Fuzzy Classification of Vegetation for Ecosystem Mapping

F. Jack Triepke

Abstract Vegetation classification and mapping are important tools for addressing natural resource management, ecosystem restoration, and other contemporary ecological issues. Though classical set theory is most often applied for mapping problems, natural landscapes are often expressed as fuzzy sets. Where contrast among map categories or geometric objects is often weak in ecological contexts fuzzy approaches offer the advantage of identifying and utilizing the degree of membership among multiple possibilities, enabling opportunities for alternative outputs and for the careful analysis of error structure. In this chapter, fuzzy systems are explored for purposes of describing ecological features, for interpretation and mapping of those features, and for analyzing the uncertainty of spatial information. Some ecological applications that lend themselves to fuzzy logic are discussed along with examples of the effective use of fuzzy techniques for mapping and analysis, with explanations of the advantages of fuzzy approaches over crisp methods. Finally, in a look to future, I discuss advanced classifier methods, some Web-based solutions, and the potential for applying fuzzy systems to interactively generate user-defined map products, neutral of á priori ecological classification, according to the precise needs of natural resource managers and researchers.

Introduction

The mapping of ecological features is fundamental to the management and study of ecosystems (Brewer et al. 2006). Maps provide readily accessible graphic representations of ecosystem features and, within the data domain, an efficient means of facilitating spatial analyses when multiple spatial layers are brought together to respond to a question or an issue. Ecological mapping is the process of delineating the geographic extent of chosen features of ecosystem structure and composition or the extent of other biophysical expressions such as potential vegetation and ecological systems (Daubenmire 1978; Comer et al. 2003). With some of these spatial data,

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remote sensing may have a limited role in their development and makeup, though image analysis and interpretation techniques are no less valuable. The reader is referred to Chapter "Mapping Forest Landscapes: Overview and a Primer" for an overview of important concepts and components of vegetation mapping and for a discussion on the variables that affect such products.

Mapping requires that map units and the underlying classification be identified prior to map development (Running et al. 1994; Brohman and Bryant 2005; Brewer 2007), without which leads to map data which are inconsistent, vague, unsuited for comparison, and problematic for GIS analysis. While fuzzy mapping approaches can offer solutions to the indiscrete nature of ecological features on the landscape, it is nevertheless important to contemplate a scientific classification so that the resulting map units are consistent in logic, comprehensive relative to the thematic resolution, and mutually exclusive. Even continuous non-categorical mapping, such as tree cover or NDVI renderings (USGS 2014), reflects classifications of some type characterized in a metric (e.g., aerial extent) and a definition that describes the feature. As detailed in the following sections, the fuzzy nature of natural landscapes challenges the common conception of mutual exclusivity among map classes.

Classic spatial analysis and image classification rely on the strengths of the underlying ecological classification and map unit framework, and the assumptions that the project area is made up of various mutually exclusive and internally homogeneous units that can be discerned and subsequently modeled with training data (Lillesand and Kiefer 2000). To an extent this perspective is the same for the ecological classification, itself, since it relies on a degree of similarity within classes and maximal dissimilarity among classes (Daubenmire 1966; Hoppner et al. 1999). However, as is more often the case, even ecological classes express themselves across landscapes as continua within and among other units—fuzzy sets. Thus the character of ecological features across landscapes often has significant fuzziness within any arbitrary class that humans impose to challenge a key assumption of conventional image classification (Wood and Foody 1993). That is not to say that fuzzy sets do not have medoid properties, objects that represent a central concept to the map unit that can be useful for understanding and conveying the unit's essence and for generating training data. But these medoid representations may have limited utility in framing a model for a fuzzy set given the variability of the unit reflected over the landscape.

The fuzziness of a map theme may even be revealed at the scale of individual image objects or pixels. In the case of mixed pixels, ecological features are of finer grain than the spatial resolution of the spectral imagery used to interpret those features (Foody 1997; Zhang and Foody 1998; Campbell 2002). The idea of mixed pixels is that their spatial extent is not completely occupied by a single homogeneous map theme. The exact issue may stem from the inherent fuzziness in the ecological features, as elaborated above, or due to the size of objects being small in relation to the underlying variability of ecological features (Li et al. 2014). It may be not only erroneous to assign one category to a mixed pixel, but by its messiness a mixed pixel confounds our ability to interpret and assign even the most likely category. At the same time, the spatial resolution of the spectral imagery may do justice to some map themes and not others so that acquisition of the preferred image source is determined as the least objectionable alternative when combining sources is not operationally feasible. With road verges, for instance, an ordinary image source such as Landsat TM may be too coarse to precisely map the narrow strip of lawn adjacent to urban roadways, though road verges may be a map theme of lesser interest. The choice of spectral imagery may also be a matter of cost, so that an affordable alternative such as Landsat TM may indirectly influence how a map legend is composed. In the case of road verges, map developers may opt for a more general and practical map theme, such as "residential," so that Landsat TM is an option, particularly if accurately mapping road verges is a low-priority objective.

Situations of gradual or mixed membership can be accommodated with fuzzy techniques. The need for fuzzy classification and related spatial analysis approaches was recognized as least since the 1990s (e.g., Wang 1990), and has since been applied in various vegetation mapping, fire severity, soils and geology, and sociological mapping (Zhang and Foody 1998; Triepke et al. 2008; Remmel and Perera 2009). In this chapter the application of fuzzy systems is reviewed within two realms: in the characterization of ecological features, both in map unit concept and in output attribution of a geodatabase. The attribution can, in turn, be used for the assessment of uncertainty. Second, fuzzy systems are explored as classifiers of image objects, expressed as rules for the interpretation of predictor data. Finally, some discussion of recent and future technology and methods is included, but first, an overview of fuzzy logic is provided.

Overview of Fuzzy Systems

Fuzzy logic is an approximate form of reasoning used in set theory to represent knowledge (Cox 1992). Since fuzzy systems represent approximate reasoning, they can provide accurate levels of abstraction for many ecological circumstances that, by their nature, are ambiguities among arbitrary human categories. In this context, fuzzy logic provides an efficient means of representing features with more effective metaphors and fewer rules than classic Boolean approaches (Rickel et al. 1998). Traditional map themes, and their associated rule sets, assume discrete boundaries among themes. Fuzzy logic, however, accommodates the gradation and overlap among map themes that is common in natural systems so that any pixel or object can be assigned a value between 0 and 1 by the strength of its identity to a theme (Wang 1990); that is, an object can have partial membership to one or more themes (Zhang and Foody 1998). Membership to a theme at any locale represented spatially by pixels or objects can be represented as "no," "yes," or "somewhat," respectively, as 0, 1, or any value between 0 and 1 (Zadeh 1965; Klaua 1966; Goguen 1969). As with Boolean logic, fuzzy logic suggests the most probable identity for a given object. But unlike Boolean functions (i.e., crisp or hard functions), fuzzy approaches leave open the possibility of partial membership to more than one map theme, offering a distinct advantage over crisp methods for refining map unit concepts, generating spatial outputs, and assessing uncertainty (see section "Fuzzy Approaches for Identifying and Utilizing Uncertainty").

Fuzzy systems are fundamentally probabilistic (Kosco 1995) and membership values can be assigned to a map object depending on the probability of membership to each of the categories conceptualized in a map legend. Membership values can be determined such that all individual memberships for each category total to 1, with classification rules constructed accordingly (Zadeh 1965; Goguen 1969). Membership is alternatively determined through suitable algorithms including unitless distance such as Euclidean or Mahalanobis functions, with outputs scaled to a range from 0 to 1 to represent the degree of inclusion to a category for each object. In the case of Mahalanobis distance, membership is the distance between an object and the distribution D of actual values for a given category (Knick and Rotenberry 1998). Here, the distance is a measure of the number of standard deviations between the object and the mean of D, with distance increasing as the value of an object and the mean of D increase. As with other approaches, Mahalanobis distance can be computed for each map category so that each object is comprised of a set of membership values for all categories. Later in the chapter other classifier approaches are explored. First however, we will step back and look at rule operators as a means to understand connections between fuzzy membership values and the classification of ecological features.

Fuzzy Systems: Key Concepts for Mapping

While fuzzy systems can be used to address either thematic or spatial mapping problems, for simplicity the following descriptions are based on familiar circumstances of thematic mapping. Some geometric situations are summarized in sections "Spatial Uncertainty" and "Simultaneous Considerations of Thematic and Spatial Uncertainty." Fuzzy logic is used for both characterizing ecological features and for classifier approaches, including the combining of rules into decision trees for image classification. Fuzzy rules can also be used to determine fuzzy membership values for categorical data for purposes of image classification and spatial analysis. The following sections describe the role of fuzzy systems for characterizing ecological features and for classifying them through the interpretation of image data.

Map Unit Concepts

To develop a system of map themes, first an ecological classification is adopted or developed based on the business needs or the research criteria of a program or project. Map units are made up of one or more ecological classes, often an iterative process that balances the capacity of the classification with mapping objectives, technological constraints, and available resources devoted to the particular map project (Jennings et al. 2003; Brohman and Bryant 2005; Brewer et al. 2006). In the

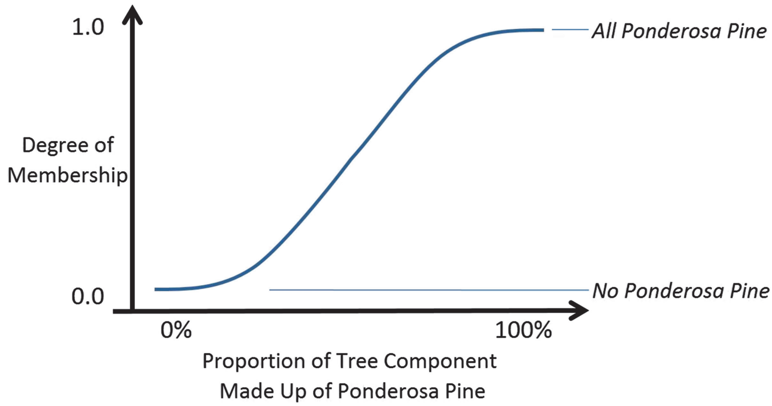

Fig. 1 Fuzzy operator used to show increasing membership to a "Ponderosa Pine" map unit as a logistic curve, based on the proportion of ponderosa pine in an image object

end, a one-to-one relationship between an ecological classification and the map units in a legend may not be possible or desired. Also, it may be necessary to normalize training samples so that there is a logical consistency between training data and the proposed map categories. While not discussed here, Wang (1990) and others have advocated attributing training data with fuzzy membership values between 0 and 1 for every map category, likewise extending the approach to accuracy samples. More recent work has shown that training maps with mixed objects, where membership to each map category is determined, can be an asset to improving map accuracy rather than an issue (Costa et al. 2017). In the end, map units are ideally underpinned by a scientific classification and characterized in fuzzy terms.

With a fuzzy mapping system, it is helpful to consider that that every pixel or object in the dataset is attributed with a membership value between 0 and 1 for every map theme. Now consider a fuzzy mapping system based on a single-species cover type concepts. Figure 1 shows a fuzzy membership function for a "Ponderosa Pine" vegetation type, where the strength of membership bears on the percentage of ponderosa pine (*Pinus ponderosa*) in the tree component of an object. With this function, membership values increase by the proportion of ponderosa pine, so that objects with tree components that are comprised only of ponderosa pine (100%) have fuzzy membership values of 1; conversely, objects with no ponderosa pine have membership values of 0. The relationship between membership and the classification can be sigmoid as shown in Fig. 2, or expressed by some other mathematical function. In the end every object of the map has a membership value for ponderosa pine between 0 and 1.

Now we will look at a more complex and realistic scenario with two map unit concepts in combination, and take an initial look at the characterization of uncertainty. Two common montane forest tree species of western North America—ponderosa pine and Douglas-fir (*Pseudotsuga menziesii*)—represent primary constituents of forests of the Cordillera in the United States and Canada (Morin

1993). These species commonly co-occur as frequent-fire components in relatively warm-dry forested settings. If a map legend includes these two conifer tree themes, and a given plant community has both species present, say, in a proportion of 60% and 40%, the community would be mapped as "Ponderosa Pine" assuming uniform classification rules. Likewise, if the respective percentages are 40% and 60%, the community would be mapped as Douglas-fir. If the proportions were equal, then a tie-breaker rule could be imposed, a mixed cover type could be introduced, or map objects could simply be attributed with fuzzy membership values for each map theme treated with no set-upon legend. In the latter case, classification schemes could be imposed á posteriori and ad hoc along with uncertainty characterizations.

Structure type concepts, such as tree size, likewise necessitate membership schemes and rule-making to determine what conditions point to the assignment of a given object to a particular map theme (Rickel et al. 1998). Where trees of more than one size class occupy the same object, as is often the case in North American forests, map unit concepts can be derived from a consistent means of assigning fuzzy membership. One possible scheme involves the expression of membership gradients within each unit of a category framework. In these situations, the overlap (fuzziness) among categories is often depicted in linear relationships between neighboring classes and by complete exclusivity in all other class-to-class relationships (Nauck and Kruse 1999). As shown in Fig. 2, an object can share properties of up to two categories, say seedling-sapling (<15 cm) and small-diameter trees (<15–25 cm); that is, the object representing a stand of trees has characteristics of both seedling-sapling trees and small trees, reflected in the canopy cover of each tree size class, and can be discerned by the comparative membership of the object to the two neighboring size classes. Of course the approach assumes consistent relationships among categories—e.g., that seedling-sapling trees do not co-occur with trees of size categories other than small. While this representation is unnecessary for univariate data such as the total tree cover, it can be useful for categorical data of

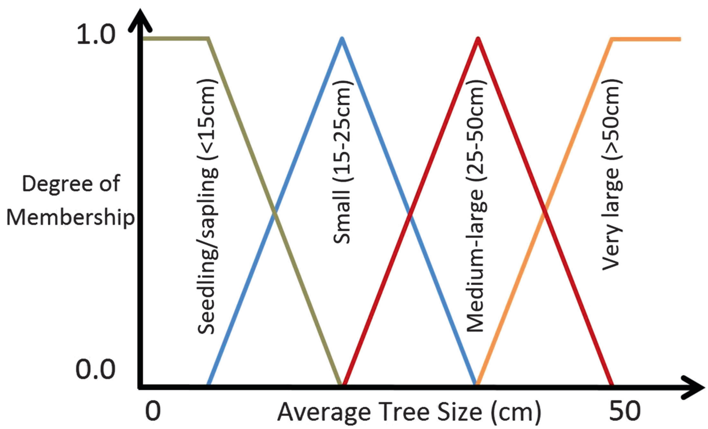

Fig. 2 Fuzzy operator for categorical data, showing hypothetical membership values for each class of tree size

multivariate conditions such as tree size or species. The approach assumes binary conditions since the object can have properties of only two categories, though the relationships could just as well be redrawn to show overlap in three or more categories granted certain additional assumptions.

