of this experiment was to determine the effect of MMU on a LC classification of the Neuse River Basin (NRB) in North Carolina. The results of this work indicate that MMU size had a significant effect on accuracy estimates only when the MMU was changed by relatively large amounts. Typically, an MMU is selected as close as possible to the original data resolution so as to reduce the loss of specificity introduced in the resampling process. Since only large MMU changes resulted in significant differences in the accuracy estimates, an analyst may have the flexibility to select from a range of MMUs that are appropriate for a given application.

Index Terms—Accuracy assessment, landscape characterization, remote sensing, vegetation mapping.

I. INTRODUCTION

LAND-COVER (LC) maps derived from remotely sensed data are often presented using a minimum mapping unit (MMU). An MMU is defined as “the smallest size areal entity to be mapped as a discrete entity” [1]. For example, a classification derived from Landsat Enhanced Thematic Mapper plus (ETM+) data will typically have a nominal spatial resolution of 30 m (pixel size). A possible MMU for a classification created from ETM+ data may be 8100 m² or 90 × 90 m (3 × 3 pixels). The following are reasons why an MMU may be employed.

- Classifications at spatial resolutions less than the effective MMU are typically not repeatable over different images and may result in a reduction in overall map accuracy.
- Raw classified data may exhibit a “salt and pepper” effect where there exist many single pixels of a particular class that are interspersed with contiguous areas of other classes. These data may be “smoothed” through the use of an MMU.
- When conducting accuracy assessment of a classification, the analyst typically compares the values of randomly chosen pixels on both the classification and a source of reference data. In many cases, it is difficult to determine which pixel on the reference data matches a given pixel on the classified map. Problems can result from geometric

and positional errors or reference data interpretation errors. Use of an MMU can reduce the effects of these problems.

- Spatial resolution of the classified map may not match the spatial resolution of the reference data. For example, comparing a 30-m pixel size classification based on ETM+ data with 0.4-ha ground-sampled reference data could be problematic due to the very different spatial scales.
- Individual pixels are not spectrally pure because diffuse directional reflectance from neighboring pixels contribute to a given pixel’s spectral signature.

Given the preceding information, the choice of an appropriate MMU is clearly important. The analyst must take into account the potential applications for the classification, the resolution of any data that will be used in conjunction with the classification, and the type and resolution of the reference data to be used to assess the accuracy of the classification.

The objective of this experiment was to determine the effect of MMU on the accuracy estimates of a LC classification of the Neuse River Basin (NRB) in North Carolina. The accuracy was judged by comparing various classification MMUs with ground reference data. An elaboration of this approach is provided in the methods section.

II. STUDY AREA

The NRB is located entirely within the boundaries of the state of North Carolina. The NRB boundaries correspond to the U.S. Geological Survey (USGS) six-digit hydrologic unit code (HUC) number 030 202. The NRB is 14 582 km² in area and contains approximately 16 900 km (1 : 24 000-scale) of stream length. The NRB is located in the piedmont and coastal plain physiographic regions [2]. Elevations within the NRB range from 276 m in the Piedmont to sea level at the confluence of the Neuse River and Pamlico Sound, which is defined by a series of barrier islands known as the Outer Banks.

III. METHODS

The NRB classification was created using a combination of supervised and unsupervised classification algorithms and a multitemporal hierarchical Geographic Information System (GIS) rule-based classifier. The classification was based on multitemporal mosaics of ETM+ 30-m and SPOT-4 (XS) 20-m multispectral data. Prior to classification, the image mosaics were resampled to 15 m [3]. The original classification levels correspond to Anderson Levels 1–3, although only Level 2 classes were used in the analysis presented here. Note that in this research we did not examine the impact of using multiple input data layers on the resulting accuracy estimates. The

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TABLE I
MMU SIZES USED IN ACCURACY ANALYSIS

MMU (pixel size)	MMU (ha)
20 meters	0.4 ha
30 meters	0.8 ha
40 meters	1.6 ha
60 meters	3.2 ha
84 meters	6.4 ha
120 meters	12.8 ha
160 meters	25.6 ha

TABLE II
ACURACY STATISTICS FOR EACH MMU

MMU (ha)	%	Kappa
0.4	58.36	0.519
0.8	60.684	0.545
1.6	63.614	0.578
3.2	65.568	0.6
6.4	67.277	0.618
12.8	66.789	0.612
25.6	68.254	0.629

classification was treated as if it had come from one input image layer.

