DISSERTATION

DEVELOPMENT OF A COMBINED GIS, NEURAL NETWORK AND BAYESIAN CLASSIFIER METHODOLOGY FOR CLASSIFYING REMOTELY SENSED DATA

Submitted by
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WE HEREBY RECOMMEND THAT THE DISSERTATION PREPARED UNDER OUR SUPERVISION BY CLAUDIO A. SCHNEIDER ENTITLED DEVELOPMENT OF A COMBINED GIS, NEURAL NETWORK AND BAYESIAN CLASSIFIER METHODOLOGY FOR CLASSIFYING REMOTELY SENSED DATA BE ACCEPTED AS FULLFILLING IN PART REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY.

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ABSTRACT OF DISSERTATION

DEVELOPMENT OF A COMBINED GIS, NEURAL NETWORK AND BAYESIAN CLASSIFIER METHODOLOGY FOR CLASSIFYING REMOTELY SENSED DATA

This research is aimed at the solution of two common but still largely unsolved problems in the classification of remotely sensed data: (1) Classification accuracy of remotely sensed data decreases significantly in mountainous terrain, where topography strongly influences the spectral response of the features on the ground; and (2) when attempting to obtain more detailed classifications, e.g. forest cover types or species, rather than just broad categories of forest such as coniferous or deciduous, the accuracy of the classification generally decreases significantly. The main objective of the study was to develop a widely applicable and efficient classification procedure for mapping forest and other cover types in mountainous terrain, using an integrated GIS / neural network / Bayesian classification approach. The performance of this new technique was compared to a standard supervised Maximum Likelihood classification technique, a "conventional" Bayesian / Maximum Likelihood classification, and to a "conventional" neural network classifier.

Results indicate a considerable improvement of the new technique over the standard Maximum Likelihood classification technique, as well as a better accuracy than

the "conventional" Bayesian / Maximum Likelihood classifier (13.08 percent improvement in overall accuracy), but the "conventional" neural network classifiers outperformed all the techniques compared in this study, with an overall accuracy improvement of 15.94 percent as compared to the standard Maximum Likelihood classifier (from 46.77 percent to 62.71 percent). However, the overall accuracies of all the classification techniques compared in this study were relative low. It is believed that this was caused by problems related to the inadequacy of the reference data. On the other hand, the results also indicate the need to develop a different sampling design to more effectively cover the variability across all the parameters needed by the neural network classification technique, while being, at the same time, economically feasible.

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CHAPTER 1. INTRODUCTION

In recent years there has been widespread use of satellite multispectral scanner data for classifying and mapping land use/land cover of the earth's surface using computer-aided analysis techniques (Jensen 1996). In general, classification of major cover types has been successfully mastered using conventional statistical classifiers (e.g. maximum likelihood algorithm) (Lillesand and Kiefer 1999). In this approach the analyst first "trains" the computer using supervised, unsupervised or hybrid techniques to identify the various cover types of interest, based on their spectral (and sometimes textural and/or contextual) characteristics. In the classification step, the computer assigns each raster cell or pixel to an informational category (e.g. land cover type such as forest, crop) based on the spectral characteristics of that particular pixel. Usually, it is assumed that the probability of encountering a particular cover type is the same for all the cover types present.

However, this conventional method has been shown to have significant limitations. When attempting to obtain more detailed classifications (for example, forest cover types or species, rather than just broad categories of forest, such as coniferous or deciduous), the accuracy of the classification often decreases significantly (Hoffer 1986). This is especially the case in mountainous terrain, where topography strongly influences the spectral response of any particular cover type (Hoffer 1979). Different forest cover

types can be confused or amalgamated into one because of their relative position on a slope or aspect.

An alternative that might improve the classification of forest cover types in mountainous terrain is the Bayesian analysis. The Bayesian approach utilizes a set of predefined probabilities, called prior probabilities, indicating the likelihood for the pixel to belong to each of the informational categories defined. In recent years, various forms of Bayesian analysis have been used with some success to classify remotely sensed data. However the greatest limitation to the Bayesian approach seems to be in developing meaningful prior probabilities. No widely applicable technique for developing priors has been produced, and without meaningful priors, the accuracy of the Bayesian classification approach decreases markedly.

In a neural network analysis, the output consists of values that can be interpreted as probabilities, indicating the likelihood that each portion of the region of interest belongs in each of the possible information categories. Such a neural network approach could therefore provide the Bayesian classifier with the required *a priori* information.

Early work by Hoffer et al. (1979) in the San Juan Mountains of southern Colorado showed that the use of topographic data significantly improved the overall classification accuracy of forest cover types as compared to using only spectral data. Information about the elevation distribution of the different species was particularly significant in helping to improve the classification accuracy. Use of elevation data in addition to the spectral data provided an improvement in overall classification accuracy of approximately 15% (from 49.4% to 65.9%).

A recent study by Blackard and Dean (1999) used artificial neural networks to predict forest cover types in a National Forest in Colorado. This neural network used as input only standard cartographic information obtained through a GIS analysis (e.g. slope, aspect, distance to surface water, etc.); no remotely sensed data was involved at all. The overall accuracy achieved through this approach was a surprisingly high 70 percent. However, this was achieved by classifying only forest cover types, with all the other cover types masked out, and also employing a total random sampling design.

The proposed study will link GIS / neural network and Bayesian classification approaches to develop an integrated method of classifying remotely sensed data. This method will be applied to classify forests, as well as other cover types in the mountains of Northern Colorado.

CHAPTER 2. OBJECTIVES

2.1 Overall Objective

The overall objective of this study is to develop a widely applicable, effective and efficient classification procedure for mapping forest and other cover types in mountainous terrain, based on computer-assisted classification using an integrated GIS/ neural network / Bayesian classification approach of remotely sensed data.

2.2 Specific Sub-objectives

The specific sub-objectives of this study are:

(1) Demonstrate the feasibility of using remotely sensed data and different types of ancillary data to improve the accuracy of classifying forest and other cover types in the mountains of northern Colorado;

(2) Develop and optimize a neural network based on geographical, topographical and ecological variables incorporated through a GIS to predict the occurrence of forest cover types in the mountains of northern Colorado;

(3) Evaluate the effectiveness of the *a priori* predictions obtained by the neural network in conjunction with a Bayesian / Maximum likelihood classification procedure;

(4) Analyze the effectiveness and efficiency of the GIS / Neural network / Bayesian approach by comparing it (1) to a standard supervised classification procedure, and (2) to a more "conventional" neural network procedure.

CHAPTER 3. LITERATURE REVIEW

3.1 Relationship between the level of classification detail and classification performance

Over the years, innumerable studies have demonstrated that, as a general rule, the more detailed the classifications level, the poorer the classification performance (i.e., the lower the accuracy of the classification. For example, an evaluation of the thematic accuracy of the MultiResolution Land Characteristics (MRLC) land cover map for the eastern United States performed by Yang et al. (2001) using 30-meter resolution Landsat TM data, resulted in an overall accuracy of 80.5 percent at an Anderson level I thematic detail, while the overall accuracy of the same classification obtained only 59.7 percent at an Anderson level II.

According to Hoffer (1986), a number of studies have attempted to identify and map individual forest cover types (i.e., Anderson level III thematic detail), but have had varying degrees of success, depending on the spectral differences among the species involved, variations in stand density, topography, season, and other factors. In general most of these studies concluded that the results were, at best, quite variable, largely due to the spectral similarity of different species. Therefore, the classification performances in many of these studies were not accurate enough to provide operationally useful results (Hoffer 1986).

An important factor limiting classification accuracy at higher levels of detail is the spatial resolution of the sensor system used. According to Jensen (1996), typically, sensors such as Landsat MSS, Landsat TM and Spot XS have been successfully used at an Anderson Level I classification detail. However, classifications at an Anderson Level II are usually performed with the aid of higher resolution sensors like SPOT Panchromatic data (i.e., 10-meter resolution) or high altitude aerial photography, acquired at 40,000 feet or above (i.e. scale < 1:80,000). Even more demanding is the resolution required to perform classifications at an Anderson Level III, usually performed with medium-altitude airborne data acquired between 10,000 and 40,000 feet (i.e., scale between 1:20:000 and 1:80:000). In brief, higher levels of classification detail are usually obtained through photo-interpretation of aerial photography, a procedure that is not very efficient in terms of time and cost when working with very large areas. On the other hand, in computer-assisted classification of remotely sensed data, the use of higher resolution sensors often results in a decrease of the classification accuracy, because of the additional spatial complexity. For instance, a study conducted by Meyer (2000), reported higher accuracies with 30-meter Landsat TM in the classification of wetlands and agricultural areas in Northern Colorado, as compared to a classification of the same area using the Indian satellite IRS-1C 5-meter resolution data. In another study, Latty and Hoffer (1981), reported that the use of successively higher spatial resolution data resulted lower overall classification accuracies, particularly in forest cover types, which are associated with relatively large levels of spectral variability across adjacent pixels.