Fuzzy approaches to building map rules and assessing uncertainty bring much-needed precision to these practices, and allow end users a greater range of options in spatial applications and the development and analysis of map data. Building on fuzzy map unit concepts, the following section provides a survey of common classifier methods that employ fuzzy approaches for the production of map data.

Fuzzy Classifiers

With concepts of fuzzy classifiers introduced in section "Mapping with Fuzzy Classifiers," what follows is a more detailed examination of these classifiers and the attribution of image objects. Here, fuzzy relationships between predictor data and ecological classes are identified and utilized as a means of building maps through image classification and often depicted in rule sets. Fuzzy classifiers do not bear on fuzzy map unit concepts (e.g., Fig. 1) nor do they necessarily result in fuzzy outputs, though there are advantages to both.

With fuzzy classifiers, rules are developed for each map unit or theme based on the fuzzy membership patterns among predictor variables including spectral information and biophysical data layers such as elevation. For example, in the southwestern USA steep slopes comprise a partial signature for fire-adapted shrubland types such as interior chaparral and mountain mahogany shrubland. In a rule-building process, each potential predictor can be represented by a membership function (Zadeh 1965). Figure 3 illustrates the relationship between one predictor variable, slope, and fuzzy membership to fire-adapted shrublands.

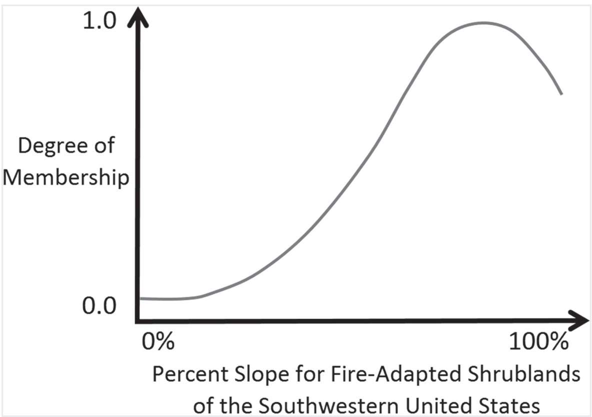

Fig. 3 Fuzzy operator showing the hypothetical relationship between fire-adapted shrublands and slope

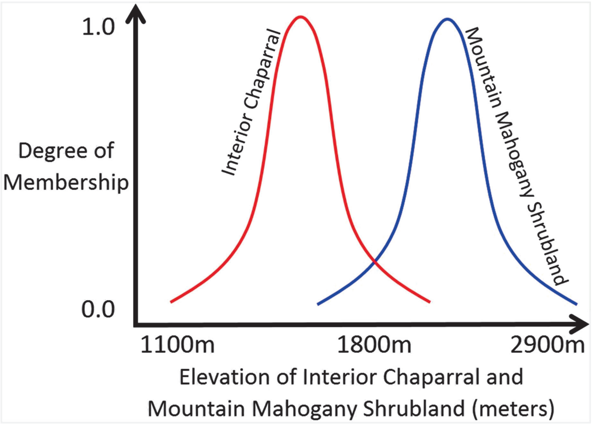

Fig. 4 Fuzzy operators showing the hypothetical relationships between elevation and the Interior Chaparral and Mountain Mahogany Shrubland types

Obviously fire-adapted shrublands are not the only cover type that can occur within the slope range represented by this function. Slope may be useful for differentiating these shrublands from other shrub types but other predictor variables, and consequently other rules and decision nodes, would be necessary to differentiate fire-adapted shrublands from forested and grassland cover types, and also to subdivide fire-adapted shrubland feature space into finer shrub units such as "Interior Chaparral" and "Mountain Mahogany Shrubland" (Brown et al. 1998).

Additional variables may be needed to more accurately model and separate themes depending on the degree of overlap among map themes for a particular model variable. For instance, the membership profiles for slope may be useful in helping to discern fire-adapted shrub systems from other shrub types in the Southwest, but additional differentia are needed to separate the two themes from one another. Figure 4 shows membership functions for elevation for the two shrubland systems that share slope affinities.

By combining variables in a decision tree, multiple membership functions can be brought together for particular classifier problems using hierarchical reasoning to combine membership functions into a rule set. Also, membership functions can be either fuzzy or Boolean and, in fact, can be combined with other algorithms such as nearest neighbor at specific decision nodes that makes up the rule set. Membership functions can be combined using classic mathematical operators such as if-then, greater than, less than, and, and or to build and join rules to determine a consequence theme (Mansoori et al. 2007). Fuzzy rule sets can be elaborate (Ishibuchi and Nakashima 2001) and require successive refinements to maximize precision and separation among map themes when developed manually. Small adjustments in membership can have considerable effects on the classifier outputs. The generation and combination of fuzzy rules can either be a manual exercise, as with eCognition software (Definiens 2003; Triepke et al. 2008) or an automated process (Nauck and Kruse 1998; de Oliveira 1999; Pajares et al. 2009), or both (e.g., Sameen and Pradhan 2017).

Finally, the map theme assignment that is ultimately given to a pixel or map feature in a decision process is the one of greatest overall membership among permutations of the decision network. In the process of assigning individual map themes, classifier outputs are defuzzified, replacing membership values with crisp outputs and map assignments (Rickel et al. 1998). By this process membership data can facilitate responses to a range of problems associated with ecological input data, ecological patterns, and demands of end users. The following sections expand on advantages of fuzzy classifiers over conventional crisp methods for addressing image classification and modeling dilemmas such as gradual membership among themes, modeling uncertainty, and possibility of multiple outcomes with changes in classification rules. Fuzzy logic in accuracy assessment is also discussed.

Fuzzy Representation with Continuous and Categorical Data

Spatial analysis with fuzzy classifiers can leverage both continuous and categorical predictor data. Continuous data in particular lend themselves to portrayal in probability surfaces and fuzzy sets. Not all continuous data may be representable in a fuzzy surface depending on whether each object in the dataset can be attributed by membership to the same theme. Typically there are also competing themes to a fuzzy set that are represented in membership values. Nevertheless many continuous data and legacy sources, such as solar insolation or wetness layers, can be depicted as fuzzy map surfaces.

The greater challenge is in representing categorical data with fuzzy surfaces, though it is possible for some datasets. A habitat model based on the amount of tree cover across the landscape can be informed by categorical data, even if continuous data are preferred, barring the need for more precise information. Categorical data can be made useful for map modeling and environmental analysis if suitable membership values can be determined for each category (Nauck and Kruse 1999). The example in Fig. 5 reflects a continuum for tree canopy cover where, conceptually, objects with no tree cover have a membership of 0 and communities with complete tree cover have a membership of 1. In this case, membership values have been determined based on the midpoint of the four a priori tree canopy cover classes—sparse (0–9.9%, midpoint 5%), open (10–29.9%, midpoint 20%), moderate (30–59.9%, midpoint 45%), and closed (60%+, midpoint 80%).

Such an approach to categorical data may be applicable for any number of datasets and ecological variables including species dominance. Again considering the abundance of ponderosa pine, the amount of ponderosa pine could be represented by cover percentages as with the example in Fig. 5 rather than a system of gradual membership suited for continuous data (Fig. 1). So a forested stand where ponderosa pine comprised 70% of the total tree cover would have a membership value for ponderosa pine of 0.80. With individual map themes, as with the amount of ponderosa pine cover or the amount of total tree cover, such a scheme is useful for exploiting categorical data within the context of a fuzzy approach.

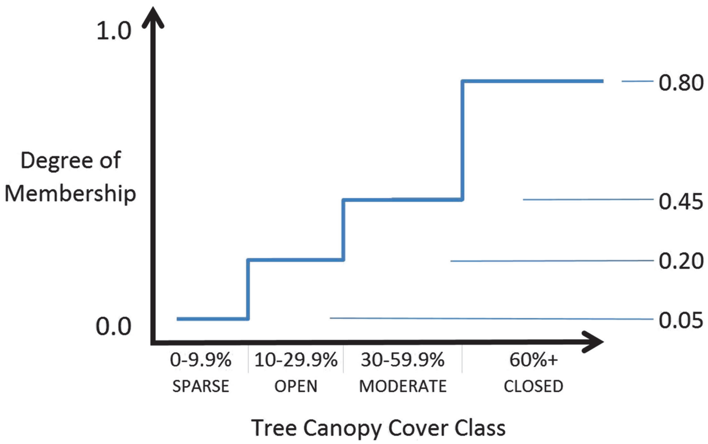

Fig. 5 Fuzzy operator for categorical data, showing hypothetical membership values for four classes of tree canopy cover

In mapping other plant composition or structural features of interest, it may be necessary to weight multiple map categories coincidentally, requiring rule-making to determine what conditions warrant the assignment of membership for a given map category to a given object. In utilizing tree cover type data, for instance, it is likely that the abundance of ponderosa pine would be factored in relation to the abundance of other tree species prompting rules that discern map units in feature space. Pixels of a mixed type, such as "Ponderosa Pine-Douglas-fir," compel the assignment of membership values for both tree species by some set of rules. In these cases, the underlying vegetation classification or map unit concepts are likely to play a role in building rules and determining standard membership values. In an upcoming example in section "Vertical Structure Mapping," rules were developed for producing membership values for forest canopy layering (storiedness) from categorical data. With ingenuity some categorical data can be made useful for map modeling purposes if the analyst can build a membership scheme that is appropriately suited to the predictor data (Rickel et al. 1998; Nauck and Kruse 1999).

Mapping with Fuzzy Classifiers

Pattern recognition and image classification of ecological features involve the search for signatures in spectral and biophysical datasets for purposes of rendering the features of interest in a two-dimensional model. While the term image classification most often refers to the classification of pixels or objects that have been generated from a remote sensing source (Lillesand and Kiefer 2000), here the term is inclusive to other ancillary predictor data including biophysical layers. Remmel and Perera in Chapter "Mapping Forest Landscapes: Overview and a Primer," provide useful overviews of mapping constructs, objectives, important data sources, and process of map development. Remmel further contrasts conventional functional forms behind image classification including binary solutions, quantification of uncertainty, and fuzzy membership. Here, only the background information that is immediately relevant to fuzzy classifier methods is given. Suffice to say that the major steps of image classification include the determination of a suitable map unit scheme, selection of training samples, preparation of the predictor data layers, selection of a classifier method, model development (training or feature extraction), post-processing of classifier results, accuracy assessment, and final processing of outputs into a geodataset (Lillesand and Kiefer 2000; Brohman and Bryant 2005; Brewer 2007; Lu and Weng 2007). Predictor data are those layers of complete coverage of the project area, sometimes referred to as census data, which are interpreted and used to model map themes. Remote sensing techniques were generated in earnest in the 1980s and included unsupervised technology such as *k*-means and ISODATA, and supervised classifiers including maximum likelihood, and various hybrid techniques (Li et al. 2014). While some of these approaches are still in use, other nonparametric classifiers have come into practice including neural networks and decision tree classifiers that include fuzzy rules and other knowledge-based classification that use both pixels and image objects as base model units (Lu and Weng 2007). Object-based techniques begin with the creation of a polygon configuration of image objects, each object a grouping of pixels with similar properties (e.g., spectral response) (Myint et al. 2011) to become the base units for an image classification exercise (see Chapter "Portraying Wildfires in Forest Landscapes as Complex Objects"). Identifying and refining suitable classifier procedures, commensurate with the input data and project objectives, are necessary for the successful development of a map layer of maximum accuracy.

This brief section focuses on the concepts of fuzzy systems in classifier methods for the development of map data. First, some clarification: fuzzy classifiers can be used to produce both crisp and fuzzy map data outputs. Also, fuzzy outputs can be post-processed to render crisp categorical mapping as described in section "Simultaneous Considerations of Thematic and Spatial Uncertainty." The application and value of fuzzy maps will be covered in this latter section. Second, interpolation and distance algorithms as well as conventional classifiers such as maximum likelihood estimation can be used to produce fuzzy maps that do not employ the fuzzy decision rules which typically comprise fuzzy classifiers. The focus of this section is on the former circumstances and the use of fuzzy classifiers to make maps, along with some advantages of fuzzy approaches over other classifier methods.

