

Continuous Datasets from Satellite Imagery for Land Cover Mapping in Mountain Cartography

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Abstract

The traditional depiction of land cover classification uses discrete, hard categories that are mutually exclusive. Remote sensing techniques exist to derive sub-pixel classification and continuous variables, these have proven to be fairly robust and accurate, yet few cartographic products or techniques have been developed to depict these more structurally complex datasets. Two maps of Gannett Peak, in Wyoming's Wind River Range (1:24,000 and 1:63,360) are used to illustrate new techniques and datasets and to propose that landscape characteristics can be used to guide land cover depiction and the choice of classifiers. A hybrid approach in which land cover elements with abrupt discontinuities such as hydrology and agriculture are depicted using traditional hard boundaries and soft transition and naturally occurring gradients such as altitudinal vegetation changes are depicted using continuous variables is illustrated. The use of a dasymetric approach to soften a hard classification obtained from image segmentation is also illustrated and the limits and potential of object oriented classification is discussed.

KEY WORDS: Continuous datasets, alpine cartography, dasymetric methods, image segmentation, Wind River Range, Wyoming, USA

1. Introduction

Landscape heterogeneity is described by Forman (1995) as being of two forms; as a series of gradients with gradual differences in concentration or as a mosaic with patches and or corridors with abrupt/hard or soft discontinuities.

In mountain environments a wide variety of transitions between land covers occurs; from vegetation to non vegetation from talus to scree to moraine, and from these to glaciated or snow covered terrain (Fig. 1a-d). These changes are often driven by glaciation, soils, water availability, and topography which may in turn dictate climatic gradients in precipitation, temperature and light availability. Fragmentation, which results in a patchwork or mosaic landscape is driven by land use and anthropogenic change as well as naturally occurring catastrophic or periodical environmental change such as fire or landslides. Depending on the scale at which these transitions are observed

they may appear as smooth transitions or abrupt but at the landscape scale, discontinuities typically predominate (Forman, 1995). Some of the questions this raises for the cartographer depicting land cover at the landscape scale is whether methods should be dictated by the composition of regions (i.e. their homogeneity or heterogeneity, their pattern, density, internal structure, texture) or by the type of transitions between homogeneous regions?

In order to depict the landscape in a topographic map landscape its elements need to be abstracted and decomposed into objects that have traditionally been represented on maps using point, line and polygon elements. These elements are then used to represent groups or classes of terrain features. Until recently, this resulted in many maps depicting a landscape primarily composed of hard, sharp edges (Fig. 2a-d) with some maps (i.e. Fig 2a) communicating the range of transitions more effectively than others using these graphic variables. Cartographic



Figure 1a: Continuous transition from grassland to wetland in the Cordillera Vilcanota, Peru. Water constraints to vegetation greenness clearly in evidence.

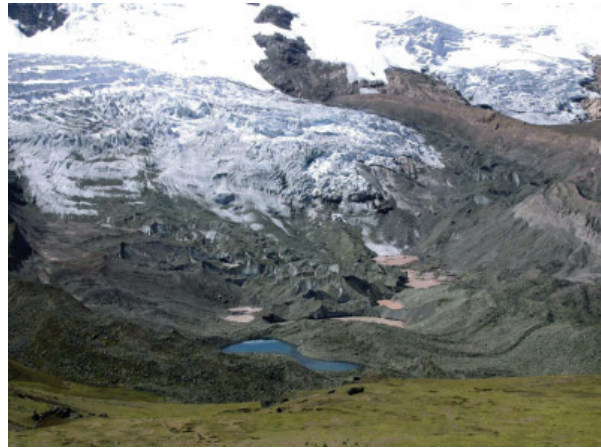


Figure 1c: Interface of glacier and moraine at the base of Nevado Auzangate, Peru.



Figure 1b: Transition from glacier to meadow along the Auzangate Circuit, Peru. Both hard and soft discontinuities are visible in this image.