Generally speaking, sensor systems with a high spatial resolution, such as photographic films, will have a low spectral resolution, while systems with a high

spectral resolution will have a low spatial resolution (Ciesla 2000). There is no ideal sensor system in terms of overall resolution. Consequently an improvement of the classification performance at higher levels of accuracy may come from the development of new classification techniques, capable of providing effective ways to incorporate data from different sensor systems, as well as different types of ancillary data to the classification process.

3.2 Classification of remote sensing data in mountainous terrain: A review of topographic normalization techniques

Classification of remotely sensed data, although successfully utilized in many instances, still presents several problems in the case of complex topographic landscapes. While the sun and viewing angles can be considered as constant within an image, the topographic characteristics of the terrain may change the illumination geometry and interfere in the spectral response of a cover type, causing errors in the spectral classification (Civco 1989, Chiou et al. 1992). This is known as the topographic effect. As stated in Holben and Justice (1980), it is produced by the variation in radiances from inclined surfaces compared to radiances in horizontal surfaces as a function of their orientation relative to the light source and sensor position.

According to Hoffer et al. (1979), early Landsat and Skylab investigations confirmed that the occurrence of different forest cover types was significantly influenced by elevation and aspect and furthermore, that the aspect, slope, and stand density all have significant influence on the spectral response of the various forest cover types. Thus, the distribution of many cover types is strongly correlated to the topographic characteristics of the terrain, making them more likely to occur on a particular slope or aspect.

Chiou et al. (1992), concluded that the spectral variation for Landsat TM data from areas of uniform cover type is significantly dependent on topography, showing a range of maximum change in the spectral response between 4 and 23%.

In the case of vegetation, the influence of topography over the ecological / phenological behavior can cause an inherent variation in the appearance of a particular plant species depending on its relative position, elevation, slope or aspect, which in turn can be reflected in its spectral response.

Traditionally, techniques used to overcome the effects of topography attempt to correct for the varying illumination and reflection by removing this topographic variability of the pixels. The correction involves an attempt to adjust the reflectance values of the original bands to values that would have been recorded if the scene's surface were flat. In order to accomplish this, two different approaches have been used (Richter 1997, Jensen 1996, Civco 1989). The first method employs band ratios and statistical transformations such as principal components or statistical regression analysis (Civco 1989, Chuvieco 1996, Conese et al. 1993). In the second approach, a Digital Elevation Model (DEM) is used along with the sun orientation of an image to compensate for a pixel's unique illumination and create a more accurate classification (Hoffer et al. 1979, Chiou et al. 1992, Conese et al. 1993). In this approach, a radiative transfer code is applied to obtain a deterministic description of the correction based essentially on two important models (Colby and Keating 1998, Richter 1997). The first, a Lambertian model, assumes that phenomena on the earth's surface reflect incident radiation equally in every direction. A non-Lambertian model assumes that objects on the ground reflect incident radiation in an anisotropic fashion in relation to the view, the illumination

geometry, and the surface roughness. To quantify the degree of non-Lambertian reflection, a Minnaert constant is used.

Although relative success has been accomplished by these methods of topographic normalization (Hoffer et al. 1979, Civco 1989, Chiou et al. 1992, Conese et al. 1993, Richter 1997, Colby and Keating 1998), their effectiveness is a function of several assumptions that pose serious limitations to their applicability. For instance, Lambertian models neglect the geometric influence, as well as the surface properties, resulting in an over-correction of the topographic effects. Nevertheless, some research shows that relatively good results are possible for topographic normalization with the Lambertian assumption (Conese et. al 1993), but good information on the atmospheric conditions (i.e. solar flux) at the time of the satellite overpass is required -- information which is not always available. In addition, large errors caused by specular reflection and backscattering make the Lambertian models valid only for a restricted range of incident angles (i.e. lower than 55 degrees) (Richter 1997, Colby and Keating 1998). The Minnaert constant required in the Non-Lambertian models depends on the spectral band, phase angle, and surface cover type, making it difficult to apply in practice, since a pixel cover type is unknown *a priori* to the classification (Richter 1997, Colby and Keating 1998).

In a comparison study, Chiou et al. (1992) evaluated four different topographic methods. The study included two Lambertian models -- the simple cosine correction, and the direct radiance correction model (Hoffer et al. 1979) -- and two non-Lambertian models -- the complex two-stage calculation of the shaded relief (Civco 1989), and the backward radiance correction transformation model (BRTCM). The results show that the

latter was the most effective model. However, the authors conclude that the main limitation of the BRTCM was the correct definition of the Minnaert constant, which can lead to inaccuracies.

In the context of the limitations of these "traditional" methods mentioned above, the introduction of a markedly different approach, such as the one proposed in this study, may represent an innovative alternative to overcome the effects of topography and improve the classification accuracy of remotely sensed data in mountainous terrain.

3.3 Neural networks in the classification of remote sensor data

Artificial neural networks are an attempt to simulate the information processing capabilities of the human brain (Civco 1994). An artificial neural network is composed of a series of interconnected nodes (Figure 3.1). The node is the fundamental processing unit of an artificial neural network. A processing node has one or more input paths, and the information transferred along these paths is combined within the node by one of a variety of mathematical functions, most commonly simple summation (Civco 1994) (Figure 3.1). This combined value is used as input to the node's activation function, which determines the magnitude of the output signal the node will send to subsequent portions of the network.

Each processing node mimics a biological neuron as a primitive information-processing unit (Paola and Schowengerdt 1993, Rojas 1996). Combined, these simple processing units constitute a system of input-output nodes that can be trained so that the network produces an effective response to a set of inputs (Landau and Taylor 1997). In

this context, training the artificial neural network consists of developing values for each node's activation function so that the output of the network matches as well as possible with known output values in a training dataset.

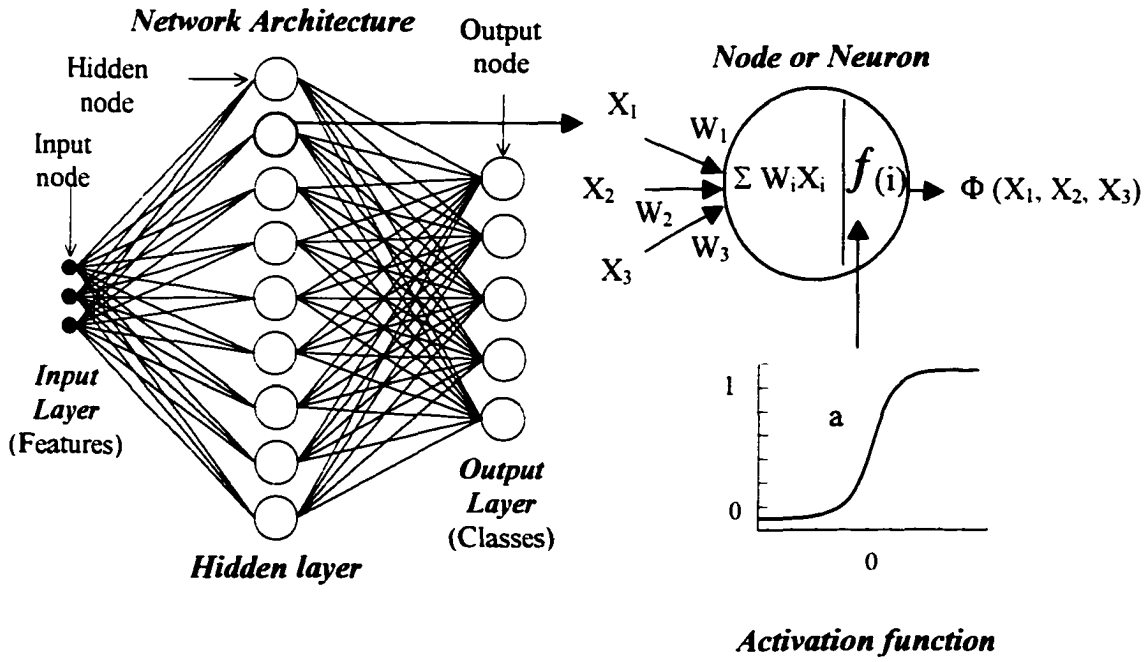


Figure 3.1: Diagram of an Artificial Neural Network

Neural networks learn by example, through establishment and reinforcement of linkages between input and output data. It is these linkages, or pathways, that form the analogy with the human learning process in that repeated associations between input and output in the training process reinforce connections that can be employed to link input and output data in the absence of training data (Campbell, 1996).