As framed at the beginning of section "Overview of Fuzzy Systems," fuzzy systems offer advantages in thinking about landscapes and responding to the heterogeneity and complexity of ecological features. In the context of classifiers, fuzzy systems offer a solution to the problem of imprecise predictor data, which Bonissone and others (Bonissone et al. 2010) summarize in this way: first, some imprecision can safely be ignored as in the case of ambiguities that are completely encompassed by relatively general map themes. Second, data which are significantly imprecise can sometimes be accommodated with the use of classifiers that effectively model the probability distribution of a map theme, such as maximum likelihood estimation. Of course, the weakness of maximum likelihood is in the assumption of Gaussian distributions, a condition often not exhibited in ecological features and fuzzy sets. Also, when representing problems of mixed pixels, fuzzy classification rules are structured to optimize the precision in classifier results relative to problems of gradual membership, both in ground conditions and in the continua that occur among map themes, and in the spatial resolution of remote sensing imagery and other predictor layers. Where membership is most gradual among themes, additional variables and more complex rule structure may be needed to optimize differentiation. Third, when imprecision is a significant issue and a probability distribution does not fit the natural pattern, the data represent a fuzzy set and the need for an alternative classifier. For such a mapping problem, fuzzy classifiers are typically represented by rule sets and often in the form of decision trees that subdivide feature space into progressively finer extents in a top-down approach (Safavian and Landgrebe 1991). A decision tree approach lessens the magnitude of image classification problems with the creation of more numerous but less complex rules with each additional layer in a decision hierarchy. As mentioned, decisions at each node of a rule set can be either crisp or fuzzy, automatically or manually generated (Gong et al. 1996), and be informed by continuous or categorical data (Nauck and Kruse 1999). Decisions, in turn, can reflect both expert and statistical relationships between observations and predictor data. In a study by Triepke et al. (2008), decision tree classifiers were used to predict the landscape distribution of Alliances and Associations of the US National Vegetation Classification (Jennings et al. 2009). The resulting decision tree represented a multi-classifier approach (Bonissone et al. 2010), combining manually generated fuzzy and crisp rules into one rule set, with nearest-neighbor classifiers applied at terminal nodes of the decision tree. In this study predictor layers were comprised of both continuous and categorical data to inform what Nauck and Kruse (1999) refer to as mixed fuzzy rules. While the development of most decision tree classifiers is automated (Nauck and Kruse 1997), the manual development of rules can be time consuming but the access to and understanding of decision rule structure offers extraordinary flexibility in addressing fuzzy sets and inputting expert knowledge of a landscape into a mapping problem.

Since the difference in fuzzy membership among a set of map categories is often subtle, as in the case of ecotones, small changes to fuzzy rules can produce significantly different classification results. Contrast among map unit concepts themselves may be weak, but greater problems may be in the lack of contrast in imagery and biophysical data or in the spatial resolution of the image data or other issues for which fuzzy systems can provide a superior solution (Cai et al. 2009). It is in these circumstances where fuzzy systems possess strengths over other classifier techniques since even slight differences expressed for a particular variable can be leveraged synergistically when variables are effectively combined to leverage the collective strength of multiple predictor data. Fuzzy classifier approaches can offer better representations of land cover features than crisp methods for the simple fact that much of the landscape is fuzzy and not described well by single map categories (Wang 1990). Even the most basic approaches for rendering geometrically fuzzy surfaces, such as interpolation and distance functions (Lowell 1994; Wang and Hall 1996), are likely to offer advantages in accuracy over crisp mapping at least for heterogeneous extents. For some types of map units such as glaciers, parking lots, lakes and ponds, riparian corridors, or scree slopes which have discrete edges, membership can change abruptly over short distances to limit the performance and suitability of a fuzzy solution (Zhang and Foody 1998). Additionally, discreteness is scale sensitive given the spatial resolution of the natural feature relative to the spatial resolution of the input imagery.

Back to automated rule development: fuzzy decision systems can and usually are generated from automated methods including fuzzy cluster analysis (Hoppner et al. 1999), neural networks (Nauck et al. 1997), and multi-classifier methods (Nauck and Kruse 1999; Bonissone et al. 2010), which have been shown to produce results that are better than individual classifier methods. In their study of fuzzy classifiers and the random forest algorithm, Bonissone et al. (2010) nicely summarize the evolution of ensemble techniques used to build decision tree rules and fuzzy systems by first describing bootstrap aggregating (Breiman 1996). Bootstrap aggregating, or bagging, is a machine learning algorithm designed to maximize the accuracy of decision tree classifiers. This approach results in an ensemble of classifiers that have been generated by resampling and replacement of individual training data in turn, where the final predictions are made by a vote of the most repeated classifications. Boosting, on the other hand, results in an ensemble of classifiers that have been added one at a time through iterative learning based on weaker classifications, with the eventual outcome of the strongest classifier (Schapire 1990). In the process, classifiers resulting in misclassification gain weight while strong classifiers lose weight, resulting in an ensemble of classifiers and the identification of their relative strength. Other key decision tree building classifiers have since been offered (e.g., Amit and Geman 1997; Ho 1998; Dietterich 2000) that lent to the development of random forest ensembles (Breiman 2001).

Random forest is another machine learning algorithm used for classification that “learns” from data (data mining) (Breiman 2001). Random forest operates through ensemble learning, based on patterns among training samples and predictor data and the construction of multiple decision trees. Classifications are ultimately assigned based on the most votes (mode) among outputs from the multitude of decision trees. As a classifier, random forest is a combination of bootstrap aggregating and the random selection of sample sets from the suite of training data through bootstrap selection and replacement (Amit and Geman 1997; Ho 1998). The only adjustable parameter of import is the out-of-bag error rate, which is used in determining the optimal range of predictor variables for inclusion in the model. Reducing the number of variables reduces both the strength of individual decision trees and the correlation (redundancy) between any two trees. Increasing the number of variables has the reverse effect. The out-of-bag error estimation is the proportion of decision tree scenarios that do not result in a correct classification according to the samples held back from selection for a given scenario—that is, not within the bag of selected samples. The out-of-bag error rate is an unbiased error output with random forest that can assist in determining the optimal range of predictor variables. Random forest can be effective and robust with the default settings, making it ideal for non-statisticians and image analysts given the limited parameters for tuning, including the number of variables tested at each split in the tree and the number of classification trees in the model. The decision trees generated by random forest are typically made up of crisp rules though fuzzy systems are a logical extension for some classification problems (Marsala 2009; Bonissone et al. 2010). Although fuzzy random forest has been used in other fields of science (Bonissone et al. 2008; Kulkarni and Sinha 2013; Lasota et al. 2013), the approach is not as yet a convention for land cover mapping. In the final section of this chapter, "A Look to the Future," the potential application and advantages of fuzzy random forest are explored.

Fuzzy Approaches for Identifying and Utilizing Uncertainty

Uncertainty determinations form a basic component of any scientific tool or product (Congalton 1991; Congalton and Green 1999; Brohman and Bryant 2005), most commonly expressed in statistical estimates of confidence. Different techniques have been applied to assess the uncertainty of map data, most often taking the form of thematic accuracy assessments summarized on confusion matrices. Objective determinations of map uncertainty are critical for informing end users, who may exacerbate error by the ways map data are misunderstood and applied (Bailey 1988; Cowling et al. 2005).

Uncertainty can be both thematic, dealing with extents that have shared characteristics of multiple map categories, or geometric, where the same spatial extents may be more or less homogenous but reflect zones of intergradation among disparate map units that make up a minor proportion of an analysis area. Put another way, the problem of shared characteristics to a mapping specialist is either one of mapped extents with attributes of more than one map theme or one of the transitional nature of ecological features across horizontal distances (Zhang and Stuart 2001). Added to the complexity in ecological patterns, and the ability to capture those patterns in a map model, is the question of model accuracy. For this question, the reader is referred to Chapters "Fuzzy Classification of Vegetation for Ecosystem Mapping" and "Portraying Wildfires in Forest Landscapes as Complex Objects" with the acknowledgement that the uncertainty in a map product in part reflects the capability and shortcomings of the underlying models used to generate map surfaces. Also, both thematic and geometric ambiguities can be augmented by, or even stem from, the relative coarseness in the spatial or thematic detail of predictor data—also a problem of model performance—not to mention possible registration errors in the various predictor layers. Chapter "Mapping Forest Landscapes: Overview and a Primer" introduces important concepts of uncertainty and poses the fundamental question: How confident can we be in the accuracy of map data? For now, the focus is on the specific problems of thematic and geometric uncertainty that can exist and be dealt with using fuzzy methods, either at the front end by improving map classification and the separation of map units or in the assessment of results and the characterization of map accuracy and fuzziness.

First, transitional areas of the landscape can share properties of multiple themes in a legend and difficult to map accurately to the most suitable theme(s), as in the case of mixed pixels (Li et al. 2014). Still, the problem may not necessarily be fixed by, say, acquisition of imagery with higher spatial resolution (e.g., Landsat TM versus RapidEye imagery, 30 m vs. 5 m resolution). In fact, the issue may be compounded if the higher resolution source is too sensitive to within-theme features of little interest that reflect greater detail than the map scheme—higher spatial resolution imagery is not always better. For example, small tree patches of a few square meters within a grassland matrix may be mappable with the high-resolution source, but nevertheless undesirable depending on the objectives and specifications of the project. In this case a satellite sensor of coarser spatial resolution may effectively blend the responses of tree and understory components to create a useful image source for mapping grassland or savannah systems without expressing within-theme features such as small shrub or tree patches (Fig. 6).

Nor would it be desirable or practical to map transitional areas of the landscape if they are only a minor element in the overall ecological pattern, unworthy of distinction in a map legend. Yet transitional areas may also occur over extensive expanses and protracted gradients, as with the zone between boreal forests and tundra on the northern Canadian Shield, where individual plant communities support

Fig. 6 Comparison of spatial resolution of satellite image sources, Landsat TM (30 m) versus RapidEye (5 m), from a grassland system with juniper encroachment east of Grants, New Mexico, USA (Earth 2014a)

both woodland and tundra components over vast areas (Barbour et al. 1998). In these environments trees and tundra co-occur with regularity and at common map scales with relative uniformity that warrant imagery and mapping systems that capture these features within the same categories. Categorical mapping assumes that, as with effective vegetation classification, the homogeneity within map units is maximized while simultaneously maximizing heterogeneity among map units. The maps then generated by these categories pose the same assumption in a spatial context. The conventional response to significantly large areas of intergradation and ambiguity is to create additional map units that capture those areas as themes unto themselves, the result being a map legend of lesser contrast but abiding mutual exclusivity. For example, in northwestern Montana of the USA there are significant swaths of forests heavily dominated by western larch (*Larix occidentalis*) and areas dominated by subalpine fir (*Abies lasiocarpa*). There are also extensive areas where these two constituents are intermingled as codominants of the same object, necessitating the representation of a mixed cover type in both the classification and mapping of vegetation (Leavell 2000; Triepke et al. 2008), albeit at the cost of additional complexity in vegetation classification and map development to address the practical needs of forest practitioners.

Fuzzy approaches can be helpful in forming vegetation classes and map units, in building maps, and then in assessing uncertainty of end products. As stated, while conventional mapping perspectives impose classical set theory on the assumption that map units are mutually exclusive rather than on continua within the landscape (Woodcock and Gopal 2000), fuzzy theory allows us to evaluate ambiguity in an ordered way and then to analyze uncertainty, both in terms of area estimates of mixed conditions and fuzziness and in terms of accuracy assessment itself. And fuzzy approaches can be applied both for thematic and spatial entities, the uncertainty of which is often intertwined (Aspinall and Pearson 1995).

Thematic Uncertainty

To explore thematic uncertainty, we will again use the example of codominant ponderosa pine and Douglas-fir and assume relative percentages of 60% and 40%, respectively, within a plant community. If an object representing the community is mapped as “Douglas-fir,” a fuzzy analysis would show that the degree of misclassification is less than an object misclassified as “Douglas-fir” but made up entirely of ponderosa pine. Even a fuzzy assessment at a more superficial level, say broadleaf versus conifer, has utility over a crisp perspective that indicates total error without nuance, as in the case of two misclassified objects that are dominated by ponderosa pine in reality but classified as Douglas-fir and quaking aspen (*Populus tremuloides*). A fuzzy approach may allow some credit for the misclassified Douglas-fir conifer object over the object misclassified as a broadleaf “Aspen” type, versus a crisp approach that would show the two objects in complete and equal error. A key advantage of a fuzzy technique is in being able to assign the degree of deviation from truth, which may be defined simply as the theme of highest membership according to an observation (accuracy sample). This theme may, in fact, hold marginal leads over other themes of partial membership. It can be very much worth knowing, for example, the degree of deviation in a misclassified pixel relative to the theme of highest membership and whether the deviation is small in comparison to other themes that, under a fuzzy approach, would reflect a much higher amount of error (Wang 1990).

In another perspective of uncertainty, Woodcock and Gopal (2000) demonstrate a means of area estimation using a vegetation map of the Plumas National Forest of northern California, to contrast the amount of extents that, respectively, fall within classic and fuzzy sets. Woodcock and Gopal applied Card's method (Card 1982) and assigned degrees of map unit membership to each accuracy sample, and then integrated membership probabilities with area-weighting to determine the extent of the map that was relatively ambiguous for six map themes—water, barren-grass, meadow, brush, hardwood, and conifer. They found that aside from the water and conifer units, very few samples from other units reflected full membership to any particular theme, further implying that much of the map extent occurred as fuzzy sets. The general relationship is that as the threshold membership value for any particular map unit is reduced more map area is represented by that map unit (Fig. 7). The area estimate of brush in particular had a strong inverse relationship with membership. Using chaparral vegetation to illustrate the relationship, the authors describe a pattern where shrub species dominate the understories of plant communities with low tree cover that still meet the chief criterion of the conifer unit (>10% canopy cover of conifer trees), representing the circumstances of about a quarter of the entire analysis area. In these communities, shrubs often have an aerial extent on par or exceeding that of conifers so that they possess strong affinity to the shrub theme. While 61% of the map area was represented by conifer, only about half that area is estimated to have full membership to the theme. Figure 7 shows that

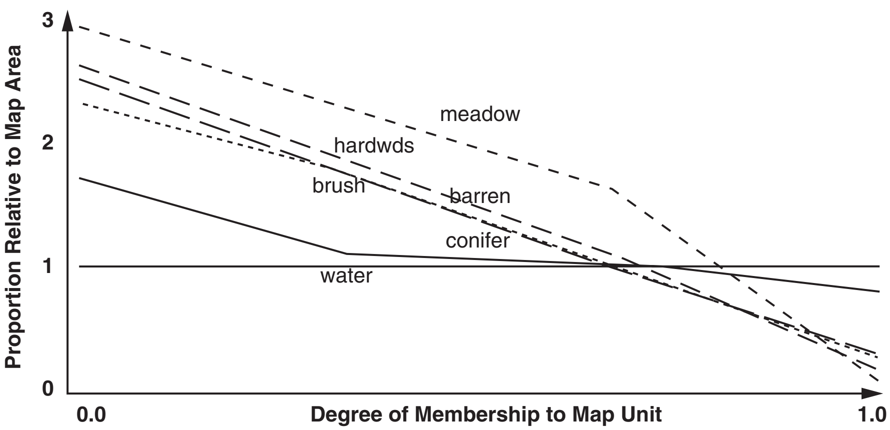

Fig. 7 Showing the relationship of fuzzy membership for six map units of the Plumas National Forest to the area estimated for each unit. Modified from Woodcock and Gopal (2000)

most of the six map units in the project represent an increasing amount of area with reduced level of membership. Approximately 49% of the analysis area is represented by degrees of membership less than full membership, so that about half the map surface occurs as fuzzy sets.