Figure 1d: Vegetation transition in Grand Teton National Park, Wyoming. Fall colors help differentiate deciduous from conifer stands.

techniques and map purpose have often dictated this depiction. For example green vegetation polygons may imply a forest density with military considerations such as ease of troop movement or availability of camouflage or management implications such as forest stand age or

composition (Monmonier, 1996). Similarly other land covers such as glaciers and moraines have been depicted as discrete object often with less attention paid to the transition or interaction between land cover visible in nature. This generalization may be both necessary and desirable

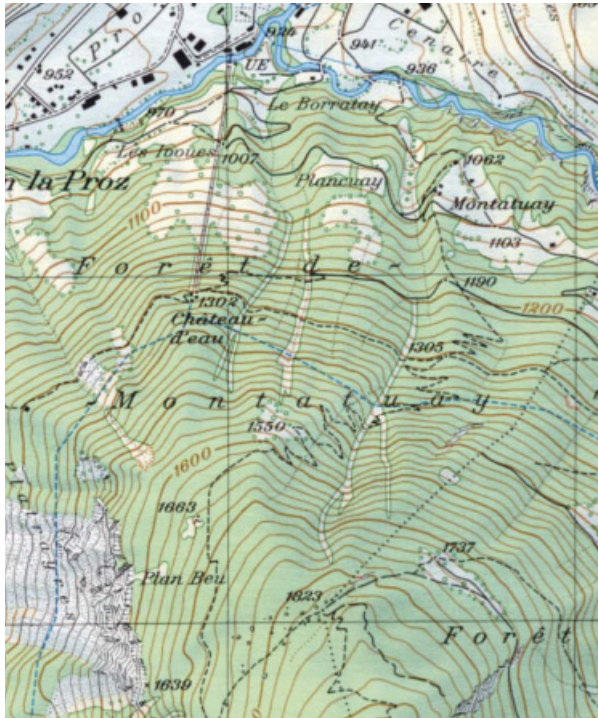


Figure 2a: 1:25,000 Swisstopo Orsières Sheet.



Figure 2c: 1:24,000 USGS Gannett Peak Quadrangle.



Figure 2b: 1:50,000 Schneider Khumbu (Nepal) Map.

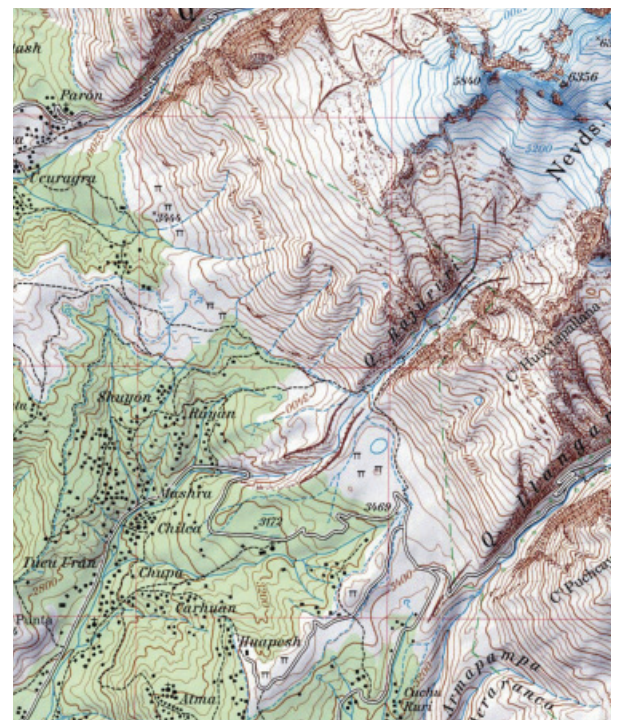


Figure 2d: 1:100,000 DAV Cordillera Blanca (Peru) North Sheet.

in some cases.

With the advent of satellite remote sensing in the early 1970's, land cover has been mapped using pixels or groups of pixels as the minimum mapping unit and can be depicted as images. These images can be manipulated through the use of filters, and can have texture applied to them. Additionally they can be combined with more traditional cartographic objects such as points, lines and polygons. This is the approach I use in my maps.

In traditional land cover mapping the minimum mapping unit (MMU) dictates which form the final classification will take. The MMU is in turn determined based on classification objectives, source data resolution and compilation scale. Land cover is typically derived on a per pixel basis from remote sensing imagery where each pixel is assigned to a class using a Euclidian or statistical distance to determine its membership. Once classified, a vector polygon for each distinct class object can be created from the class image. Alternatively classification can be directly compiled in an object form from imagery by an expert interpreter or increasingly from satellite imagery using image segmentation and object oriented classifiers.