Several types of neural networks have been developed over the years for remote sensing applications. Some examples of these networks (e.g., Kohonen Self-organizing features, Learning Vector Quantization) can be found in Paola and Schowengerdt (1993), EUROSTAT (1997), and Wilkinson (1997). However, the majority of applications of neural networks used in remote sensing employ the multilayer feedforward neural network (Paola and Schowengerdt 1993, EUROSTAT 1997). The design of a typical feedforward neural network, commonly referred to as the network's architecture, consists of a series of interconnected layers of nodes (Figure 3.1). The first layer is the input layer, followed by one or more layers, usually called hidden layers. These hidden layers, in turn, are connected to the output layer at the other end of the network. The networks can either be completely connected, meaning that each node in any layer is connected to all the nodes in the previous or subsequent layers, or they can be only partially connected. One input node is required for each predictive variable in the model. In the same way, one output node is required for each response variable of the model.

In a typical scenario, a neural network is presented iteratively with a set of samples, known as the training set, from which the network can learn the values of its internal parameters. In the training set, the samples, also known as the target output values, are arranged so that a value of one is assigned to the true class, and a value of zero is assigned to all the other classes. When applied to classification of satellite imagery, for example, an artificial neural network is concerned with the transformation of data from the spectral feature space to informational class space (Atkinson and Tatnall 1997, EUROSTAT 1997). When data from an input pattern is supplied to the input layer, the network nodes perform calculations in the successive layers until an output value is

computed at each of the output layer nodes (see Figure 3.1). The output signal should be an indication of which is the appropriate class for the input data (i.e., we expect to have a high output value on the correct class node and a low output value on all the rest).

Perhaps the most important quality of neural networks in remote sensing is that they represent a robust alternative to traditional statistical classifiers. While standard classification methods usually require assumptions about the underlying statistical characteristics of the data (e.g., the data for each ground cover class should have a Gaussian distribution), neural networks are distribution-free, meaning that no underlying model is assumed for multivariate distribution of the class-specific data in feature space (Atkinson and Tatnall 1997, Civco 1994, Kanellopoulos and Wilkinson 1997, Paola and Schowengerdt 1993). This means that, in feature space, it is possible for a single informational class to be represented as multiple clusters rather than as a single cluster. Therefore, a fundamental difference between statistical and neural approaches to classification is that while statistical approaches depend on an assumed model, neural networks require no foreknowledge of the nature of the classes, since they rely totally on an empirical use of the training samples (Landgrebe, 1998).

While development of reliable training statistics is crucial to obtaining accurate classification results, much can be done to improve the results by integrating spectral data with ancillary data (Jensen 1996). An additional important advantage of neural classifiers over statistical classifiers is the fact that neural networks behave as general pattern recognition systems, allowing the combination of data from a variety of sources in the same classification procedure (Paola and Schowengerdt 1993, Wilkinson 1996, Atkinson and Tatnall 1997, Benediksson and Sveinsson 1997). This ability to handle data having

different levels of measurement precision and noise (e. g., GIS data and remote sensor data) makes the neural network approach a more flexible classification method (Foody and Arora 1997).

The desirable properties of non-normality and non-linearity of an artificial neural network can be attributed not only to the network's massively parallel-distributed structure but also to the transfer function in each node (Haykin 1994 in Jensen 1999). According to Kimes et al. (1998) neural networks employ a more powerful and adaptive nonlinear form as compared to traditional linear and simple nonlinear analysis. This power and flexibility is gained by repeating nonlinear activation functions in a network structure.

The essence of the network operation is the learning algorithm. A learning algorithm is a mathematical process performed iteratively until the total error of the network is reduced to an acceptable level. It aims to achieve a set of weights that will produce outputs most resembling the target. While many learning algorithms exist, the most widely used learning algorithm in remote sensing applications is the standard back-propagation (Paola and Schowengerdt 1993, EUROSTAT 1997). Back-propagation is a gradient-descent algorithm that minimizes the error between predicted and known outputs in the training data. In this procedure, the network output is compared with the ground truth or reference data and the difference between them is determined (i.e. an error is calculated). This error is back propagated through the network in order to modify the weights of the connections, which are initially assigned at random, following the generalized delta rule. A detailed explanation of the back-propagation algorithm and generalized delta rule can be found in Rojas (1996).

The prevailing back-propagation procedure and the generalized delta rule as the driver in artificial neural network structures have proven to be efficient. However, they have two main shortcomings: first, they are a computationally very slow type of optimizing algorithm, and second, it is possible for the gradient-descent algorithm to get trapped in the local minima that sometimes occur in complicated solution spaces (Dutra and Huber 1999, Mokken 1995). To solve this problem, other optimization methods have been developed, that provide better convergence speeds without impeding consistency and accuracy of estimation (Kanellopoulos and Wilkinson 1997). However, in most cases, with today's ever-increasing computer capabilities the training time no longer represents a problem.

While the number of iterations suggests that an artificial neural network is training intensive, previous research has shown that (a) the neural network can produce accuracies similar to those obtained with the k-nearest neighbor and discriminant analysis using smaller training sets; and (b) once trained, neural networks are computationally more efficient than statistical classifiers (Lee et al. 1990 in Yool 1998).

One of the most important factors to take into consideration when training a neural network is to maintain its ability to generalize. This refers to the ability of a neural net to interpolate and extrapolate to a new set of data (Atkinson and Tatnall 1997). If the network is trained too intensively on the training data it might not perform accurately on the rest of the image; conversely, if the training is deficient it will not be able to discriminate between classes, even in the training data, to an acceptable level (Paola and Schowengerdt 1993). This is a problem of generalization versus specialization, in which a compromise should be achieved between reducing the error of the network as a whole

and maintaining its ability to generalize. To measure generalization ability, it is common to have a set of data to train the network and a separate set to assess the performance of the network during or after the training is complete (EUROSTAT 1997). This second data set is known as the validation data set, and it gives the neural network the unbiased data it needs to evaluate its performance independently of the training data.

At this point it is pertinent to underscore the significance that the development of an accurate, reliable set of training statistics has in the final outcome of the any classification method. In relation to this, Foody and Arora (1997) conclude that the accuracy of neural network classifications is significantly influenced by the size of the training set, discriminating variables and the nature of the testing set used. Bigger training sets would generally achieve better accuracies. In regard to number of variables, Arora and Foody (1997) show in a comparative study that the highest accuracy was obtained when all eleven spectral wave bands were included as opposed to using fewer bands. Benediksson and Sveinsson (1997) indicate that if the input variables show significant differences from one class to another, the classifier can be designed more easily, resulting in better performance. According to Foody and Arora (1997), neural networks have the ability to weight the importance of the discriminating variables in the classification, thereby effectively ignoring redundant variables. However, the premise of keeping the neural model simple suggests the need for applying feature extraction techniques to make the model more efficient. Feature extraction techniques, such as the "decision boundary feature extraction" have been used successfully in recent research (Benediksson and Sveinsson 1997).

Comparison studies between artificial neural network and statistical classifiers have been described in Benediksson et al. (1990), and Paola and Schowengerdt (1994) as well as in many other comparative studies. Although these studies show that neural network may be used to classify remote sensor data at least as accurately as their statistical counterparts, no single classification algorithm can be regarded as the ultimate solution. The superiority of one algorithm over the other strongly depends on the selected data set and on the efforts devoted to the development phases of algorithms (Roli et al. 1997). Results have shown that neural networks usually perform better than statistical classifiers when strong nonlinear components exist in the system being studied and when spectral data are indistinct or sparse (Kimes et al. 1998, Yool 1998). However, in many instances similar accuracy can be achieved using statistical classifiers without having to deal with a slow and sometimes inconsistent training process, and obscure starting parameters (Paola and Schowengerdt 1993).

An alternative to this would be the development of a technique that exploits the complementary characteristics of both types of classifiers. Integrated neural network / statistical approaches for the classification of remotely sensed data have been studied by Wilkinson et. al (1995), Roli et al (1997) and Benediksson and Kanellopoulos (1999). In the first study a neural network and statistical classifier were used in a parallel classification, followed by a second neural network for handling ambiguous samples. In the second study the classification results of neural network and statistical classifiers were merged according to statistical combination methods (i.e. combination by voting principle, combination by Bayesian average and combination by belief function). The third study was developed for hyperspectral data and was a combination of the technique

used by Wilkinson et al. (1995) and several decision fusion schemes, such as the weighted consensus theory and the consensus-based voting and rejection schemes. All studies provided significantly better classification accuracies than the single classifiers working independently (e.g. Wilkinson reported an accuracy improvement of 12%).

However, the techniques described above differ from the one proposed in this study in that they are essentially a comparison and combination of results obtained with both methods in parallel, instead of using the best qualities of both classifiers sequentially in a two step approach.