The Woodcock and Gopal (2000) study illustrates an area estimation approach based on fuzzy sets that quantifies the amount of area for each map theme by degrees of membership. This type of area estimation provides important details to end users and those developing map unit descriptions. Such an approach allows for a considerable range of analyses and queries within a GIS, and may be vital for accurate change detection and monitoring (Álvarez-Martínez et al. 2010).

Another study by Gopal and Woodcock (1994) provides an example of the use of fuzzy methods to assess thematic uncertainty for purposes of accuracy assessment. The study demonstrates a means of fuzzy accuracy assessment for crisp image classification outputs of map categories that reveals additional information about error structure, including the four dimensions of error given by the authors—the map categories in error, frequency (rate of error), magnitude (degree of confusion), and error source. As before, their approach provides a solution commensurate with inherently fuzzy ecological features and allows for variable membership by accuracy samples to each map category. They point to three main issues of conventional accuracy assessment:

- The premise of crisp assessments is that each object is unambiguously assigned to one map category.
- Accuracy results regarding the magnitude of error can only be inferred by the pattern of confusion between observations and predictions among map categories.
- The nature of accuracy results limits the ability of producers to interpret and respond to error, and limits the user's ability to effectively apply map data.

In response to these issues, Gopal and Woodcock (1994) decompose the basic question "how accurate is the map?" into two more exacting inquiries: "How frequently is the mapped category the best choice for the site?" "How frequently is the mapped category acceptable?" As mentioned, thematic accuracy assessment is most often facilitated with an error matrix or confusion matrix (Card 1982; Congalton and Green 1999), if map accuracy is evaluated at all. Accuracy results by this approach may only be derived for outputs of crisp classifiers and do not provide information on the true proximity of any map categories let alone the assigned category. The lack of such information impedes the examination of the characteristics and sources of map error. As important, the lack of interpretation also limits awareness of the error structure by end users, and precludes their ability to construct other outputs from the map data representing a posteriori mixed categories.

Accordingly, Gopal and Woodcock (1994) generated a scale, from 1 to 5, to rate the level of agreement in conditions at each accuracy sample site to each map unit concept, where 1 is "absolutely wrong" and 5 is "absolutely right." This expert assessment resulted in a set of membership values for each accuracy sample site that represented every map category, while the mapped value remained unknown.

Table 1 summarizes the accuracy assessment that they generated from a hypothetical image classification with four crisp map categories, A, B, C, and D. The image classification was intersected by 40 accuracy samples that had each been rated on the scale of agreement between 1 and 5 for every map category.

For accuracy assessment, there is more value in knowing both crisp and fuzzy agreement than in knowing either one alone. Case in point, at only 40% agreement the crisp assessment of category C shows this map unit to be a considerable issue in terms of accuracy of the image classification (Table 1). But by considering the amount of agreement occurring at an acceptable level, the fuzzy assessment indicates more promising results at 80% agreement. In fact, at the acceptable level of accuracy category C shows greater agreement than category B (60%) even though more samples in B are in agreement at the level of being "absolutely right."

To compute the magnitude of error, shown in the final column of Table 1, Gopal and Woodcock (1994) constructed a difference Table 2, by tabulating the magnitude of error within each map category. Error was calculated by comparing the fuzzy rating of each accuracy sample of each assessment site to the highest agreement level assigned to all other map categories, generating a simple and relative index of error severity. If the agreement level given to the map category was higher than the highest rating for all other labels, the resulting difference value was positive. A negative value resulted when the agreement level for the map category was lower than the highest level assigned for a differing map category. Difference values of −1 through 4 generally corresponded to the correct map labels. All difference values were averaged for each sample and map category, resulting in the values shown in the last column of Table 2.

Table 1 Accuracy assessment summary table adapted from Gopal and Woodcock (1994) showing agreement for both crisp (and absolutely right) and fuzzy (acceptable) assessments

Map category	Accuracy samples	Samples absolutely right (frequency)	Samples acceptable (frequency)
A	10	10 (100%)	10 (100%)
B	10	6 (60%)	6 (60%)
C	10	4 (40%)	8 (80%)
D	10	6 (60%)	8 (80%)
	40	26 (65%)	32 (80%)

Table 2 Difference table adapted from Gopal and Woodcock (1994) used to detect the magnitude and source of error

		Mismatches				Matches					
Map category	Accuracy samples	−4	−3	−2	−1	0	1	2	3	4	Mean
A	10	0	0	0	0	0	1	0	1	8	3.60
B	10	1	1	0	2	2	1	0	2	1	0.20
C	10	0	0	2	4	0	2	1	1	0	−0.10
D	10	0	0	1	3	4	0	0	2	0	0.10

The resulting differences between fuzzy ratings and the associated map categories are summarized in the columns and then averaged

In terms of magnitude, Tables 1 and 2 show that map categories B and D have similar rates of error (60%) but vary substantially in the magnitude of error. Category D has a greater number of 0 differences as a general indication that the magnitude of error for B exceeds that of D. The last column of Table 2 has the arithmetic mean of all difference values for each map category, so that the categories with the least magnitude of error would have the highest corresponding mean. For example, the mean once again shows greater magnitude of error in D than in B. The most accurate class, A, also has the least magnitude of error, with a mean difference of 3.60. The least accurate category, C, also shows the highest severity of error. Being able to convey the magnitude or seriousness of error is one of the main advantages of a fuzzy accuracy assessment.

Finally, the sources of error can also be explored using fuzzy accuracy assessment techniques given by Gopal and Woodcock (1994). The frequency of matches and mismatches given in a difference table can give clues about ecological complexity and error sources for map producers. In general, if there are greater numbers of mismatches in the single membership sites, then mapping issues may be concentrated in unambiguous locations (e.g., pure ponderosa pine stands of uniform structure). Conversely, if the mismatches are concentrated in the multiple membership sites, resources to improve map performance are better concentrated in areas of environmental heterogeneity. For instance in Table 2, notice that the frequency of multiple memberships is not the same for all categories, and that the proportion of matches for single membership sites, as in category A, is greater than in multiple membership sites (e.g., category B), contrary to a pattern expected by random effects. If the accuracy samples revealed single membership patterns across map categories, suggesting minimal ambiguity, there would be no need for a fuzzy accuracy assessment. Conversely, the number of accuracy samples representing multiple membership provides an indication of the extent of fuzzy sets on the landscape. The error structure expressed in a difference table can indicate the sources of map error among categories to map producers (Sarmento et al. 2010, 2013).

The studies cited in this section suggest several advantages of fuzzy techniques over more conventional crisp methods in assessing thematic uncertainty. Not only is it more problematic to explore and determine error patterns with crisp methods (Wang 1990), but fuzzy techniques also set the stage for a more functional integration of remote-sensed imagery with other ancillary census data. Techniques reflected in the Gopal and Woodcock (1994) study have since been applied over broad extents in the USA (Brewer et al. 2006). Though the Gopal and Woodcock approach is ideal for illustration, more sophisticated means of fuzzy assessment of both fuzzy and crisp outputs have since been created and applied (Zhang and Foody 1998).

Spatial Uncertainty

As with solutions for thematic uncertainty, fuzzy approaches can assist in the formation of map units, map development, and assessment of uncertainty of map products. Though fuzzy sets often represent an intertwining of thematic and spatial uncertainty (Aspinall and Pearson 1995), the two dimensions are first treated separately in this chapter for a clearer explanation of some of the concepts important within each dimension.

Conceptually, mapping that is produced by crisp classifiers could account for gradual boundaries and ambiguity among map themes if the grain of the objects, or pixels, is fine enough. That is, individual pixels can locally express the transitional nature of ecological features if class gradations are captured in the legend, and barring the commensurate spatial resolution of the imagery and effectiveness of the classifiers. In reality, mappers are often faced with relatively coarse imagery and census data, training data which are essentially crisp, and classifiers that may be limited in their ability to accurately portray fine gradation. The spatial uncertainty of mapping, in both developing and assessing the vagueness of boundaries, has been accommodated through other means, with some examples to follow.

Again from the perspective of thematic uncertainty, accuracy assessment is most often expressed in an error matrix without regard for spatial accuracy, where calculations for producer and user accuracies are generated on opposing axes based on a set of independent accuracy samples and the difference between predicted and observed outputs. By this conventional approach, overall accuracy, area-weighted user accuracy, and kappa statistic are often the measures of most interest (Rosenfield and Fitzpatrick-Lins 1986; Congalton 1991; Janssen and van der Wel 1994). The spatial uncertainty of boundaries between objects has been evaluated for positional error using different methods such as the epsilon band (Perkal 1956; Chrisman 1989), likely the most used error model for map delineations themselves (Leung and Yan 1998). The epsilon band allows for the characterization of spatial uncertainty and is most often directed at crisp map products. For purposes here, spatial uncertainty refers to the fuzziness and breadth of boundary conditions, and not to boundary location error for which the epsilon band is often applied (Shortridge and Shi 2012).

In its simplest form, the epsilon band produces a rectangular distribution of width 2ε imposed on a mapped line to indicate an area of uncertainty, manifested in vagueness of the map data and controlled by specifications of the program or project. The epsilon band was originally devised by Perkal as deterministic models represented in parallel-sided polygons such as running the length of map boundaries. The epsilon band has since been superseded by probabilistic data models (Leung and Yan 1998; Kronenfeld 2011), with the most recent adaptations of the model taking on irregular shape complexities to more realistically depict the uncertainty of horizontal transition zones between opposing map themes otherwise assumed as mutually exclusive (Fig. 8).

Whether deterministic or probabilistic, uncertainty banding offers a means of objectively characterizing ambiguity in boundaries among map categories. Advanced shape analysis tools, such as *ShrinkShape2* (Remmel 2015), further give users the means to quantify boundary complexity. This tool creates internal polygon buffers iteratively, generating summary metrics with each shrinking iteration for the characterization of spatial structure and complexity. Such methods can in turn be used to refine classifier outputs by the way map features are depicted in a product.

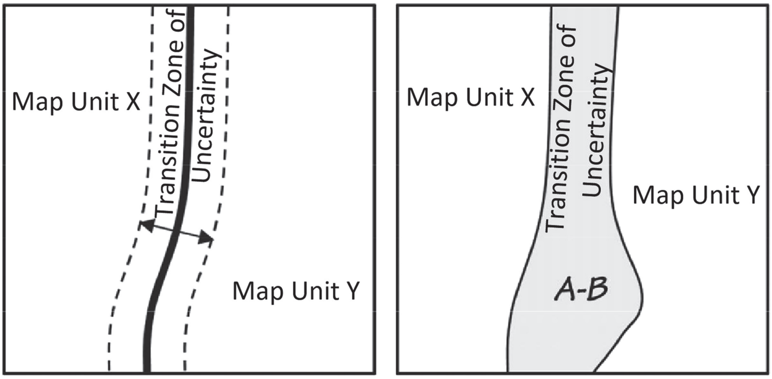

Fig. 8 Spatial uncertainty at the boundary of two opposing map themes, *X* and *Y*, represented by a deterministic epsilon band of standard width (*left*), and a probabilistic model of variable width (*right*). Modified from Kronenfeld (2011)

Crisp maps can be rendered fuzzy in part by redrawing delineations or using symbology to infer the fuzziness of boundaries according to distance-based functions (Lowell 1994).

Remmel (2009) introduced another means for assessing spatial uncertainty by applying coincidence matrices for separate map products of the same area. Coincidence matrices are often used for assessing map accuracy based on a set of observations, but can also be used in the comparison of different map products. In this way, Remmel applies the matrices to assess thematic uncertainty, and to assess spatial uncertainty by the geographic configuration of map features. Essentially the method uses the coincidence matrix as an expression of spatial complexity by applying two or more map products and representing the potential complexity by an accounting of the number of possible configurations in the matrix. A fixed amount of agreement can be reflected in multiple spatial configurations for the same set of map objects. The process results in a quantification of uncertainty that can be applied at local or full extents to determine both spatial and thematic uncertainty.

Simultaneous Consideration of Thematic and Spatial Uncertainty

As mentioned the nature of thematic and spatial uncertainties can be intertwined (Aspinall and Pearson 1995) though most published works have treated the two entities separately. What follows is a brief summary of a study by Zhang and Stuart (2001) that demonstrates a means of concurrent assessment for thematic and spatial uncertainty, and how that uncertainty is characterized while producing spatial outputs that optimally balance uncertainty with utility. In this study, the authors developed a geodatabase of suburban land cover classes. They created a technique for capturing the uncertainty of those map units using aerial photo interpretation and image classification procedures that produced a series of fuzzy surfaces for each map category, rather than establishing the fuzziness of individual sample points and then assessing the map product as in the case of Woodcock and Gopal (2000). These surfaces allow the user to quantitatively and graphically determine the underlying patterns of thematic and spatial uncertainty before assigning map categories to each object.

Zhang and Stuart (2001) began by summarizing the means of image classification that results in a set of fuzzy surfaces that each represents a map category. That is, each surface is developed by classifier methods that result in membership values for each category and image object. Fuzzy surfaces can be derived through any number of classifiers including manual rule building within eCognition (Definiens 2003), distance measures for spectral channels or other census data (Knick and Rotenberry 1998), from the Random Forest algorithm (Bonissone et al. 2008), or other classifier conventions. To be sure, both classic and fuzzy classifiers can result in fuzzy outputs, and the intention of this chapter is to highlight some advantages of both fuzzy classifiers and fuzzy map renderings. By the approach that Zhang and Stuart propose, it is necessary to use a classifier approach that produces membership values for every pixel or object, produced in surfaces of all potential land cover categories through the classification of spectral and other census data.