Regardless of the classification method used, image pixels are classified and generalized into single, discrete, exclusive categories of land cover such as glacier, snow, wetland, forest, meadow etc, where one pixel belongs to one class exclusively. This can be described as a binary approach where a pixel is either in or out of a class and the classification dataset is the union of a series of binary classes (Milne and Cohen, 1999). Once classified, these pixel assemblages become entities with hard boundaries (Foody 1996, Wang 1990). I will refer to this model as the Hard, Discrete Class model (Fig. 3a).

In an attempt to address the limitations inherent in the above model, analytical techniques have appeared that seek to extract fuzzy classifications. This approach recognizes the inherent heterogeneity present in nature and within pixels and attempts to recover fractions of land cover components that may be present within individual pixels. Independent from these fuzzy and sub-pixel mixture analysis approaches there has been a significant amount of work done to quantify biophysical landscape parameters from satellite imagery in particular related to vegetation. Such metrics as Leaf Area Index (LAI), and Fraction Photosynthetic Absorbed Radiation (FPAR) provide means of measuring biomass which in turn can be expressed as a continuous, spatially variable quantity such as canopy cover or used as inputs to algorithms that in turn derive fractions of specific cover types. These two distinct paradigms within remote sensing have yielded products that quantify and can be used to depict land cover as continuous, complex and fuzzy. I will refer to this approach as the soft, continuous or fuzzy model (Fig. 3b). There are obvi-



Figure 3a: Hard classification of the Gannett Peak Region (maximum likelihood classification).

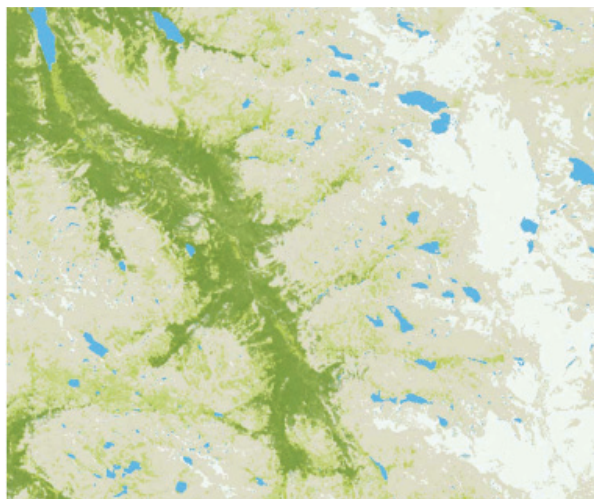


Figure 3b: Hybrid classification of the Gannett Peak Region using canopy cover and NDVI masks for vegetation.

ous distinctions between the sub pixel classification approaches and the biophysical approaches but for the purpose of this discussion, within the context of cartographic applications I treat them jointly.

Woodcock and Strahler (1987) in a seminal paper on the factor of scale in remote sensing provided a rationale and a demonstration of the relationship between the size of features being mapped and sensor resolution. They outline appropriate approaches for the type of image classification that could be used based not only on scale but on landscape types and local variance. This discussion approaches the topic where they leave off, from the perspective of the end user of these classifications for cartographic output and as an analyst creating classifications intended for specific cartographic purposes rather than resource inventories that are rarely expressed in map form. I propo-

se that hybrid classification or multi-step approaches as suggested by Franklin and Wilson (1992) or the multi scale, multi granular paradigm proposed by Ju et al. (2005) may be the most desirable in mountainous settings and that at the least, as hinted to by Woodcock and Strahler, landscape characteristics be taken into consideration.

2. Methods

One of the methods I have commonly used to soften hard classifications has relied on filtering the output from hard classifiers using image editing software such as Photoshop. Patterson (2002) described numerous image manipulation techniques in the context of cartographic realism in his work for the NPS. In particular filters such as the median and Gaussian blur filters are quite effective at blurring the hard boundaries between classes. This approach, while it can produce aesthetically effective results, introduces errors and degrades the information content of the dataset which is at times already limited. It does not add any information nor does it indicate the variance that exists within the class itself.