3.4 Application of Bayesian statistics to the classification of remote sensing data

In Bayesian classification of remotely sensed data, spatial information is incorporated by combining data with an *a priori* image model that describes the expected relationships between the neighboring pixels (Warrender and Augusteijn 1999). This *a priori* information is expressed as the probability of a pixel to belong to a particular feature class. By including this probability, for example in a Maximum Likelihood classifier, one feature class distribution is favored over another because the probability of occurrence of the corresponding attribute values of given patterns are maximized. As a result of this, the assignment of a greater weight to one class implies a shift of the boundaries of its density function, increasing its extent relative to another class (Swain 1978, Schowengerdt 1983, Chuvieco 1996), thus providing the minimum probability of error for the classification (Landgrebe, 1998). For example, if it is known that due to its elevational distribution Douglas Fir is more likely to occur in a particular pixel than Ponderosa Pine, a higher prior probability can be assigned to Douglas Fir in the Bayesian / Maximum Likelihood algorithm, maximizing its chances to be classified correctly.

In recent years, various forms of Bayesian analysis have been used with some success to classify remotely sensed data (Moffet and Besag 1996). Previous applications of Bayesian classification either make use of a subjective estimation of *a priori* probabilities for all classes or, alternatively, use classification results to adjust the *a priori* probabilities. According to Liu et al. (1998) the former could not be expected to obtain good results for all the classes discussed, and in the latter, the iteration operation required would be a problem of efficiency versus accuracy, where the final results depend strongly on those of the initial classification.

Pedroni (2000) developed prior probabilities for an entire Landsat TM scene of central Costa Rica derived from frequencies modeled with ancillary data and a Mahalanobis Distance selection of previously classified pixels. The results of this study evidenced an improvement of 20.3% overall classification accuracy (from 68.7% to 89.0%) if compared to a Maximum Likelihood classification using equal prior probabilities.

However, in most cases we cannot effectively measure the prior probability of classes and we have to solve the problem by estimating them subjectively. Thus, the greatest limitation to the Bayesian approach seems to be in developing meaningful prior probabilities. No widely applicable technique for developing priors has been produced, and without meaningful priors, the accuracy of the Bayesian classification approach is decreased markedly.

In recent times, there have been some results that combine statistical signal processing theory and neural network theory. Neural net classifiers have been shown to approximate the "Bayes discriminant" (Kimes et al. 1998). Along these lines, it is

possible to view neural network outputs as Bayesian a posteriori class probabilities, which give a basis for their interpretation (Kanellopoulos and Wilkinson 1997, Bernard et al. 1996). The identification of these *a posteriori* probabilities associated with a classification provides pixel-based information on the reliability of the classification (Bernard et al. 1997).

The inherent fuzzy nature of the output data in a neural network has potential to provide class membership values and indicate class-mixing membership with little subsequent processing (Paola and Schowengerdt 1993). By allowing for multiple classes per pixel, each with a relative membership likelihood, soft classification algorithms have the potential to "unmix" the pixel data into proportions of individual components (Schowengerdt 1996). Recent research in *soft* or *fuzzy* classification using neural networks is discussed in Foody and Arora (1996), Bernard et al. (1997) and Foody (1997). Results indicate that neural networks have a great flexibility to accommodate mixed pixels and therefore provide a more realistic representation of the continuous transition present in nature. Consequently, more appropriate and useful outputs may be derived from such a classification. Ultimately, these outputs can be used to enhance the performance of a robust statistical classifier. The resulting class membership values produced by the neural network may be seen as a probability map that can then be entered as the *a priori* information required in a Bayesian / Maximum Likelihood classifier in order to improve classification accuracy.

CHAPTER 4. MATERIALS AND METHODS

4.1 Study area description

The study site consists of several forested areas located approximately 70 miles northwest of Denver, Colorado (see Figure 4.1). The selection of the areas depended on the availability of GIS and ground truth data. The project was divided into a development/testing phase, and a validation phase located in two different areas.

For the development/testing phase, the study area consisted of the Rawah (29,628 hectares), Comanche Peak (27,389 hectares), Neota (3,904 hectares) and Cache la Poudre (3,817 hectares) wilderness areas of the Roosevelt National Forest. The validation phase was performed in the Rocky Mountain National Park area.

The range in elevation for the areas corresponding to the development/testing phase varies from a minimum of 1,819 meters in the Cache la Poudre River to a maximum of 3,926 meters in the Rawah wilderness area. In the case of Rocky Mountain National Park, the elevation range varies between 2,390 meters and 4,345 meters at Longs Peak. In general both areas can be described as rolling to mountainous terrain.

The main reasons for the selection of these study sites are the following:

(1) The sites contain forested lands that have been exposed to a relatively reduced amount of human disturbance. In regard to the study site for the first phase, Blackard and Dean (1999) affirms that due to the lack of human disturbance,

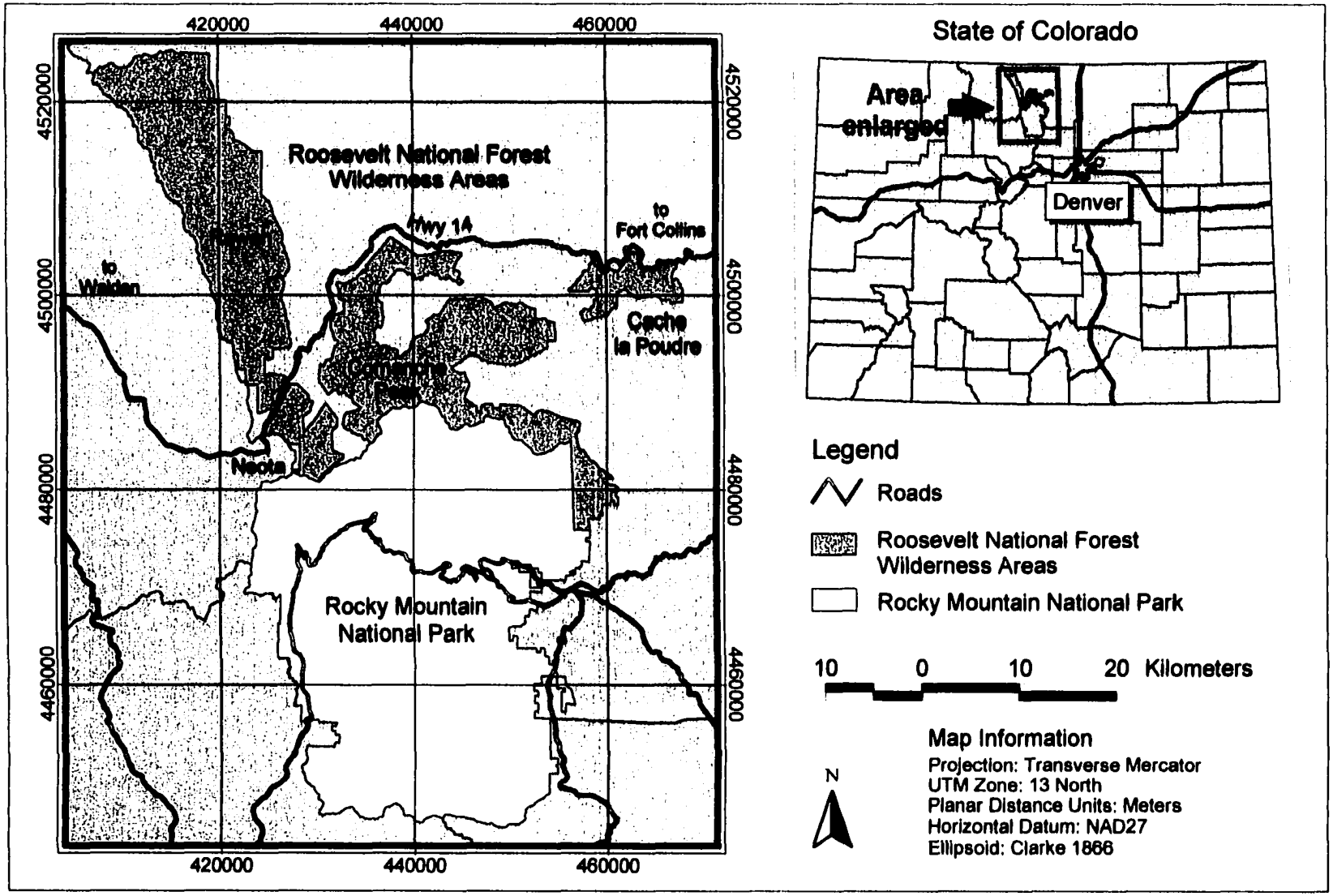


Figure 4.1: Location map of the study areas

the current composition of vegetative cover types within these areas are primarily a result of natural ecological processes rather than a product of active forest management. The same could also be said about the study site within Rocky Mountain National Park.