As a basis of the method proposed by Zhang and Stuart (2001), the most obvious land cover assignment within uniform extents of a landscape has more certainty than the most obvious assignment in transition zones, where vegetation conditions are heterogeneous and there is greater parity among potential categories. Their approach bears on the capacity to make fuzzy determinations in the development of training data that are very certain, a requirement that is operationally demanding but supports the creation of multiple fuzzy surfaces based on fixed points of knowledge. From there, a spatial technique of interpolation such as kriging (Krige 1951; Cressie 1990) is applied to generate membership values across unsampled zones of greater uncertainty, anchored by sampled areas of relative certainty. With this type of intermediate product, categorical maps can then be produced to the satisfaction of end users. For any given object, this process of post-classification typically represents a maxima among fuzzy membership values (Leekwijck and Kerre 1999; Islam and Metternicht 2005) from the underlying fuzzy surfaces to arrive at one land cover category—that is, a defuzzification resulting in one crisp value. Object attribution includes fuzzy membership values from all category surfaces, which can help to form various error models, not the least of which is the previously summarized epsilon band. Again, spatial uncertainty can be an expression of positional error as with orthorectification, but as mentioned the related focus of this chapter in on the uncertainty of classification.

In their approach to defuzzification, Zhang and Stuart (2001) demonstrate a thresholding technique that allows for the analysis of transitional zones among land cover types. Rather than simply classifying each object according to the maximum membership value among category surfaces, the application of thresholds provides a means of identifying areas of high thematic certainty to nominal map categories

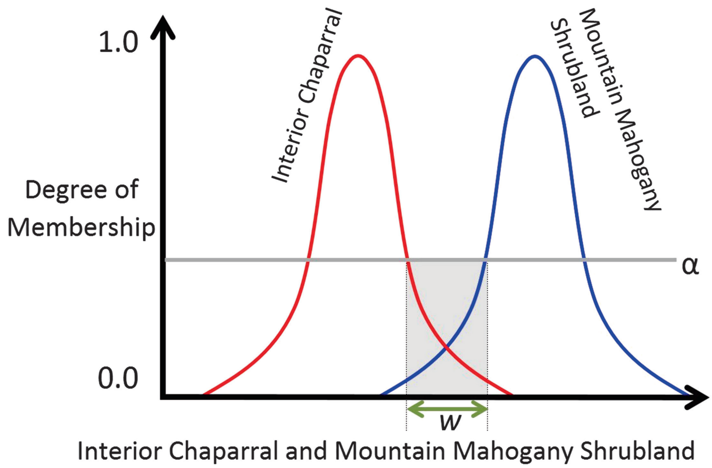

Fig. 9 Fuzzy operators showing the hypothetical relationship between two neighboring shrubland units. Here, a threshold value of α has been added to Fig. 4 to discern extents of high and low uncertainty, with a resulting unclassified region of width "w"

while simultaneously characterizing uncertainty spatially according to tolerance thresholds of the producer (Islam and Metternicht 2005). In converting raw classifier outputs to crisp map products, thresholding is achieved when all extents that meet the value of the threshold, α, are included within the given map categories. Given the capacity for quantitative analysis and solutions, this type of processing is compatible with the complex and nonuniform ecological patterns that make up fuzzy sets and that would otherwise require subjective responses or indifference. Extents that do not meet classification thresholds can simply be coded as highly uncertain. Figure 9 represents two contiguous shrubland units and the application of an uncertainty threshold. The region of uncertainty that exists between the two categories is shown by the width *w* in the figure and may be labeled as unclassified, or as a possible third mixed category not apparent in the initial map legend (Zhang and Foody 1998). To sum up, a thresholding technique can lead to zones of uncertainty that may either be represented thematically, by a legitimate mixed map unit (e.g., "Mixed Interior Chaparral-Mountain Mahogany Shrubland"), or spatially by an epsilon band of fixed uncertainty.

Zones of high uncertainty between map categories that are identified by thresholding can form the basis of epsilon models and offer a means to generate widths as a quantitative and geometric approach to characterizing error (Fig. 8) and refining crisp map units. By varying the uncertainty threshold, α, the epsilon band can be widened or narrowed to generate a range of epsilon models according to expectations of producers or clients. This approach may be particularly useful for assessing habitat quality including those species with affinities towards ecotones (Lloyd et al. 2012). In a sense the epsilon width can be varied continuously to reflect the relative certainty of all competing categories. In their study of suburban land cover mapping, Zhang and Stuart (2001) determined that epsilon band widths corresponded to standard deviation values and resulted in sizable spatial variation as uncertainty thresholds were altered. The degree to which epsilon bands varied locally according to threshold values suggests that deterministic epsilon models, of constant width, may be less suited to spatially depict land cover patterns. The reader is again referred to Fig. 8 for a visual comparison of deterministic and probabilistic epsilon bands. Using classifiers that result in multiple fuzzy surfaces allows mappers the ability to build probabilistic epsilon models, and to characterize uncertainty and leverage the knowledge in many constructive ways.

Multiple Outputs: Fuzzy Geodatabase

As examined in Chapter "Fuzzy Classification of Vegetation for Ecosystem Mapping," the variability in fuzzy membership for a given pixel or image object suggests that fuzzy approaches lend themselves to a range of mapping and analysis applications for natural features. Membership values can be used to inform the development of more precise map themes, or conversely to suggest more general themes of higher accuracy. As previously discussed the development of geodatasets that are comprised of fuzzy membership surfaces for each map unit offers the greatest flexibility in balancing map accuracy and precision for any given application, and for analyzing thematic and spatial uncertainty in the data.

Fuzzy surfaces can be constructed from satellite imagery, aerial photography, or other census data alone or in combination, using automated classifiers or manual interpretation to generate outputs that represent the ecological features of interest. The classification of map objects or pixels from the geodataset is usually a matter of assigning map units according to the surface of maximal membership value (Leekwijck and Kerre 1999; Islam and Metternicht 2005), so that each object is attributed by both the most likely category resulting in a conventional crisp map rendering. The thresholding technique described previously allows for outputs to be controlled by uncertainty criteria, with the possibility of disqualified extents that are significantly uncertain, or that comprise candidates for additional "mixed" feature classes.

Such a geodataset also permits a data-driven approach to describing uncertainty and estimating error. The overall effect is to allow substantial flexibility in generating multiple outputs from one spatial dataset, laying the groundwork to empower end users to generate map themes on their own terms in a GIS that are specific to a given purpose. The user is able to co-analyze uncertainty for an optimization of particular outputs along with a comprehensive characterization of uncertainty. In this way, the end user can develop rules and thresholds to produce tailored outputs for particular spatial applications and in response to their own uncertainty criteria. In his project on urban mapping, Hansen (2003) provides a helpful example of a fuzzy geodatabase using the case of urban land-use mapping in Denmark (Fig. 10). In this study, Hansen notes that fuzzy modeling offers a more useful product than a crisp map since it can simultaneously show the primary, secondary, etc. land use

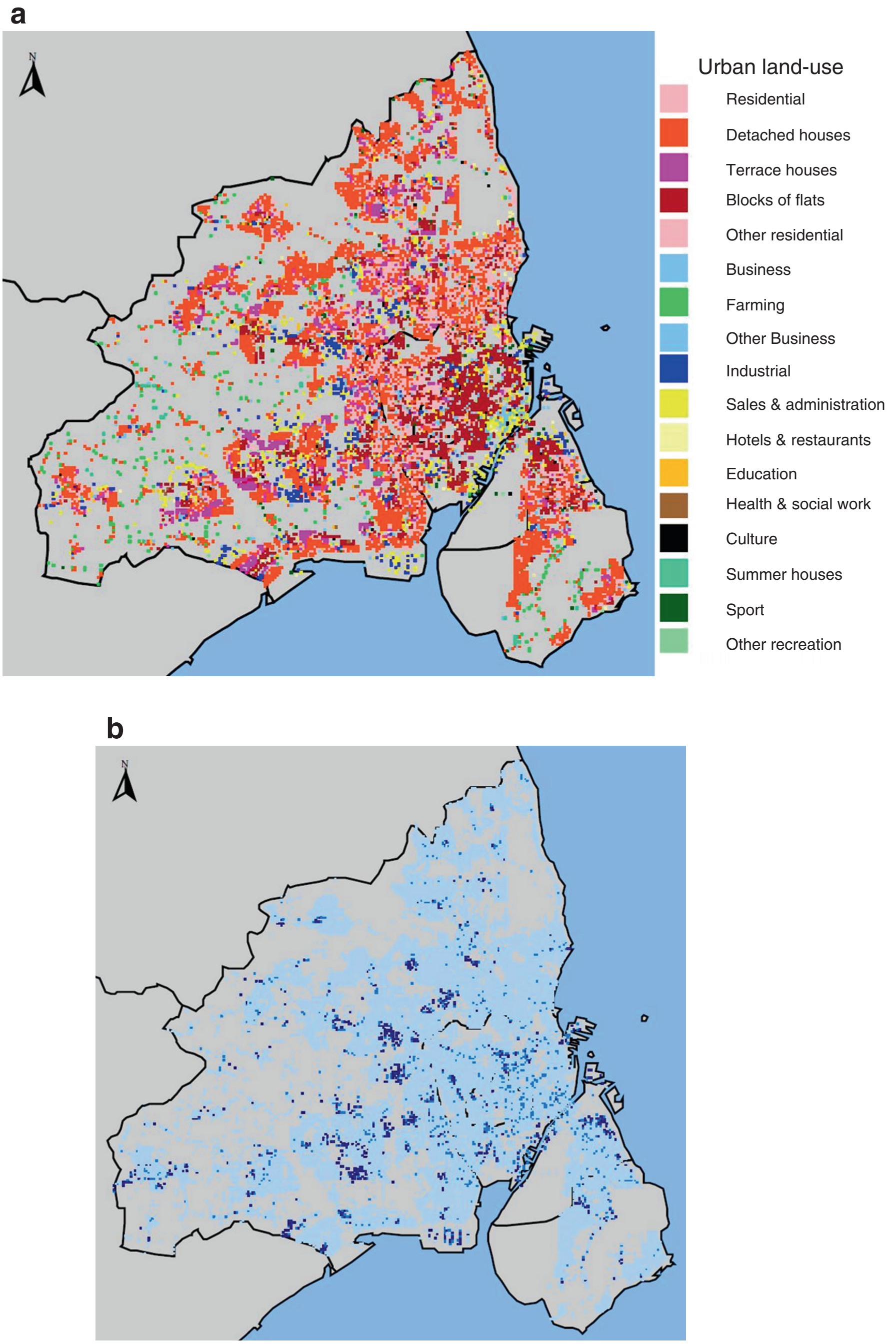

Fig. 10 Urban land use for Copenhagen, Denmark, including crisp (**a**) and fuzzy (**b**) maps. The fuzzy map is of one class, “Industrial,” showing increasing levels of membership with darker shades of blue. Modified from Hansen (2003)

categories. At the top of Fig. 10, the map gives the dominant land use category for each 100 m pixel across greater Copenhagen. This crisp map was developed through defuzzification of other map unit values, assigning each pixel a map unit according to the map unit of highest membership for that pixel. As with the second map at the bottom of Fig. 10, individual fuzzy membership surfaces for each map category can be displayed separately. The second map has one theme, “Industrial,” and shows that surfaces of continuous values for one theme reveal much more information about that theme than can be offered in the corresponding crisp output. In a variation on this approach, geodatasets comprised of the most basic themes, such as “Impervious Surface” or “Vegetation Life Form,” can be used as primitives from which to combine and produce any number of map typologies as part of a “legend-less” mapping system (ADPC 2016), giving end users substantially more ability to determine and customize viewing and analysis.

It also bears mentioning that many legacy raster map, generated through conventional image classification, can be augmented by combining the data with image segments using zonal processing techniques. In this way, multiple outputs can be generated from many existing ecological map datasets, not only by subjecting raster inputs to different rules and thus generating different outputs, but also by linking rule sets across more than one dataset or feature class to create polythematic outputs such as state-class units representing combinations of dominance, canopy cover, and size class (Westoby et al. 1989; Steele 2000). Though legacy raster mapping usually lacks fuzzy membership attribution, the pixels that fall within a given image object can be weighed collectively using crisp or fuzzy rules to classify the objects. The technique assumes that the imposing objects have ecological features that are relatively uniform, spatially and thematically, so that pixels are grouped in a meaningful way (USDA Forest Service 2012). Depending on the rule set, this post-processing method can be used to improve data accuracy beyond the underlying raster data by using majority, average, or other statistics that effectively combine pixel values within an object to reduce noise and improve accuracy with the exchange of thematic or spatial precision of the raster data. Alternatively, the approach can be used to derive additional map themes: the following section details a hypothetical example where fuzzy rules are used to develop an additional map theme from legacy raster data.

Vertical Structure Mapping

Until now, the chapter has focused on fuzzy applications within two horizontal dimensions, thematic and spatial, where membership is determined by the degree of alignment of an object to multiple map themes of an area, or geometrically according to the horizontal irregularities or gradation of boundary zones between map themes (Remmel and Perera 2009). This section focuses on another dimension based on vertical vegetation structure, where membership is determined for canopy layering, tree height stratification, or other local habitat attributes of canopy architecture. In this dimension, the membership of an object bears on its affinity to one or more vertical features, such as canopy layering or "storiedness," as in the example to come. The affordability of producing digital surface models (DSMs) from stereo imagery or from LiDAR data to detect vertical features, and the demand for information on vegetation structure, will only improve the technology and availability of these data sources with time. Hirschmuller (2005) and others have developed semi-global matching, or "phodar," and other technologies to efficiently build digital surface models (DSMs) from high-resolution stereo imagery (Gehrke et al. 2010; Clark et al. 2016), thereby allowing for image classification of vegetation composition and dense terrain extraction for vegetation structure from the same data. Chapter "Mapping the Abstractions of Forest Landscape Patterns" provides further details of LiDAR for forest mapping.