The fuzziness I have sought to create by using these filters is often best introduced into the dataset at the classification step. An arsenal of remote sensing approaches has been used to derive sub pixel composition from satellite imagery. As stated previously my goal is not to review in details these techniques which would be beyond the scope of this paper. Rather it is to explore the notion that cartographic land cover depiction does not need to be limited to the hard classification paradigm and that in fact in some cases it may be desirable to let compilation scale and landscape properties determine the best classifier.

Linear and Non Linear Spectral mixture analysis (SMA) has been used extensively to generate sub-pixel composition estimates. Small (2004) provides a good description of the Landsat ETM+ spectral space in the context of SMA. In mountain environments it has been used by Klein and Isacks (1999, personal communication) to map tropical glaciers in South America and Africa, and by Nolin et al. (1993), Rosenthal and Dozier (1996), Solberg (2000) to map alpine snow cover. Neural networks (ARTMAP in particular), have also been used to calculate subpixel compo-



Figure 4: Tom Patterson's Natural Earth dataset derived from MODIS Vegetation Continuous Fields, the Wind River Range is the NW-SE trending range at A.

sition, (Atkinson et al., 1997, Carpenter et al., 1999, Foody, 1998, Moody et al., 1996) with some specific cases in the Sierra Nevada of California. Ju et al. (2003) compared mixture discriminant analysis to linear mixture analysis (LMA) and neural networks and found it to rank between neural networks and LMA in terms of accuracy but to be conceptually more easily understood when compared to the 'black box' approach of neural networks. Fuzzy Set Classification and fuzzy Maximum likelihood classification have also been used (Foody 1996 and Foody et al., 1992).

Regression trees have been used primarily with coarser scale data by McIver and Friedl (2002) and Defries et al. (1997). The MODIS Vegetation Continuous Fields product used by Patterson and Kelso (2004a, b) for Natural Earth (Fig. 4) is calculated using a supervised regression tree algorithm described by Hansen et al (2003). Logical Regression analysis in the form of a regression tree is also used by the US multi-Resolution Land Characteristics Consortium to generate tree canopy density and imperviousness datasets for the continental US. This is the primary soft dataset used in our three continental United States case studies. Huang et al. (2001) describe a test study done to determine the feasibility of estimating tree canopy density in Landsat imagery from a canopy density model derived from 1m Digital Orthophoto Quadrangles (DOQs). Homer et al. (2004) reported mean absolute errors ranging between 8.4% and 14.1%. The dataset which has yet to be completed for the entire continental United States has not been adequately validated.

In three of the cases discussed I also make use of what Strahler et al. (1986) term "direct inference" through the use of the Tasseled Cap image transformation greenness component (Jackson, 1983, and Crist and Cicone, 1984) and the Normalized Difference Vegetation Index (NDVI). The assumption in these cases is that for some vegetation land cover NDVI or greenness can be used as a simple proxy for biomass and through basic image manipulation yield a continuous vegetation surface. NDVI is an indicator of photosynthesis, however, the relationship with biomass is not always linear (Peterson et al. 1987), as such this technique is used to other forest datasets depict shrubs, and grasses.

3. Gannett Peak Map

The Gannett Peak project consists of two maps currently being compiled at 1:24,000 and 1:63,360 largely from USGS data (NED 10m DEM), and from 2002 Color Infrared (CIR) DOQs and Landsat ETM + data. This map is the first to use what I will describe as a landscape dictated hybrid land cover approach. I make use of a combination of the canopy density dataset from the NLCD 2000 at 30m resolution. This is combined with an inverted NDVI mask

for non glaciated/non-vegetated areas and a manual digitization for lakes and glaciers for the 1:24,000 map. I am also experimenting with image segmentation as a tool for refining the pixel based classification. In this case three classification methods were tested; isodata, maximum likelihood, and a neural network (fuzzy ARTMAP). Preliminary accuracy assessment suggests the maximum likelihood classification of the pan-sharpened Landsat TM bands with ancillary data (elevation, slope, texture, vegetation indices) performs best (>80% overall accuracy). Vegetation class definition is based on apparent vegetation density as determined from the 14.25m Landsat panchromatic band, 1m DOQ image and NDVI values (no field work has been done to quantify vegetation density). Thus, rather than extract vegetation classes based on vegetation types such as deciduous vs. evergreen, vs. mixed vs. shrub, I am attempting to class vegetation based on dense, moderately dense, light and to incorporate parameters such as elevation as a variable. I am also experimenting with an NDVI based continuous mask for sparse vegetation (Fig. 3a and 3b).