(2) In addition to the lack of human disturbance, a comprehensive GIS database is available for both sites. This will facilitate the process of the selecting effective variables in the development of the GIS/Neural Network model.

4.2 Data description

4.2.1 GIS data

The selection of the predicting variables applied in the model follow ecological criteria. Consequently, the most relevant ecological factors affecting the distribution of the vegetation cover-types in mountainous terrain was taken into consideration. Topographic variables (e.g. elevation, aspect and slope) have a particular significance for the distribution of forest cover types in mountainous terrain (Hoffer 1979, Blackard and Dean 1999). However, other factors like soil type, distance to surface water sources, exposure to sunlight, and disturbance, which specific relevance is described in detail later in this Chapter, were also included in the model. On the other hand, to avoid dependence upon data that is either unique to our study areas or difficult to obtain, the majority of the GIS data used in this study was restricted to commonly available sources.

A significant part of the data used in the developing/testing phase of this study was the same data used in a study conducted by Blackard and Dean (1999). The reason for this was mainly the availability of data, already prepared for a very similar neural network modeling process. Because of the high number of inputs required by the model,

data preparation was the part of the study that demanded the greatest amount of time. Although it was necessary to perform a number of modifications described in detail in the following paragraphs, the availability of this data saved a considerable amount of time to the entire experimental process.

The main sources of the data used in this study area are the Rocky Mountain Two Resource Information System (RIS) of the United States Forest Service (USFS), a 1:24000 scale USFS ecological land type units database, and the U.S. Geological Survey (USGS). In the validation phase, the main data sources were the extensive GIS database of Rocky Mountain National Park developed by the GIS Program of the park, and the U.S. Geological Survey (USGS). The following datasets were derived from these data sources:

1) ***Reference cover type maps***: The first step of the study consisted of defining the cover types to be mapped. This involved considering the level of classification detail according to the objectives of the classification and the capabilities of the satellite imagery. Because the purpose of the study was to develop a widely applicable, effective and efficient classification procedure for mapping forest and other cover types in mountainous terrain, forest cover types had a higher priority and were classified in more detail. However, other cover types were also included to widen the scope of possible applications, and to perform a complete cover type classification of the study area. The definitive number of cover types was derived from the existing US Forest Service and Rocky Mountain National Park cover type maps.

In the four Roosevelt National Forest Wilderness areas, the reference cover type map consisted of seven major forest cover types as well as three additional non-forest cover types described in the following list:

(1) Lodgepole pine (*Pinus contorta*),

(2) Spruce/fir (*Picea engelmanii, Abies lasiocarpa*),

(3) Ponderosa pine (*Pinus ponderosa*),

(4) Krummholz (*Picea engelmanii, Abies lasiocarpa, Pinus aristata*),

(5) Douglas-fir (*Pseudotsuga menziesii*),

(6) Aspen (*Populus tremuloides*),

(7) Riparian (*Populus angustifolia, Populus deltoides, Salix bebbianna, Salix amygdaloides*),

(8) Other-vegetation (grass, shrubs, alpine tundra),

(9) Non-vegetation (bare soil, rock outcrops, snow),

(10) Water.

This cover type map was created by the U.S. Forest Service from large-scale aerial photography. The minimum mapping unit was 5 acres. Approximately one half of the forest stands were field checked for accuracy (Blackard 1998). The digital version of this map is shown in Figure 4.2.

In the case of the Rocky Mountain National Park area, the source data allowed the distinction between grass in the lower elevations and tundra in higher altitudes. Consequently, the latter was added as an additional, eleventh cover type class to the

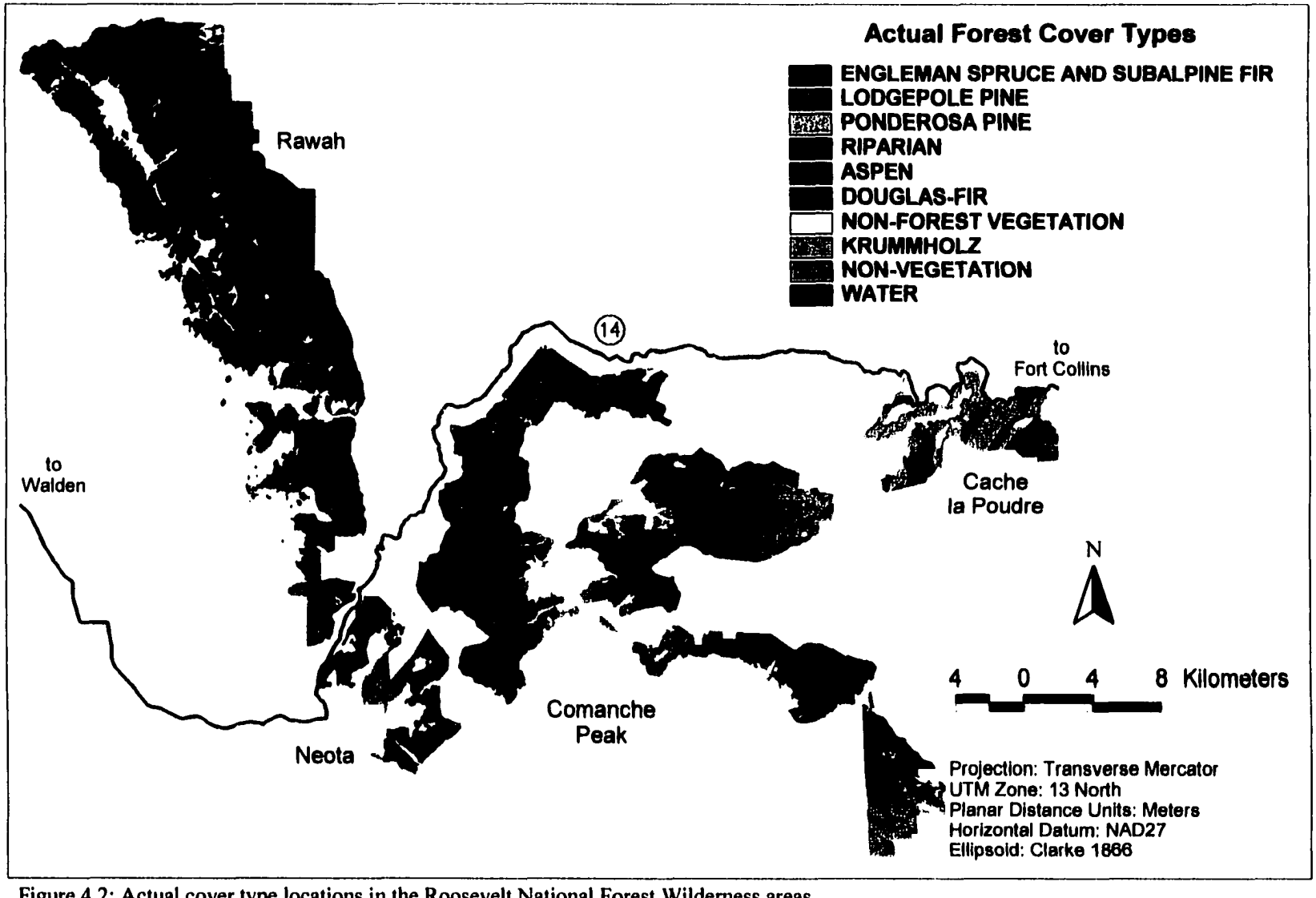


Figure 4.2: Actual cover type locations in the Roosevelt National Forest Wilderness areas