The accuracy assessment sample design for the NRB classification consisted of 819 systematic unaligned samples based on the USGS Quarter Quadrangle enumeration system. These 0.4-ha sites were sampled in the field over the 1998 and 1999 summer sampling seasons. Field measurement and imagery (digital camera) data were collected and then interpreted by Environmental Protection Agency (EPA) analysts to determine the correct cover class for each site [4]. These reference data were used to assess the accuracy of the NRB LC map. The original NRB classification product had an MMU of 0.4 ha [3]. This MMU was selected so that it would match the 0.4-ha ground sites.

As was mentioned above, the objective of this study was to determine the effect of MMU on the accuracy estimates for the NRB classification. The following approach was used to achieve this objective:

- 1) NRB classification was resampled using a nearest neighbor spatial filter from its original 15-m resolution to a set of resolutions corresponding to successive doublings of the MMUs, starting with the original 0.4-ha value. The resolutions used are presented in Table I.
- 2) The accuracy of the resampled NRB classification was computed for each of the MMUs. In this process, the reference LC labels were compared on a site-by-site basis with the NRB classification. An "error" for a particular reference site constituted a mismatch at Anderson thematic Level 2 between the reference data and the NRB classification. The match or mismatch was computed as follows. If the majority value of the NRB 3 x 3 pixel window matched the reference class, then the site was counted as a match. If the majority value did not match the reference data, then the site was counted as a mismatch.
- 3) Kappa accuracy values for each of the MMUs were compared for statistically significant difference using a Z-test.
- 4) MMU accuracy results were analyzed to determine how the accuracy varied with respect to MMU.

IV. RESULTS AND DISCUSSION

The results of the NRB MMU accuracy analysis are presented in Tables II and III and Figs. 1 and 2. Table II and Fig. 1 show that, as the MMU size was increased, both the overall percent accuracy and the Kappa value increased. However, the increase was not linear in nature (i.e., the rate of increase varied as the MMU size was increased). The accuracy estimates increased gradually until the MMU reached 6.4 ha, at which point the

TABLE III
Z-TESTS RESULTS COMPARING MMUs. * Z-TEST IS SIGNIFICANT AT $\alpha = 0.05$

MMU (ha)	Z statistic
0.4 vs. 1.6+	3.13*
0.8 vs. 3.2+	2.7*
1.6 vs. 25.6	1.99*
3.2 vs. 25.6	1.1
6.4 vs. 25.6	0.41
12.8 vs. 25.6	0.65

NRB Classification Accuracy

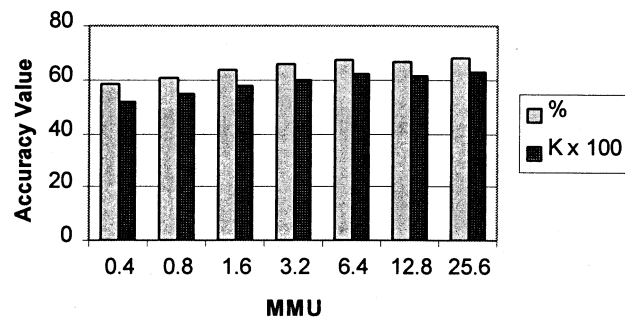


Fig. 1. Percent accuracy and kappa statistic for each MMU.

curve began to level off. The accuracy estimates actually decreased slightly at the 12.8-ha level. The likely explanation for the slowing rate of increase in the accuracy estimates is that the MMU became sufficiently large that a smaller percentage of areas changed LC value during the resampling process.

Table III presents the results of Z-test comparisons of the Kappa values for each MMU. Only the threshold of significance for each MMU is shown. Table III shows that statistically significant differences in the Kappa values occurred only between very different MMUs (e.g., between 0.4 and 1.6 ha).

Fig. 2 shows the classes, organized by cover type, for which the Kappa values changed. For reference, Table IV presents the cover types used and their class codes. A majority of the classes maintained the same, or very similar, accuracy as the MMU increased. Overall, only ten of the 20 classes in the NRB classification contributed to the changing accuracy estimates. Classes such as row crops (A-RC) and deciduous forest (F-D) exhibited a very small change as the MMU increased. Other classes, such as mixed forest (F-M), showed substantial increases in accuracy. Some classes, such as high-density urban (U-HD), exhibited a cyclic effect where the accuracy increased temporarily and then fell. This cyclic pattern contributed to the smaller increases in overall accuracy statistics as the MMU increased.