The logic for this approach is that I suspect that most of our users are not concerned with these distinctions. In terms of cross-country travel an indication of density for determining ease of travel or the location of tree line for determining where to setup a camp out of the wind is likely more important. I am hoping this will provide our land cover a more organic textured look that will impart to the user a more intuitive understanding of the landscape.

As there are two maps involved within this project, different approaches and data sources need to be considered. The 1:24,000 map contains a smaller diversity of biomes thus has fewer transitions and less complexity but needs to show land cover at a greater resolution. As such I am likely to rely more on textures and land cover polygons extracted from the higher resolution CIR DOQs. Conversely the smaller scale map has a greater variety of terrain and more transitional areas. It needs to reflect the character of the greater region being portrayed and provide useful information for trip planning as well as navigation. It will benefit from some of the continuous datasets I plan on using.

4. Discussion & Conclusion

As a cartographic output, few uses of continuous land cover datasets have been made. The MODIS vegetation continuous fields (VCF) product has been used at continental to global scales by Patterson and Kelso (2004a, b) to great advantage and is the most notable (Fig. 4). Adams et al. (1995) used triangular two-dimensional color legend to map class composition. However, as class membership begins to be composed of more than 3 end members, de-

piction in CMYK color space becomes more challenging. I suspect there remains some work to do to develop products and techniques suitable for medium to large scale cartographic output. In the cases illustrated here there is a range of techniques of varying success demonstrated. The measure of that success is also quite qualitative. In fact, no usability studies for this type of cartographic depiction are known to the author and future work on this topic will need to address this lacuna. It is also possible that good legend and cartographic design will be sufficient to successfully communicate these complex elements.

For Gannett Peak several land cover classification methods were compared. A maximum likelihood classification (Fig. 3a) produced the best overall accuracy (over 80%) when using a combination of spectral, topographic and texture inputs. Vegetation classes were defined based on apparent densities rather than vegetation types. From my perspective this has advantages as the resulting classification is easier to incorporate into our style of maps and lends itself better to generalization and blending and is more intuitive, i.e. the lighter the green tint the less vegetation there is. A second approach to which the MLC is compared (Fig. 3b) uses a combination of the canopy cover dataset in the same way as on the granite peak map with an attempt to address its limitations by adding a second continuous surface derived from an NDVI image at 14.25m resolution. This yields a very pleasing effect. Non vegetation components are generated by inverting the NDVI mask. By combining these three layers a certain amount of mixing takes place which renders a richer, smoother image than that of the pixel based MLC classification. This is a good demonstration of the potential in combining continuous datasets derived from Landsat imagery for larger scale maps.

It is my hope to implement a hybrid method that characterizes continuous land cover components using continuous classes with object oriented classification for area with discontinuities such as the agricultural areas found at lower elevations and to some extent water and glacial areas. Because two maps will be compiled in this case this will provide an opportunity for testing the type of multiscale, multigranular approach described by Ju et al. (2005).

This paper begins to examine the limitations imposed on cartographic depiction by object oriented derived classification. Softening their output is problematic and not trivial, particularly when their definition is limited to shape metrics and descriptive statistics. Although fuzzy classification is an option in the classification stage it is tied to the segmented objects and “defuzzification” (eCognition’s term in Baatz et al., 2004) is used to output single class membership in the last stage of classification. This approach is advantageous for certain land cover classes and future work will combine this approach with continuous variables and also compare the two side by side in a car-

tographic setting rather than only at the accuracy level where most evaluation of object oriented outputs are now taking place.

Dasymetric approaches using higher resolution datasets show some promise for deriving sub-object level information on composition and distribution assuming they are available. In this case I demonstrate the use of a simple greenness surface calculated from a Landsat image to derive a vegetation layer. It is my hope that more sophisticated approaches such as decision trees will be used to derive sub-pixel mixtures that can better approximate landscape composition. It’s also possible that alternate vegetation indices that address the litter and soil component may be better suited for the approach presented here.