What follows is a synopsis on how outputs for vertical diversity were rendered from raster map data of tree size class, leveraging size-height relationships in combination with the heterogeneity among contiguous pixels representing the same forested stand (Helms 1998) (Fig. 11). In this example, the pixels retained their original classification for tree diameter size class from a previous mapping effort (USDA Forest Service 2014) and were expressed in different vector outputs for vertical diversity, according to the relationships of neighboring pixels and the local inferences of tree diameter on vertical diversity. As is often the case, size class data, from forest inventory or map models, are more affordable and available than tree age data that are derived from tree coring and intensive field sampling (e.g., Triepke et al. 2012). Tree size is often used as a surrogate for tree age for locally characterizing cohort patterns

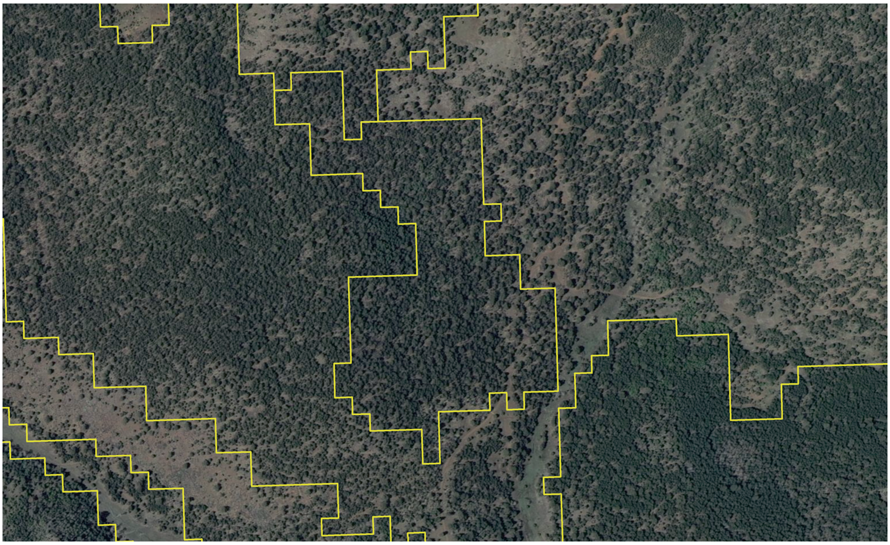

Fig. 11 Polygon configuration generated from segmentation of Landsat ETM+ to represent existing vegetation and forested areas of similar tree composition and structure. Excerpt of 2011 aerial photography taken of the National Agriculture Imagery Program (NAIP 2014), for the northern San Mateo Mountains of New Mexico, USA

(Curtis 1967; Huang et al. 1992; Schmidt et al. 2011), as with silvicultural applications that require the assessment and management of tree age diversity (Triepke et al. 2011). Where the relationships between size and age are marginal at broad scales, the relationship is strengthened at more local scales (Ferguson and Carlson 2010).

Fuzzy math lends itself to analyzing the vertical complexity or "storiedness" of forest communities where vertical structure can be difficult to characterize objectively. As a first step in mapping vertical diversity of forested systems in Arizona and New Mexico, a segmentation layer was generated from Landsat 7 ETM+ imagery to depict existing (actual) vegetation at the spatial scale of plant communities or stands (USDA Forest Service 2012). In this way, communities of similar tree dominance, size, canopy cover, and vertical diversity were delimited to the form of a polygon configuration of plant communities with similar vegetation pattern (Fig. 11).

With a polygon configuration of plant communities across Arizona and New Mexico in place, zonal processing techniques were used to vectorize raster mapping of existing vegetation and diameter class from the Integrated Landscape Assessment Project (ILAP) (USDA Forest Service 2014). Polygons averaged from 10 to 20 ha. In the zonal processing of raster data, various rule sets were applied to collectively assess the pixel values within each polygon using ILAP themes of tree size, canopy cover, and dominance to produce a range of feature class outputs for vegetation composition and structure. Rules were also generated for storiedness mapping, utilizing the inference of tree diameter on tree height, and then assessing the pattern of height conditions among contiguous pixels of the same image segment (Fig. 12).

The rule set used in this case relates the variability and abundance of tree size classes, number of canopy layers, and fuzzy membership to the storiedness theme (USDA Forest Service 2012). Similar to the canopy cover class scenario illustrated in Fig. 5, fuzzy membership was expressed in categories, either 0.2 (one story), 0.4 (two story), or 0.6 (three-plus story). In this case, forested image segments with a membership of 1 would represent layering maxima for a storiedness theme. The perspective of fuzzy logic assumes that a given object can have membership to more than one class of storiedness, which is fitting given the considerable structural variability of natural communities and the complexity in conceptualizing, interpreting, and conveying structure conditions meaningfully to biologists and land managers. Accordingly, storiedness rules have been written to accommodate different end-user needs and to produce different spatial and tabular outputs from the same input data, as in the case of tree canopy layering (Vandendriesche 2011). Canopy layering is but one possible variable of the third dimension of vertical structure (Fig. 13). Other structural variables, such as above-ground biomass, canopy base height, canopy texture, and stream embeddedness, likewise lend themselves to fuzzy classification algorithms for the interpretation of map data and vertical features. Also, vertical information can be stored in image stacks where each layer, either a crisp or fuzzy surface, represents an upward sequence of height classes that collectively reflect the vertical profile at any given point.

Fuzzy membership values and rules can simplify the integration of vertical and horizontal features and represent map objects with multiple attributes simultaneously. Membership thresholds among fuzzy surfaces can be used in image classifi-

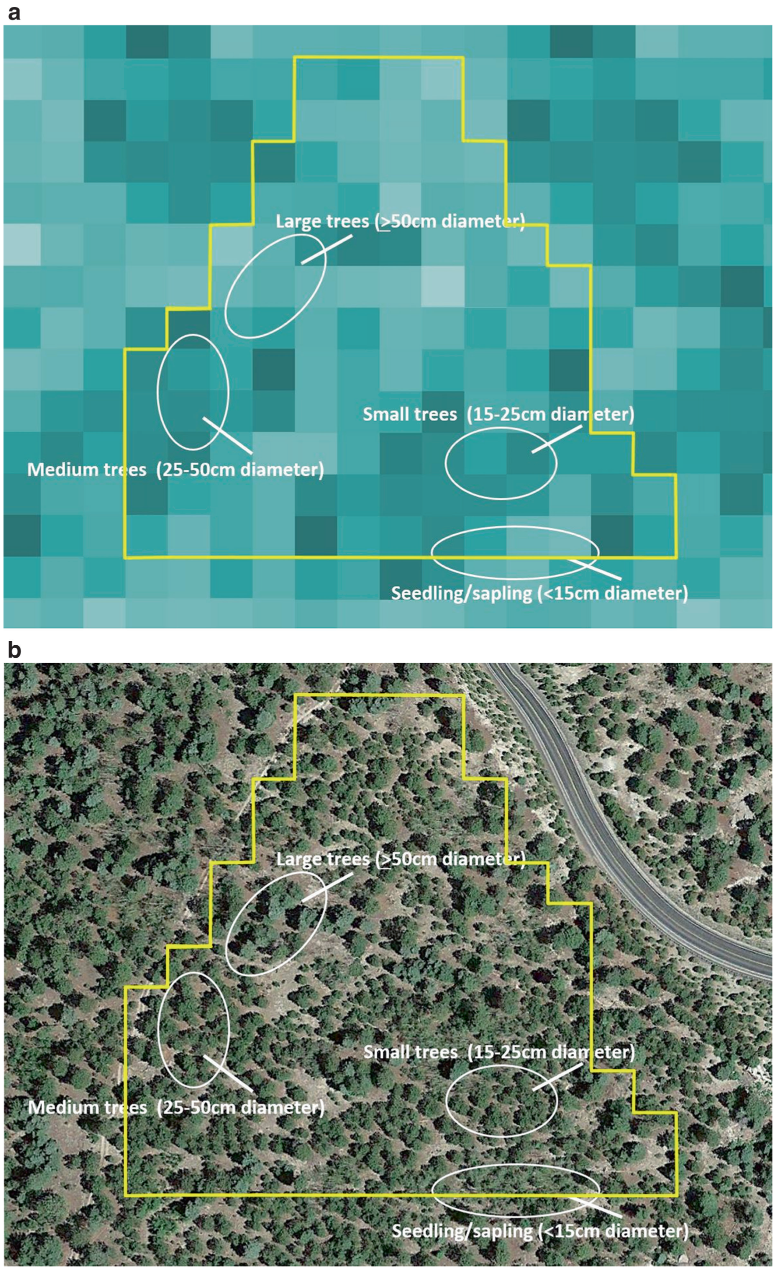

Fig. 12 Image segment derived from Landsat ETM+ showing multi-storied forest conditions in a ponderosa pine ecosystem of the Jemez Mountains of northwestern New Mexico, USA (Google Earth 2014b). The first illustration (**a**) shows tree diameter class mapping from the Integrated Landscape Assessment Project (USDA Forest Service 2014), while the second illustration (**b**) shows a true color image (NAIP 2014) of the same area and image segment

Fig. 13 Pine flatwoods community in northern Florida, USA, showing longleaf pine (*Pinus palustris* Mill.) of similar height in a single-story forest structure (photo by Jack Triepke)

cation (see section "Fuzzy Representation with Continuous and Categorical Data") or to delineate areas of interest, like old growth forest, with rule sets that combine key surfaces. Having fuzzy membership values further allows users an easy means to apply compensatory factors, where appropriate, among the habitat variables at play (e.g., storiedness for tree cover). As with the scenario involving storiedness, fuzzy techniques give us many opportunities to integrate information sources and to make map data go further.

A Look to the Future

This closing section briefly explores some of the immediate opportunities for fuzzy applications. By the innate potential of fuzzy systems, not to mention the accessibility and rate of related technology evolution, many advances remain underexploited and some latent applications for fuzzy systems are considered here.

Current mapping applications that output fuzzy membership values, some covered in this chapter, allow for end-user computation according to specific needs. The generation of fuzzy surfaces, as with the study by Zhang and Stuart (2001), offers the most obvious example of spatial outputs that can be readily interpreted and post-processed into a tailored deliverable. In this case every object has a fuzzy membership value for every established map category. Although outputs are still constrained by the makeup of the original legend and the training data, the resulting fuzzy surface outputs offer what is otherwise a geodataset that is neutral of classification schemes and a priori stratifications. End users would, for example, be able to map a ponderosa pine cover type according to a given project design and specific class concepts of tree species proportions, and to assess thematic and spatial uncertainty according to the same fuzzy membership values. Having access to these values allows clients the power to post-process spatial information in GIS in response to specific uncertainty specifications. In the case of raster data, having an associated segmentation layer that depicts patterns of structure and composition at somewhat coarser scales (Figs. 11 and 12) would allows users yet another level of capacity in forming products by the rules used to classify parent segments by the makeup of resident pixels. Such an approach has also been used to generate a vertical dimension to mapping according to the relationship in structural attributes among pixels (USDA Forest Service 2012) (Fig. 12). Including fuzzy membership values in classifier outputs allows the generation of a range of map products from the same dataset within a common GIS platform according to the mapping and uncertainty analysis needs of natural resource managers and researchers.

Web-based interfaces are the obvious next step for user-derived map products, once spatial data are attributed with fuzzy membership values. While GIS environments offer an accessible means for organizations and specialists with software and training to manage and analyze spatial information, Web-based applications are the logical means of circulating spatial information and cultivating crowdsourcing and the development of post-products, analyses, and tools. OpenStreetMap (OSM 2014), Google Earth Plug-in (Earth 2014c), and other map viewers and data management applications employed by lay people offer potential outlets for sharing, viewing, and processing geodata that has been attributed with fuzzy, continuous, or categorical values (ADPC 2016). In this environment, end users can extract fuzzy data from Web resources, not only in terms of a specific extent, but also according to the precise characteristics of ecological features. While one user, for instance, interested is wildlife habitat is able to output a map of forest plant communities of 20–45% tree cover with at least three canopy layers, the next user can generate an output for communities with 10–30% tree cover and four canopy layers from the same dataset without constraints of predetermined map categories (e.g., Zabihi et al. 2017). And by combining multiple datasets likewise attributed by fuzzy membership, the potential for developing wide-varying map themes becomes even less limited. Also, based on a range of potential outputs on available map themes, users will be able to game membership scenarios interactively on each of the themes to generate very precise outputs for a particular purpose. Finally, users will be able to build products that express the desired relationship of accuracy and precision, make adjustments to membership thresholds to satisfy uncertainty requirements, and characterize uncertainty similarly as spatial analysts in a GIS lab.

The adoption and evolution of advanced classifier methods also hold promise for map development and spatial analysis. In addition to the classifier technology surveyed in section "Mapping with Fuzzy Classifiers," other image classification methods that build on machine learning include neuro-fuzzy classifiers (Sun and Jang 1993; Nauck et al. 1997; Nauck and Kruse 1997). Neural networks, inspired by the nervous systems of animals, offer supervised learning ability to generate classification algorithms based on potentially large numbers of inputs (Aitkenhead and Dyer 2007). Neuro-fuzzy classifiers, that combine neural networks with fuzzy systems, have been applied in various fields for over a decade and have been used to map ecological features. Neuro-fuzzy systems combine the learning power of neural networks with the knowledge represented in fuzzy inferences, integrating key advantages of neural networks and fuzzy systems (Hosseini and Zekri 2012). Despite their obvious strengths, neuro-fuzzy classifiers have yet to realize their potential for purposes of mapping in natural resources.