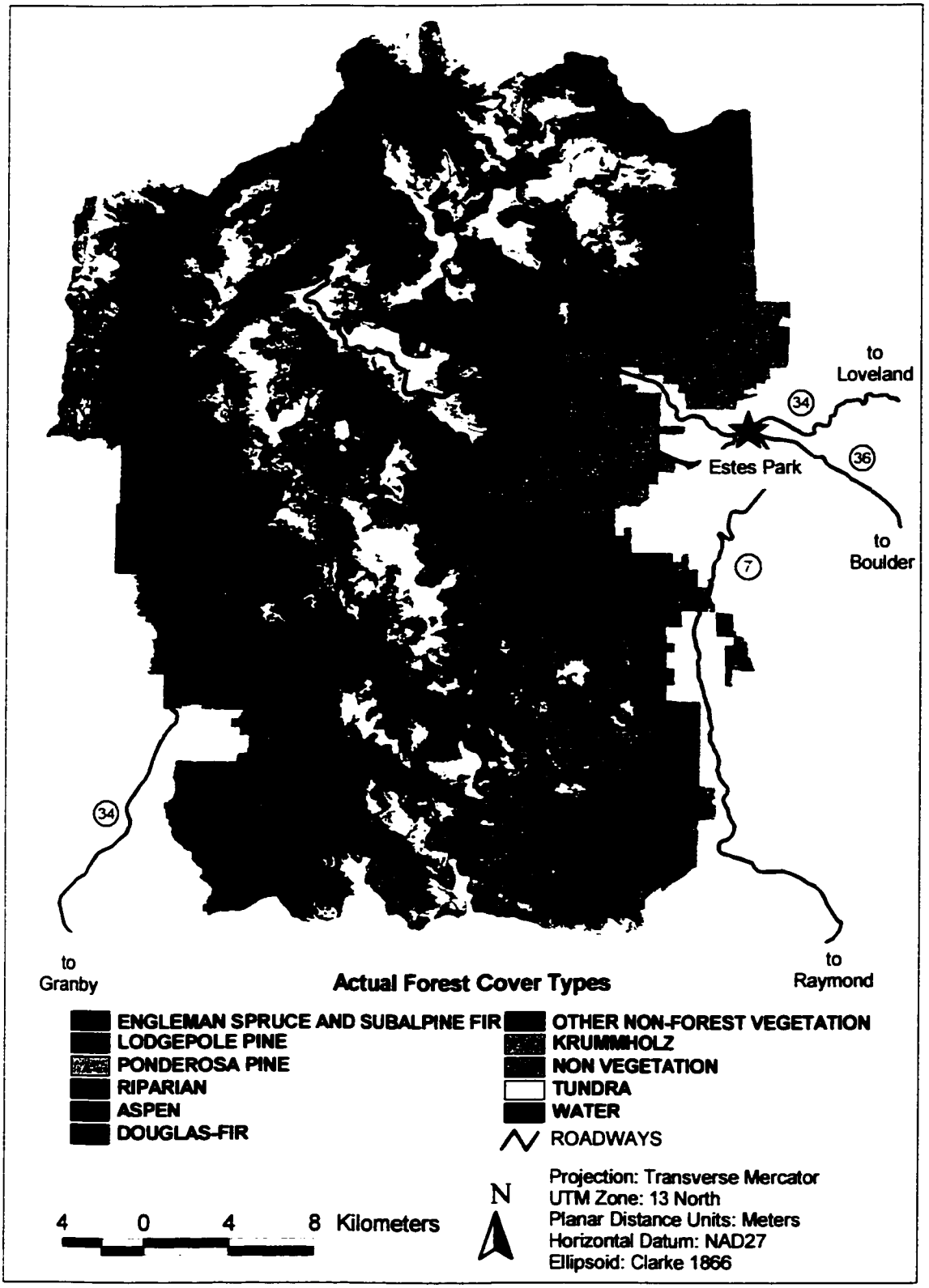


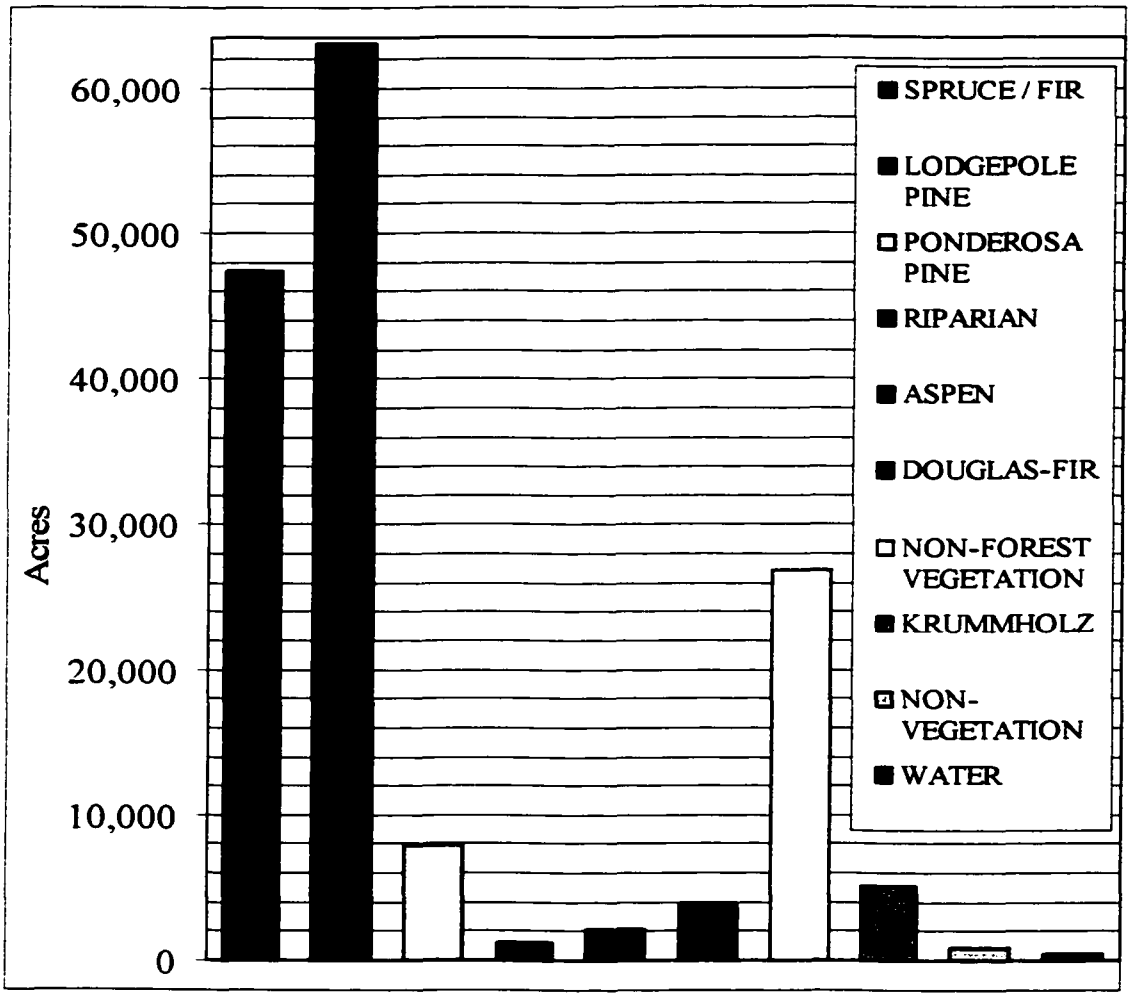
Figure 4.3: Actual cover type locations in the Rocky Mountain National Park area

classification of this area (see Figure 4.3). In this case, the cover type map was developed by the GIS Program of RMNP from 1:15840 scale aerial photography with a minimum mapping unit of 1 acre for non-forest cover types and 5 acres for forest cover types. The map was extensively checked in the field and is accurate between 80 and 85%. Figures 4.4 and 4.5 display the area distribution of the cover types in the Roosevelt Wilderness Areas and Rocky Mountain National Park, respectively, obtained from the final reference cover type maps.

2) ***Elevation*** (meters): The Digital Elevation Model (DEM) for the Roosevelt National Forest Wilderness areas was created by appending 16 U.S. Geological Survey (USGS) DEM quadrangles. This 30 x 30 meter raster cell data, was originally created by USGS based on 71/2 minute, 1:24000 scale quadrangles. For the Rocky Mountain National Park study area, a total of 20 USGS DEM quadrangles were appended together to create one elevation model that encompassed the totality of this study area (see Figure 4.6).