The maps I describe here are a starting points for a discussion on how and when to generalize land cover depiction in topographic maps at the landscape scale in which I am interested, and in particular in mountain environments. Most of the research on sub pixel analysis results in pixel mixture composition as numerical values used for class labeling (Woodcock et al. 1996). Unfortunately analysis conducted to quantify sub-pixel mixtures is rarely depicted on maps as such; in fact Ju et al. (2003) imply that one of the strengths of continuous classification lies in the possibility that discrete classification can always be produced from the dominant cover as per Adams et al. (1995). The implication is that the dominant cover is the only interesting and desired component. This may in fact be true in most managerial and custodial mapping applications, aesthetically, however, the case for the richness in the mixtures has strongly been made in the author’s mind by the Natural Earth dataset and the superior results in the Gannett case discussed in this paper.

References

- ADAMS, J.B., SABOL, D.E. and KAPOV, V., et al. 1995: Classification of multispectral images based on fractions of endmembers: application of land-cover change in the Brazilian Amazon. In: *Remote Sens. Environ.* 52:137–154.
- ATKINSON, P.M., CUTLER, M.E.J. and LEWIS, H., 1997: Mapping sub-pixel proportional land cover with AVHRR imagery. *Int. J. Remote Sens.*, 4:917– 935.
- BAATZ, M., BENZ, U., DEGHANI, S., HEYNEN, M., HÖLTJE, A., HOFMANN, P., LINGENFELDER, I., MIMLER, M., SOHLBACH, M., WEBER, M. and WILLHAUCK, G., 2004: *eCognition Professional: User guide 4*. (Munich: Definiens-Imaging).
- CARPENTER, G., GOPAL, S., MACOMBER, S., MARTENS, S. and WOODCOCK, C., 1999: A neural network method for mixture estimation for vegetation mapping. In: *Remote Sensing of Environment*, 70, 138– 152.

CRIST, E. and CICONE, R., 1984: A physically-based transformation of Thematic Mapper data—the TM Tasseled Cap. In: *IEEE Trans. Geosci. Remote Sens.* GE-22: 256–263.

DEFRIES, R., HANSEN, M., STEININGER, M., DUBAYAH, R., SOHLBERG, R. and TOWNSHEND, J., 1997: Subpixel forest cover in central Africa from multisensor, multitemporal data. In: *Remote Sensing of Environment*, Vol. 60, No. 3, pp. 228–246.

DE GENST, W., CANTERS, F., JACQUET, W. and VERMEERSCH, S., 1999: Development of a technique to decompose heterogeneous mapping units in a categorical map of the biotic environment using correlated categorical data. In: *International Journal of Geographical Information Science*, 13 (6), 591–614.

FOODY, G., 1996: Approaches for the production and evaluation of fuzzy land cover classifications from remotely-sensed data. In: *International Journal of Remote Sensing*, 17(7), 1317–1340.

FOODY, G., 1998: Sharpening fuzzy classification output to refine the representation of sub-pixel land cover distribution. In: *International Journal of Remote Sensing*, 19, 2593–2599.

FOODY, G.M., CAMPBELL, N.A., TRODD, N.M. and WOOD, T. F., 1992: Derivation and applications of probabilistic measures of class membership from maximum likelihood classification. In: *Photogramm. Eng. Remote Sens.* 58(9):1335–1341.

FORMAN, T.T., 1995: *Land Mosaics*, Cambridge University Press, Cambridge, 632 pp.

FRANKLIN, S.E. and WILSON, B.A., 1992: A three-stage classifier for remote sensing of mountain environments. *Photogrammetric Engineering and Remote Sensing*, 58, 449–454.

HANSEN, M., DEFRIES, R., TOWNSHEND, J.R., CARROLL, M., DIMICELI, C. and SOHLBERG, R., 2003: 500m MODIS Vegetation Continuous Fields. College Park, Maryland: The Global Land Cover Facility.