Some discussion is warranted regarding the use of fuzzy random forest as a classifier approach for making maps. Although fuzzy random forest classifiers (Bonissone et al. 2008) have been used in other scientific fields (Bonissone et al. 2010; Kulkarni and Sinha 2013; Lasota et al. 2013) it is as yet conventional for land cover mapping. The classification trees in conventional random forest classifiers are unpruned trees in that each terminal node is represented by one observation, leading to a crisp ruleset within each tree—i.e., one answer only. Yet, the amalgamation of outputs for multiple crisp trees results in information that is inherently fuzzy because of the disagreement among votes (Grossmann et al. 2010). In their 2010 study, Bonissone and others (Bonissone et al. 2010) combined random forest classifiers made up of fuzzy decision trees to build classification outputs for various types of data. Their work included image segmentation, but not specifically ecological feature extraction. In short, the approach combines the flexibility found with fuzzy systems with the efficiency and interpretability of decision tree classifiers, with the robustness provided in a multiple-classifier approach, and the ability of randomness to build tree diversity and the most plausible range of outputs. The advantages of decision tree methods, fuzzy classifiers, and random forest were summarized in section "Mapping with Fuzzy Classifiers." Prior to the application of random forest (Breiman 2001), fuzzy systems had been combined with decision trees for classifier applications (Lee et al. 1999; Mendonça et al. 2007). Given the innate elasticity of fuzzy logic, the fuzzy component has the key advantage of bringing stability to noise, gaps, and incongruences in input data (Bonissone et al. 2008). It was with this premise that Bonissone and others generated a fuzzy random forest as a base classifier (Bonissone et al. 2010). Several classifier methods were compared, all based on the "majority vote" for random forest ensembles, and including an algorithm using fuzzy membership values to weight decisions among classification trees. In the latter case, the underlying premise was that since classifiers of the ensemble are not of identical accuracy, the more capable classifiers would be weighted to reflect a greater competency. They found that the classification approach using weighted functions provided better accuracy in comparison to the non-weighted method typical of random forest ensembles. Overall the study showed that the fuzzy random forest systems produced accuracy on par with the best classifiers when applied to the range of conventional datasets in the test. But unlike the non-fuzzy approaches, the fuzzy random forest classifiers had consistent accuracy results when faced with datasets of noisy and missing values. Fuzzy random forest classifiers will likely continue to improve technologically and see growing application for mapping purposes in natural resources.

Fuzzy classifiers, online tools, and other technologies are advancing existing applications and creating new possibilities. Online tools that are accessible to the masses are the future in the way that open-source technology, citizen science, and big data are used to support shared environmental goals and concerns. Climate change, loss of habitat and biotic diversity, and other global issues are propelling both research and development and the widespread application of remote sensing technologies that were until understood and used by a relative few until recently. While fuzzy methods offer solutions to the ambiguities of natural landscapes, they are likewise suited to future problems, temporal analysis, and “what-if” scenarios involving drought, fire, sea-level rise, temperature and precipitation regimes, and other factors that, when considered as fuzzy parameters, can lead to output ranges that may be correlated with measures of prediction, uncertainty, and opportunity. Recent Web-based tools such as Collect Earth (FAO 2016) give users with minimal experience simple means to quickly generate reference data for land cover mapping as well as for monitoring and capturing conditions at multiple points in time with readily available archived imagery. Collect Earth is a free open-source solution that integrates with Google Earth, Google Earth Engine, and other Web-based tools to gather, analyze, and display geographic information and ecological features. These tools can be easily structured to capture current land cover and land-use attributes as well as change mechanisms depicted or inferred by multiple archived satellite scenes. Such technology enables fuzzy membership to be represented simultaneously across map themes, spatial scales, and temporal scales, giving fuzzy methods a growing role in addressing environmental challenges into the future.

Summary

Widespread concerns about biodiversity and ecosystem integrity worldwide have spurred natural resource monitoring (Miura et al. 2008) and development of analysis tools to assess current conditions and risk (Suter 2006). Emphasis on ecological restoration, climate change, and other important aspects of conservation has driven the gathering of observational data, analysis and interpretation, and development of technology such as advanced land cover mapping applications (Lillesand and Kiefer 2000; Kulkarni and Sinha 2013; Li et al. 2014). Map data generated to depict various ecological features are being used increasingly for purposes of research, analyzing ecosystems, land management, and planning (Goetz and Maus 2006; Friggens et al. 2013; USDA Forest Service 2014; Triepke 2016). Ecological mapping can be developed through image classification or from mining of existing map sources as with the approach described in section "Multiple Outputs: Fuzzy Geodatabase." Fuzzy approaches have given map producers advanced solutions for not only generating map outputs but also characterizing them through the analysis of uncertainty (Lowell 1994; Sarmento et al. 2010; Kronenfeld 2011).

Conventional mapping and uncertainty analysis has relied on crisp approaches, based on mutually exclusive hard ecological categories among the objects or pixels of a given extent. As described, these objects may reflect multiple categories (Wood and Foody 1993) as in the case of tree size (Fig. 2), or may reflect unrecognized categories of a more general nature as in mixed types (Fig. 9). Fuzziness can be expressed in mixed pixels, where the spatial resolution of the base models units is coarse relative to the resolution of ecological features being mapped (Foody 1997; Zhang and Foody 1998; Campbell 2002). Such objects may be an expression of a fuzzy set or simply be a mixture of map themes with hard boundaries at a local scale. In the latter situation, the pixel size is greater than the spatial extent of map themes so that multiple themes are expressed within the space of the same pixel. In either case, a crisp solution may be to create a mixed type in the map legend, provided that the type occurs often enough to warrant distinction. The problem may be remedied more efficiently and precisely with a fuzzy approach where partial membership is assigned to each theme present in the pixel.

In contrast to crisp approaches, and the constraints they impose on responding to ambiguity, fuzzy system classifications respond through assignment of varying levels of fuzzy membership (Zadeh 1965) for each object and apparent map category. That is, fuzzy systems represent gradual change from membership to non-membership among objects among multiple categories and dimensions. From the standpoint of logic, fuzziness is expressed in one of the two ways: first, ambiguity and the difficulty in classification may stem from the vagueness and authenticity among available categories (Rocchini and Ricotta 2007). Second, ambiguity may stem from the lack of distinctiveness in the object itself; or it may stem from both. The replacement of classical set theory with fuzzy set theory marks an advance in our ability to deal with ambiguity and to depict or analyze ecological features which are often inherently fuzzy (Rickel et al. 1998). In addition, fuzzy systems offer more wide-ranging and flexible solutions for representing geographic information.

As detailed in Chapter "Fuzzy Classification of Vegetation for Ecosystem Mapping," the flexibility of fuzzy approaches demands clear spatial and thematic specifications in the development of map products. Their development and application will only become more flexible in time, as specialists take advantage of the increasing availability of ecological mapping and the power of fuzzy operators in building and applying map data. Clear specifications and definitions are essential for consistency across themes in mapped data.

References

ADPC (2016) Regional land cover typology workshop report summary. Asian Disaster Preparedness Agency Resource report available www.adpc.net/igo/contents/Publications. Accessed May 2016

Aitkenhead M, Dyer R (2007) Improving land-cover classification using recognition threshold neural networks. Photogramm Eng Remote Sens 73:413–421

Álvarez-Martínez JM, Stoorvogel JJ, Suárez-Seoane S, Calabuig EL (2010) Uncertainty analysis as a tool for refining land dynamics modelling on changing landscapes: a case study in a Spanish Natural Park. Landsc Ecol 25:1385–1404. doi:10.1007/s10980-010-9492-z

Amit Y, Geman D (1997) Shape quantization and recognition with randomized trees. Neural Comput 9:1545–1588

Aspinall RJ, Pearson DM (1995) Describing and managing uncertainty of categorical maps in GIS. Innov GIS 2:71–83

Bailey RG (1988) Problems with using overlay mapping for planning and their implications for geographic information systems. Environ Manag 12:11–17

Barbour MG, Burk JH, Pitts WD, Gilliam FS, Schwartz MW (1998) Terrestrial plant ecology, 3rd edn. Benjamin Cummings, Menlo Park

Bonissone PP, Cadenas JM, Garrido MC, Dıaz-Valladares RA (2008) A fuzzy random forest: fundamentals for design and construction. In: Proceedings of the 12th international conference on information processing and management of uncertainty in knowledge-based systems (IPMU'08), Malaga, June 2008. pp 1231–1238

Bonissone P, Cadenas JM, Carmen Garrido M, Andrés Díaz-Valladares R (2010) A fuzzy random forest. Int J Approx Reason 51:729–747. doi:10.1016/j.ijar.2010.02.003

Breiman L (1996) Bagging predictors. Mach Learn 24:123–140

Breiman L (2001) Random forests. Mach Learn 45:5–32

Brewer CK (2007) Remote sensing applications to support sustainable natural resource management. Dissertation, University of Montana

Brewer C, Bush R, Berglund D et al (2006) Integrating vegetation classification, mapping, and strategic inventory for forest management. In: Aguirre-Bravo C, Pellicane PJ, Burns DP, Draggan S (eds) Monitoring science and technology symposium: unifying knowledge for sustainability in the Western Hemisphere, Denver, September 2004. USDA Forest Service proceedings RMRS-P-42CD. Rocky Mountain Research Station, Fort Collins

Brohman R, Bryant LD (eds) (2005) Existing vegetation classification and mapping technical guide: version 1.0. USDA Forest Service, Washington DC

Brown DE, Reichenbacher F, Franson SE (1998) A classification of north American biotic communities. University of Utah Press, Salt Lake City

Cai Z, Li Z, Kang Z, Liu Y (eds) (2009) Computational intelligence and intelligent systems: 4th international symposium on intelligence computation and applications (ISICA 2009), Huangshi, October 2009. Springer, New York

Campbell JB (2002) Introduction to remote sensing, 3rd edn. Guildford Press, New York

Card DH (1982) Using known map category marginal frequencies to improve estimates of thematic map accuracy. Photogramm Eng Remote Sens 48:431–439

Chrisman NR (1989) Modeling error in overlaid categorical maps. In: Goodchild MF, Gopal S (eds) Accuracy spatial databases. Taylor & Francis, London

Clark A, Stam C, Goetz W, Maus P, Megown KA, Triepke FJ, Matthews B, Muldavin E (2016) Mapping riparian vegetation on the Gila National Forest using photogrammetric techniques. USDA Forest Service technical report RSAC-10121-RPT1 available www.fs.fed.us/eng/rsac/documents/pdfs. Remote Sensing Applications Center, Salt Lake City

Comer PJ, Faber-Langendoen D, Evans R et al (2003) Ecological systems of the United States: a working classification of US terrestrial systems. NatureServe. Available www.natureserve.org/publications. Accessed Sept 2011

Congalton RG (1991) A review of assessing the accuracy of classifications of remotely sensed data. Remote Sens Environ 37:35–46
Congalton RG, Green K (1999) Assessing the accuracy of remotely sensed data: principles and practices. Lewis Publishers, Boca Raton
Costa H, Foody GM, Boyd DS (2017) Using mixed objects in the training of object-based image classifications. Remote Sens Environ 190:188–197
Cowling RM, Kerley GIH, van Cauter A (2005) The consequence of inaccuracies in remote-sensed vegetation boundaries for modelled mammal population estimates. South Afr J Wildl Res 35:1–7
Cox E (1992) The great myths of fuzzy logic. AI Expert 7:40–45
Cressie N (1990) The origins of kriging. Math Geol 22:239–252. doi:10.1007/BF00889887
Curtis RO (1967) Height-diameter and height-diameter-age equations for second-growth Douglas-fir. For Sci 13:365–375
Daubenmire R (1966) Vegetation: identification of typal communities. Science 151:291–298
Daubenmire R (1978) Plant geography with special reference to North America. Academic Press, New York
Definiens (2003) eCognition object-oriented image analysis – user guide, 3rd edn. Definiens Imaging, Munich
Dietterich TG (2000) An experimental comparison of three methods for constructing ensembles of decision trees: bagging, boosting, and randomization. Mach Learn 40:139–157
Google Earth (2014a) Grassland system east of Grants, New Mexico, USA. 34°59’18″ N and 107°08’47″ W. Accessed Aug 2014
Google Earth (2014b) Ponderosa pine forest system northwest of Jemez Springs, New Mexico, USA. 35°52’29″ N and 106°40’02″ W. Accessed Aug 2014
Google Earth (2014c) Google Earth Plug-In. In: Google Earth products. Available www.google.com/earth/explore/products. Accessed Nov 2014
FAO (2016) Food and Agriculture Organization of the United Nations, Open Foris tools for environmental monitoring. Available www.openforis.org. Accessed June 2016
Ferguson DE, Carlson CE (2010) Height-age relationships for regeneration-size trees in the northern Rocky Mountains, USA. Res Pap RMRS-RP-82WWW. USDA Forest Service Rocky Mountain Research Station, Fort Collins
Foody GM (1997) Fully fuzzy supervised classification of land cover from remotely sensed imagery with an artificial neural network. Neural Comput Appl 5:238–247. doi:10.1007/BF01424229
Friggens M, Bagne K, Finch D, Falk D, Triepke FJ, Lynch A (2013) Review and recommendations for climate change vulnerability assessment approaches with examples from the Southwest. USDA Forest Service Gen. Tech. Rep. RMRS-GTR-309. Rocky Mountain Research Station, Fort Collins
Gehrke S, Morin K, Downey M, Boehrer N et al (2010) Semi-global matching: an alternative to LiDAR for DSM generation. Int. Arch Phot & Rem Sens, Calgary 38:Part B1
Goetz W, Maus P (2006) LANDFIRE existing vegetation products – How useful for midlevel forest needs? USDA Forest Service, Remote Sensing Tips 0074-TIP1, available www.fs.fed.us/eng/rsac/documents/pdfs. Washington Office, Remote Sensing Applications Center, Salt Lake City
Goguen JA (1969) The logic of inexact concepts. Synthese 19:325–373. doi:10.1007/BF00485654
Gong P, Pu R, Chen J (1996) Elevation and forest-cover data using neural networks. Photogramm Eng Remote Sens 62:1249–1260
Gopal S, Woodcock C (1994) Theory and methods for accuracy assessment of thematic maps using fuzzy sets. Photogramm Eng Remote Sensing (United States) 60:181–188
Grossmann E, Ohmann J, Kagan J, May H, Gregory M (2010) Mapping ecological systems with a random forest model: tradeoffs between errors and bias. Gap Anal Bulletin 17:16–22
Hansen HS (2003) A fuzzy logic approach to urban land-use mapping. In: In: proceedings of the 9th Scandinavian research conference (ScanGIS) on geographical information science, June 2003. Espoo, Finland, pp 41–56
Helms JA (1998) The dictionary of forestry. Society of American Foresters, Bethesda