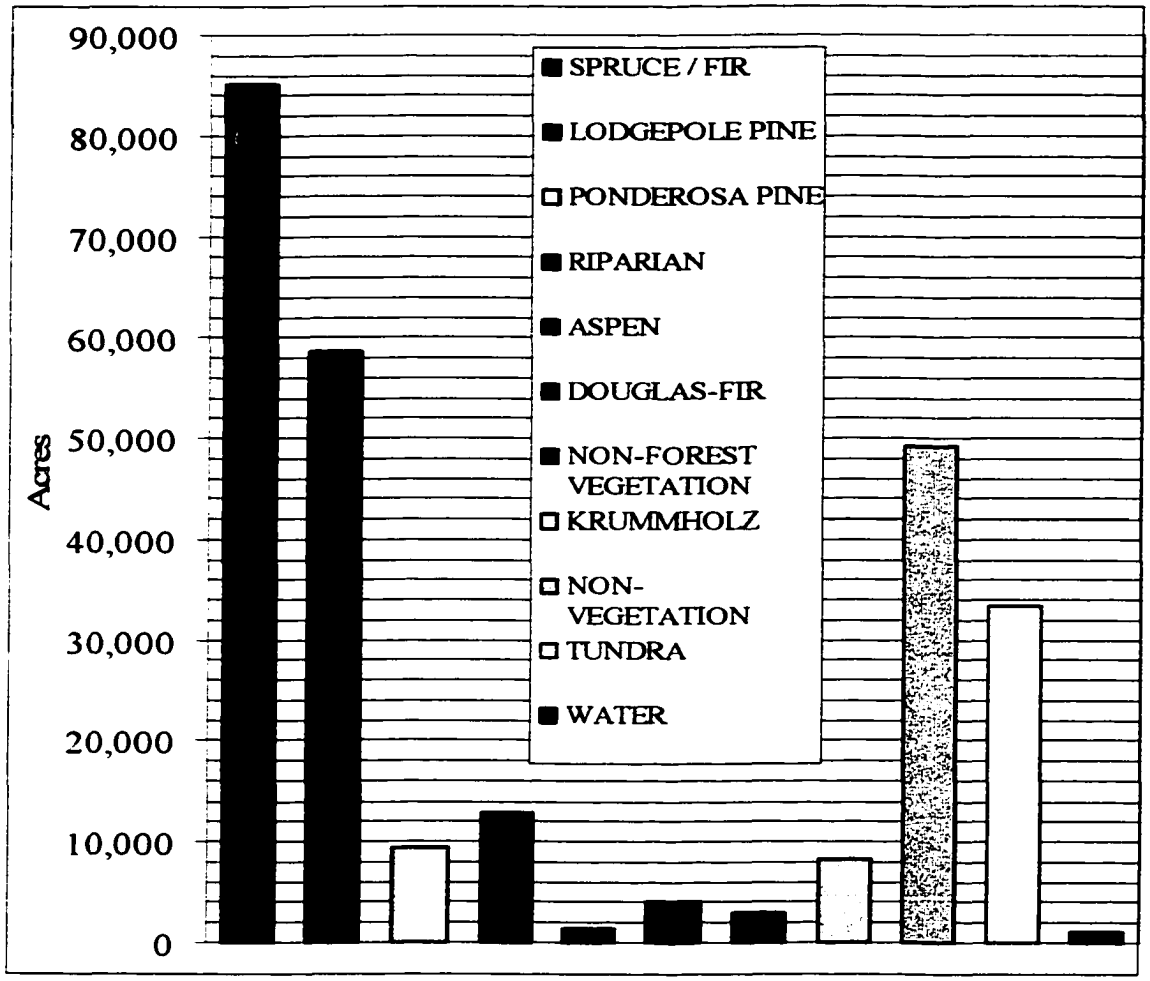
   Because a number of the cartographic features to be incorporated in the model were derived from the DEMs, a thorough quality check was performed in order to eliminate errors inherent to the production of the data (e.g. sink holes produced by digitizing errors), as well as errors caused in the appending procedure of the DEM quadrangles on both datasets.

   As stated before in this document, early Landsat and Skylab investigations by Hoffer et al. (1979), confirmed that the occurrence of different forest cover types was significantly influenced by elevation and aspect and furthermore, that the aspect,



Cover type	Acres	Percentage
SPRUCE / FIR	47,351.9	29.78%
LODGEPOLE PINE	63,102.7	39.68%
PONDEROSA PINE	7,954.4	5.00%
RIPARIAN	1,220.0	0.77%
ASPEN	2,112.5	1.33%
DOUGLAS-FIR	3,863.1	2.43%
OTHER VEGETATION	26,896.1	16.91%
KRUMMHOLZ	5,154.3	3.24%
NON-VEGETATION	912.5	0.57%
WATER	460.1	0.29%
Total	**159,027.6**	**100.00%**

Figure 4.4: Area distribution of the cover types in the Roosevelt National Forest Wilderness areas.



Cover type	Acres	Percentage
SPRUCE / FIR	85,174.3	31.93%
LODGEPOLE PINE	58,564.8	21.95%
PONDEROSA PINE	9,458.2	3.55%
RIPARIAN	12,846.4	4.82%
ASPEN	1,479.6	0.55%
DOUGLAS-FIR	4,077.3	1.53%
NON-FOREST VEGETATION	3,009.8	1.13%
KRUMMHOLZ	8,379.0	3.14%
NON-VEGETATION	49,226.7	18.45%
TUNDRA	33,424.3	12.53%
WATER	1,123.1	0.42%
Total	**266,763.5**	**100.00%**

Figure 4.5: Area distribution of the cover types in Rocky Mountain National Park.