HOMER, C., HUANG, C., YANG, L., WYLIE, B. and COAN, M., 2004: Development of a 2001 National Landcover Database for the United States. In: *Photogrammetric Engineering and Remote Sensing*, Vol. 70, No. 7, July 2004, pp. 829–840. http://www.mrlc.gov/pdfs/July_PERS.pdf

HUANG, C., YANG, L., WYLIE, B. and HOMER, C., 2001: A Strategy for Estimating Tree Canopy Density Using Landsat & ETM+ and High Resolution Images over Large Areas. In: The proceedings of the Third International Conference on Geospatial Information in Agriculture and Forestry held in Denver, Colorado, 5–7 November, 2001, 1

disk. http://landcover.usgs.gov/pdf/canopy_density.pdf

JACKSON, R.D., 1983: Spectral indices in n-space. *Remote Sensing of Environment*, 13, 409–421.

JU, J., KOLACZYK, E.D. and GOPAL, S., 2003: Gaussian mixture discriminant analysis and sub-pixel land cover characterization in remote sensing. In: *Remote Sensing of Environment*, 84, 550–560.

JU, J., GOPAL, S. and KOLACZYK, E.D., 2005: On the choice of spatial and categorical scale in remote sensing land cover characterization. In: *Remote Sensing of Environment*, 96(1):62–77.

KLEIN, A.G. and ISACKS, B.L., 1999: Spectral mixture analysis of Landsat thematic mapper images applied to the detection of the transient snowline on tropical Andean glaciers. In: *Global and Planetary Change*, 22: 139–154.

MCIVER, D.K. and FRIEDL, M.A., 2002: Using prior probabilities in decision-tree classification of remotely sensed data. In: *Remote Sensing of Environment*, 81, 253–261.

MILNE, B.T. and COHEN, W.B., 1999: Multiscale assessment of binary and continuous landcover variables for MODIS validation, mapping, and modeling applications. In: *Remote Sensing of Environment*, 70, 82–98.

MONMONIER, M., 1996: *How to Lie with Maps*, 2nd Ed. University of Chicago Press, Chicago.

MOODY, A., GOPAL, S. and STRAHLER, A.H., 1996: Sensitivity of neural networks to subpixel land-cover mixtures in coarse-resolution satellite data. In: *Remote Sens. Environ.* 58: 329–343.

NOLIN, A.W. and DOZIER, J., 1993: Estimating snow grain size using AVIRIS data. In: *Remote Sensing of Environment*, 44(2–3), 231–238.

PATTERSON, T., 2002: Getting Real: Reflecting on the New Look of National Park Service Maps. In: *Cartographic Perspectives* 43:43–56.

PATTERSON, T. and NATHANIEL, K., 2004: Hal Shelton Revisited: Designing and Producing Natural-Color Maps with Satellite Land Cover Data. In: *Cartographic Perspectives* 47:28–55.

PETERSON, D.L., SPANNER, M.A., RUNNING, S.W. and TEUBER, K.B., 1987: Relationship of Thematic Mapper Simulator Data to leaf Area Index of Temperate Coniferous Forests. In: *Remote Sensing of Environment* 22:323–341.

ROSENTHAL, W. and DOZIER, J., 1996: Automated mapping of montane snow cover at subpixel resolution from the Landsat Thematic Mapper. In: *Water Resources Research*, Vol. 32, No. 1, pp. 115–130.

SMALL, C. 2004: The Landsat ETM+ spectral mixing space. In: Remote Sensing of Environment 93: 1–17.

SOLBERG, R. 2000: A new method for sub-pixel snow-cover mapping using hyperspectral imagery - first results. In: Proceedings of EARSeL-SIG-Workshop Land Ice and Snow, Dresden/FRG, June 16 – 17, 2000.

STRAHLER, A.H., WOODCOCK, C.E. and SMITH, J.A., 1986: On the nature of models in remote sensing. In: Remote Sensing of Environment, 20:121–139.

WANG, F., 1990: Fuzzy supervised classification of remote sensing images. In: IEEE Trans. Geosci. Remote Sens., 28, 194–201.

WOODCOCK, C.E. and STRAHLER, A.H., 1987: The factor of scale in remote sensing. In: Remote Sensing of Environment 21:311–332.

WOODCOCK, C.E., GOPAL, S. and ALBERT, W. 1996: Evaluation of the potential for providing secondary labels in vegetation maps. In: Photogramm. Eng. Remote Sens. 62:393–399.

Wu, J.G. and David, J.L., 2002: A spatially explicit hierarchical approach to modeling complex ecological systems: Theory and application. Ecological Modelling, 153, 7– 26.



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