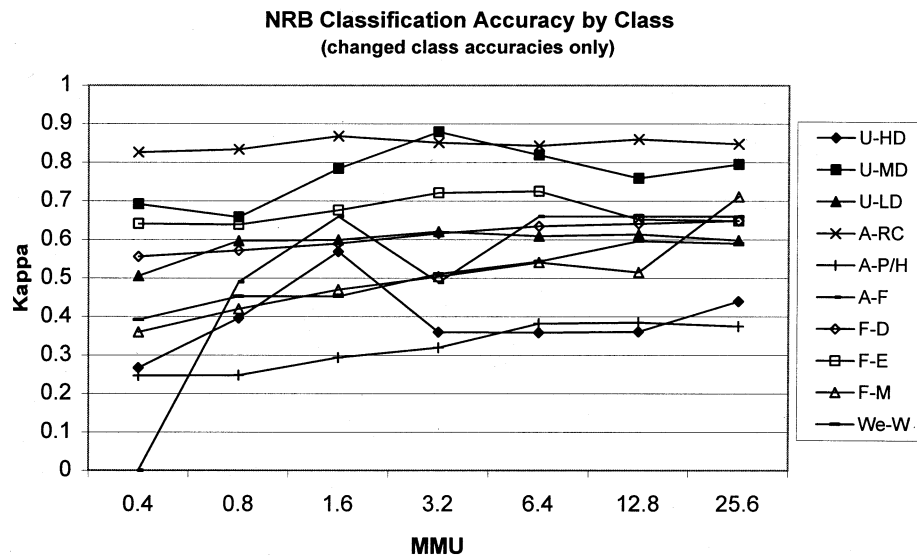


Fig. 2. Kappa statistic for each MMU by class (classes with changed accuracies only).

TABLE IV
CLASS LIST

Class Code	Class Name
U-HD	Urban-High Density
U-MD	Urban-Medium Density
U-LD	Urban-Low Density
A-P/H	Agriculture-Pasture/Hay
A-F	Agriculture-Fallow
A-RC	Agriculture-Row Crops
F-D	Forest-Deciduous
F-E	Forest-Evergreen
F-M	Forest-Mixed
G-N	Grassland-Natural
G-M	Grassland-Maintained
W-R	Water-River
W-L	Water-Lake
W-Res	Water-Reservoir
W-Est	Water-Estuary
W-P	Water-Pond
We-H	Wetland-Herbaceous
We-W	Wetland-Woody
B-R	Bare-Rock, Sand
B-T	Bare-Transitional

The likely cause for these disparate class accuracy results stems from the fact that the classes occur in different cluster sizes, depending on their composition. For example, F-M areas were typically large and relatively heterogeneous; thus, one would expect, that as the MMU is increased, these areas would become more uniform due to the smoothing effect of the resampling filter. This uniformity could result in those areas having a higher accuracy. Conversely, A-RC areas were typically very homogeneous, and as the MMU is increased, these areas change very little. As a result, the accuracy stayed relatively constant.

Fig. 1 and Table II show that the overall accuracy of the classification increased steadily up to approximately the 6.4-ha range and then slowed. Given that the increase in the accuracy estimates obtained by expanding the MMU beyond this point are small, the 6.4-ha MMU may represent an appropriate stopping point in this case. However, the choice of MMU to be used in

a particular application must consider the need to keep the data as close as possible to the original image resolution to minimize the loss of specificity that is introduced during the resampling process.

V. CONCLUSION

The results for this classification, which was created from SPOT and TM data, indicate that relatively large MMU size differences significantly affected the accuracy estimates of the classification. While the accuracy estimates at the 6.4-ha MMU appear to represent a good tradeoff between MMU size and accuracy, one could use an MMU as small as 1.6 ha and still maintain a statistically insignificant difference from the 6.4-ha MMU in the overall accuracy estimates for this classification. Clearly, an important goal in selecting an appropriate MMU is to use as small a value as possible for the intended application of the classification, while maintaining an acceptable level of accuracy. This study shows that an analyst may have the flexibility to choose from a range of MMUs that provide similar accuracy estimates.

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