Hirschmuller H (2005) Accurate and efficient stereo processing by semi-global matching and mutual information. In: Proceedings of the 2004 IEEE Computer Society conference on computer vision and pattern recognition, San Diego, California, June 2005
Ho TK (1998) The random subspace method for constructing decision forests. IEEE Trans Pattern Anal Mach Intell 20:832–844
Hoppner F, Klawonn F, Kruse R, Runkler T (1999) Fuzzy cluster analysis: methods for classification, data analysis, and image recognition. John Wiley & Sons, New York
Hosseini MS, Zekri M (2012) Review of medical image classification using the adaptive neuro-fuzzy inference system. J Med Signals Sens 2:49–60
Huang S, Titus SJ, Wiens DP (1992) Comparison of nonlinear height-diameter functions for major Alberta tree species. Can J For Res 22:1297–1304
Ishibuchi H, Nakashima T (2001) Effect of rule weights in fuzzy rule-based classification systems. IEEE Trans Fuzzy Syst 9:506–515. doi:10.1109/91.940964
Islam Z, Metternicht G (2005) The performance of fuzzy operators on fuzzy classification of urban land covers. Photogramm Eng Remote Sens 71:59–68
Janssen LL, van der Wel FJ (1994) Accuracy assessment of satellite derived land-cover data: a review. Photogramm Eng Remote Sens 60:419–426
Jennings M, Loucks O, Peet R et al (2003) Guidelines for describing associations and alliances of the U.S. National Vegetation Classification, version 3.0. Ecological Society of America. Available http://www.vegbank.org/vegdocs/panel. Accessed Feb 2013
Jennings MD, Faber-Langendoen D, Loucks OL et al (2009) Standards for associations and alliances of the US National Vegetation Classification. Ecol Monogr 79:173–199
Klaua D (1966) Über einen zweiten Ansatz zur mehrwertigen Mengenlehre. Monatsber Dtsch Akad Wiss Berl 8:161–177
Knick ST, Rotenberry JT (1998) Limitations to mapping habitat use areas in changing landscapes using the Mahalanobis distance statistic. J Agric Biol Environ Stat 3:311–322. doi:10.2307/1400585
Kosco B (1995) Combining fuzzy systems. In: Fuzzy systems. Proceedings of the 1995 international joint conference of the fourth IEEE international conference on fuzzy systems and the second international fuzzy engineering symposium, Yokohama, Mar 1995, vol 4. IEEE, pp 1855–1863. doi: 10.1109/FUZZY.1995.409933
Krige D (1951) A statistical approach to some mine valuation and allied problems on the Witwatersrand. Dissertation, University of the Witwatersrand
Kronenfeld BJ (2011) Beyond the epsilon band: polygonal modeling of gradation/uncertainty in area-class maps. Int J Geogr Inf Sci 25:1749–1771. doi:10.1080/13658816.2010.518317
Kulkarni VY, Sinha PK (2013) Random forest classifiers: a survey and future research directions. Int J Adv Comput 36:1144–1153
Lasota T, Telec Z, Trawiński B, Trawiński G (2013) Investigation of random subspace and random forest regression models using data with injected noise. In: Graña M, Toro C, Howlett RJ, Jain LC (eds) Knowledge engineering, machine learning and lattice computing with applications. Springer, Berlin
Leavell DM (2000) Vegetation and process of the Kootenai National Forest. Dissertation, University of Montana
Lee KM, Lee KM, Lee JH, Lee-Kwang H (1999) A fuzzy decision tree induction method for fuzzy data. In: Fuzzy systems conference proceedings, Seoul, Aug 1999, vol 1. IEEE, pp 16–21. doi:10.1109/FUZZY.1999.793199
Leekwijck WV, Kerre EE (1999) Defuzzification: criteria and classification. Fuzzy Sets Syst 108:159–178. doi:10.1016/S0165-0114(97)00337-0
Leung Y, Yan J (1998) A locational error model for spatial features. Int J Geogr Inf Sci 12:607–620
Li M, Zang S, Zhang B et al (2014) A review of remote sensing image classification techniques: the role of spatio-contextual information. Eur J Remote Sens 47:389–411
Lillesand TM, Kiefer RW (2000) Remote sensing and image interpretation, 4th edn. John Wiley & Sons, New York

Lloyd H, Sevillano RíOs S, Marsden SJ, ValdéS-VeláSquez A (2012) Bird community composition across an Andean tree-line ecotone. Austral Ecol 37:470–478. doi:10.1111/j.1442-9993.2011.02308.x
Lowell K (1994) An uncertainty-based spatial representation for natural resources phenomena. In: Waugh TC, Healey RG (eds) Advances in GIS research: proceedings of the sixth international symposium on spatial data handling, Edinburgh, 1994. International geographical union commission on GIS and the Association for Geographic Information, vol 2. Taylor & Francis, London, pp 933–944
Lu D, Weng Q (2007) A survey of image classification methods and techniques for improving classification performance. Int J Remote Sens 28:823–870. doi:10.1080/01431160600746456
Mansoori EG, Zolghadri MJ, Katebi SD (2007) A weighting function for improving fuzzy classification systems performance. Fuzzy Sets Syst 158:583–591. doi:10.1016/j.fss.2006.10.004
Marsala C (2009) Data mining with ensembles of fuzzy decision trees. In: IEEE symposium on computational intelligence and data mining, Nashville, Mar–Apr 2009. IEEE symposium, pp 348–354. doi: 10.1109/CIDM.2009.4938670
Mendonça LF, Vieira SM, Sousa JMC (2007) Decision tree search methods in fuzzy modeling and classification. Int J Approx Reason 44:106–123
Miura T, Yoshioka H, Fujiwara K, Yamamoto H (2008) Inter-comparison of ASTER and MODIS surface reflectance and vegetation index products for synergistic applications to natural resource monitoring. Sensors 8:2480–2499
Morin NR (ed) (1993) Flora of North America north of Mexico, volume 2: pteridophytes and gymnosperms. Oxford University Press, New York
Myint SW, Gober P, Brazel A et al (2011) Per-pixel vs. object-based classification of urban land cover extraction using high spatial resolution imagery. Remote Sens Environ 115:1145–1161. doi:10.1016/j.rse.2010.12.017
NAIP (2014) National Agricultural Imagery Program, Salt Lake City. http://www.lta.cr.usgs.gov/node/300. Accessed Sept 2014
Nauck D, Kruse R (1997) What are neuro-fuzzy classifiers? In: Proceedings of the seventh international Fuzzy Systems Association world congress, Prague, 1997, vol. 97. IFSA, pp 228–233
Nauck D, Kruse R (1998) How the learning of rule weights affects the interpretability of fuzzy systems. In: Fuzzy systems proceedings, 1998. IEEE world congress on computational intelligence, Anchorage, May 1998, vol 2. IEEE, pp 1235–1240
Nauck D, Kruse R (1999) Fuzzy classification rules using categorical and metric variables. In: Proceedings of the 6th international workshop on fuzzy-neuro systems, Leipzig, Mar 1999
Nauck D, Klawonn F, Kruse R (1997) Foundations of neuro-fuzzy systems. John Wiley & Sons, New York
de Oliveira JV (1999) Semantic constraints for membership function optimization. IEEE Trans Syst Man Cybern Part Syst Hum 29:128–138. doi:10.1109/3468.736369
OSM (2014) OpenStreetMap. Available http://www.openstreetmap.org/copyright. Access Nov 2014
Pajares G, Guijarr M, Herrera PJ, Ribeiro A (2009) Combining classifiers through fuzzy cognitive maps in natural images. Comput Vis IET 3:112–123. doi:10.1049/iet-cvi.2008.0023
Perkal J (1956) On epsilon length. Bull Acad Pol Sci 4:399–403
Remmel TK (2009) Investigating global and local categorical map configuration comparisons based on coincidence matrices. Geogr Anal 41:144–157
Remmel TK (2015) ShrinkShape2: a FOSS toolbox for computing rotation-invariant shape spectra for characterizing and comparing polygons. Canadian Geogr 59:532–547
Remmel TK, Perera AH (2009) Mapping natural phenomena: boreal forest fires with non-discrete boundaries. Cartogr Int J Geogr Inf Geovisualization 44:274–288. doi:10.3138/carto.44.4.274
Rickel BW, Anderson B, Pope R (1998) Using fuzzy systems, object-oriented programming, and GIS to evaluate wildlife habitat. AI Appl 12:31–40
Rocchini D, Ricotta C (2007) Are landscapes as crisp as we may think? Ecol Model 204:535–539. doi:10.1016/j.ecolmodel.2006.12.028
Rosenfield GH, Fitzpatrick-Lins K (1986) A coefficient of agreement as a measure of thematic classification accuracy. Photogramm Eng Remote Sens 52:223–227

Running SW, Loveland TR, Pierce LL (1994) A vegetation classification logic based on remote sensing for use in global biogeochemical models. Ambio 23:77–77

Safavian SR, Landgrebe D (1991) A survey of decision tree classifier methodology. IEEE Trans Syst Man Cybern 21:660–674

Sameen MI, Pradhan B (2017) A two-stage optimization strategy for fuzzy object-based analysis using airborne LiDAR and high-resolution orthophotos for urban road extraction. J Sensors. doi:10.1155/2017/6431519

Sarmento P, Carrão H, Caetano M et al (2010) Incorporating uncertainty in the accuracy assessment of land cover maps using fuzzy numbers and fuzzy arithmetic. In: Tate NJ, Fisher PF (eds) Proceedings of the 9th international symposium on spatial accuracy assessment in natural resources and environmental sciences, Leicester, July 2010

Sarmento P, Fonte CC, Caetano M, Stehman SV (2013) Incorporating the uncertainty of linguistic-scale reference data to assess accuracy of land-cover maps using fuzzy intervals. Int J Remote Sens 34:4008–4024

Schapire RE (1990) The strength of weak learnability. Mach Learn 5:197–227

Schmidt M, Kiviste A, von Gadow K (2011) A spatially explicit height-diameter model for scots pine in Estonia. Eur J For Res 130:303–315

Shortridge A, Shi M (2012) Changing the TIGER's stripes: detecting road network change under positional uncertainty. In: Vieira C, Bogorny V, Aquino R (eds) Proceedings of the tenth international symposium on spatial accuracy assessment in natural resources and environmental sciences, Florianópolis, July 2012

Steele BM (2000) Combining multiple classifiers: an application using spatial and remotely sensed information for land cover type mapping. Remote Sens Environ 74:545–556

Sun CT, Jang JS (1993) A neuro-fuzzy classifier and its applications. In: Proceedings of the second IEEE international conference on fuzzy systems, San Francisco, Mar 1993, vol 1. IEEE, pp 94–98. doi: 10.1109/FUZZY.1993.327457

Suter GW (2006) Ecological risk assessment, 2nd edn. CRC Press, Boca Raton

Triepke, FJ (2016) Assessing the climate change vulnerability of ecosystem types of the southwestern U.S. Dissertation, University of New Mexico

Triepke FJ, Brewer CK, Leavell DM, Novak SJ (2008) Mapping forest alliances and associations using fuzzy systems and nearest neighbor classifiers. Remote Sens Environ 112:1037–1050

Triepke FJ, Higgins FB, Weisz RN et al (2011) Diameter caps and forest restoration—evaluation of a 16-inch cut limit on achieving desired conditions. USDA Forest Service Forestry Report FR-R3–16-3 available www.fs.usda.gov/Internet/fse_documents. Southwestern Region, Albuquerque

Triepke FJ, DeMeo TE, Al Otoum M, Al-Azzam L (2012) Composition and structure of Aleppo pine (Pinus halepensis) communities in the Dibeen Forest reserve, Jordan. Nat Areas J 32:356–366

USDA Forest Service (2012) Existing vegetation map of the Southwestern United States. In: Southwestern Region GIS Datasets. Available www.fs.usda.gov/detail/r3/landmanagement/gis. Accessed Feb 2014

USDA Forest Service (2014) Integrating, social, economic, and ecological values across large landscapes. Gen Tech Rep PNW-GTR-896. Pacific Northwest Research Station, Portland

USGS (2014) US Geological Survey western U.S. 250m eMODIS remote sensing phenology data, Sioux Falls. http://www.phenology.cr.usgs.gov/ndvi_foundation.php. Accessed Jan 2014

Vandendriesche DA (2011) A compendium of NFS regional vegetation classification algorithms. USDA Forest Service, Southwestern Region. Available http://www.fs.fed.us/fmsc/ftp/fvs/docs/gtr. Accessed Jan 2014

Wang F (1990) Fuzzy supervised classification of remote sensing images. IEEE Trans Geosci Remote Sens 28:194–201

Wang F, Hall GB (1996) Fuzzy representation of geographical boundaries in GIS. Int J Geogr Inf Syst 10:573–590

Westoby M, Walker B, Noy-Meir I (1989) Opportunistic management for rangelands not at equilibrium. J Range Manag 42:266–274

Wood TF, Foody GM (1993) Using cover-type likelihoods and typicalities in a geographic information system data structure to map gradually changing environments. In: Haines-Young R, Green DR, Cousins SH (eds) Landscape ecology and GIS. Taylor & Francis, London
Woodcock CE, Gopal S (2000) Fuzzy set theory and thematic maps: accuracy assessment and area estimation. Int J Geogr Inf Sci 14:153–172
Zabihi K, Paige GB, Hild AL, Miller SN, Wuenschel A, Holloran MJ (2017) A fuzzy logic approach to analyse the suitability of nesting habitat for greater sage-grouse in western Wyoming. J Spatial Sci. doi:10.1080/14498596.2017.1292965
Zadeh LA (1965) Fuzzy sets. Inf Control 8:338–353
Zhang J, Foody GM (1998) A fuzzy classification of sub-urban land cover from remotely sensed imagery. Int J Remote Sens 19:2721–2738
Zhang J, Stuart N (2001) Fuzzy methods for categorical mapping with image-based land cover data. Int J Geogr Inf Sci 15:175–195. doi:10.1080/13658810010005543

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