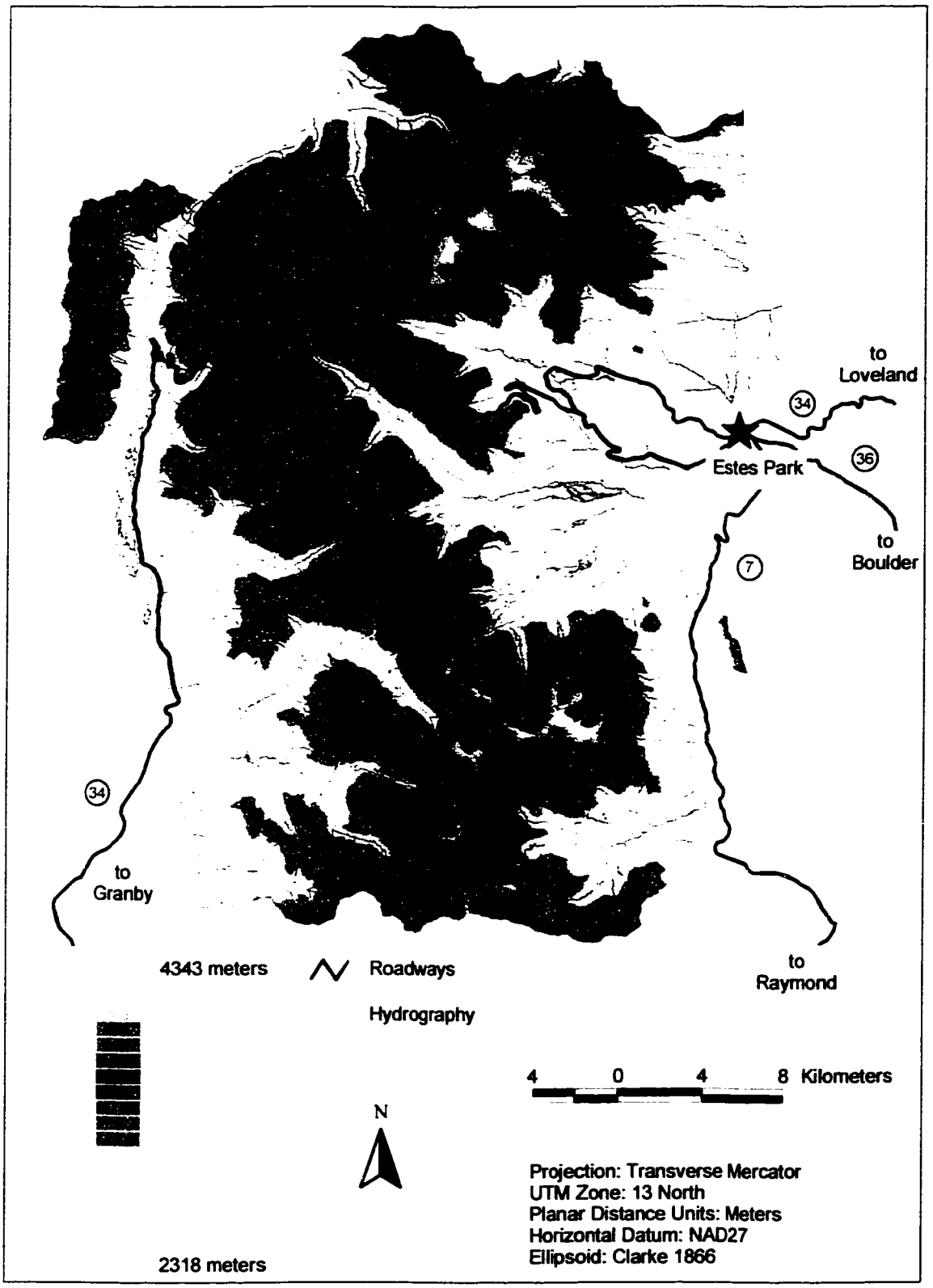
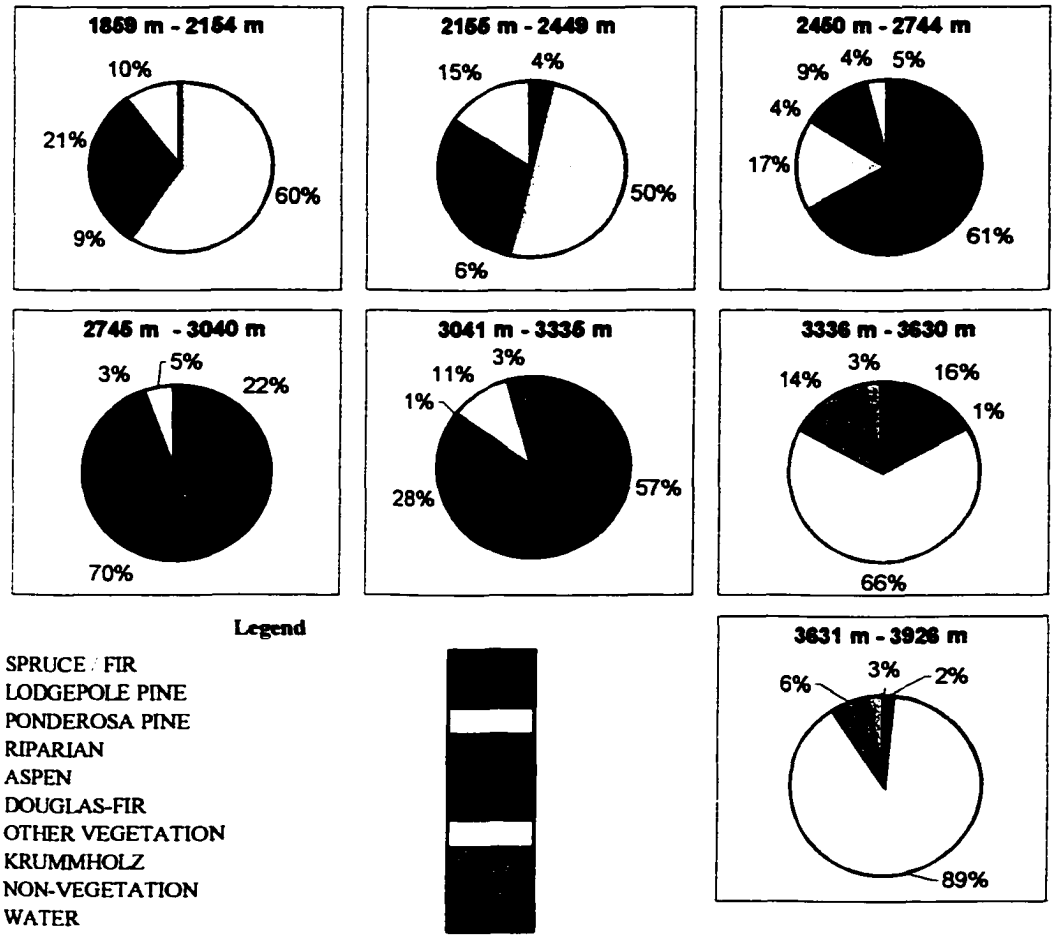
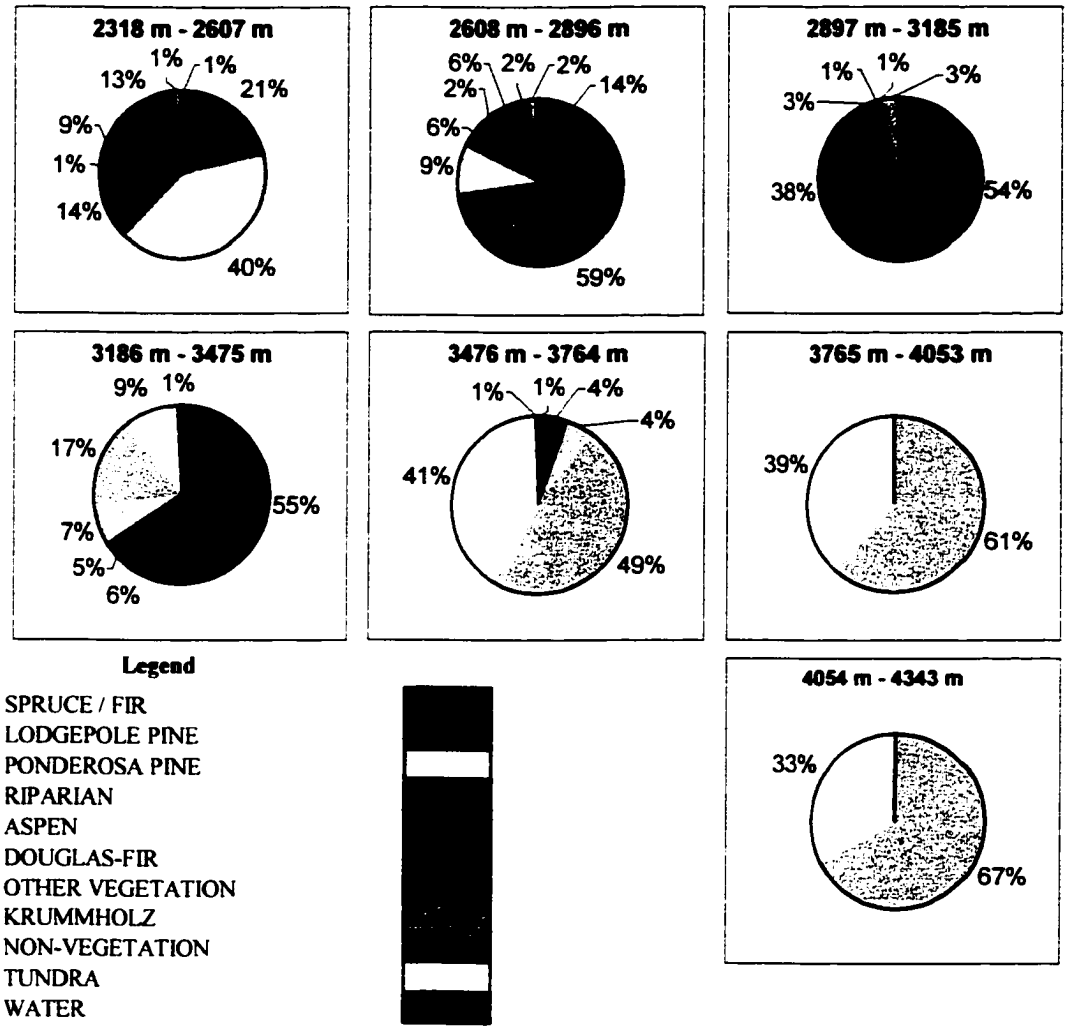


Figure 4.6: Digital Elevation Model of the Rocky Mountain National Park study area



Cover type	Area (Acres) by elevation zone							Total
	1859 m - 2154 m	2155 m - 2449 m	2450 m - 2744 m	2745 m - 3040 m	3041 m - 3335 m	3336 m - 3630 m	3336 m - 3630 m	
SPRUCE / FIR	0.0	0.0	861.1	11,574.5	31,427.3	3,457.1	32.0	29.8%
LODGEPOLE PINE	1.3	260.2	11,304.1	35,544.4	15,749.9	242.8	0.0	39.7%
PONDEROSA PINE	1,103.5	3,557.1	3,098.8	195.0	0.0	0.0	0.0	5.0%
RIPARIAN	172.1	433.4	18.2	102.3	415.2	78.7	0.0	0.8%
ASPEN	0.0	0.0	638.3	1,474.2	0.0	0.0	0.0	1.3%
DOUGLAS-FIR	394.3	1,762.9	1,584.8	121.2	0.0	0.0	0.0	2.4%
OTHER VEGETATION	185.9	1,088.2	692.3	2,663.6	5,854.4	14,649.1	1,762.7	17.0%
KRUMMHOLZ	0.0	0.0	0.0	32.0	1,895.4	3,100.1	126.8	3.2%
NON-VEGETATION	0.0	0.0	16.7	20.7	178.6	642.7	53.8	0.6%
WATER	6.4	28.9	0.7	120.3	217.5	86.3	0.0	0.2%
Total	1.2%	4.5%	11.5%	32.6%	35.0%	14.0%	1.2%	100.0%

Figure 4.7: Area distribution of the cover types in relation to their elevation in the Roosevelt National Forest Wilderness areas.



Cover type	Area (Acres) by elevation zone							Total
	2318 m - 2307 m	2608 m – 2896 m	2897 m - 3185 m	3186 m - 3475 m	3476 m - 3764 m	3765 m - 4053 m	4054 m - 4343 m	
SPRUCE / FIR	85.4	6,376.8	33,882.7	44,109.1	720.3	0.0	0.0	31.9%
LODGEPOLE PINE	2,539.0	27,034.0	23,703.9	5,278.2	9.8	0.0	0.0	22.0%
PONDEROSA PINE	4,983.1	4,298.6	176.6	0.0	0.0	0.0	0.0	3.5%
RIPARIAN	1,688.6	2,963.8	1,831.8	4,267.7	2,088.5	6.0	0.0	4.8%
ASPEN	120.1	1,047.0	270.9	38.0	3.6	0.0	0.0	0.6%
DOUGLAS-FIR	1,118.8	2,535.2	422.1	1.1	0.0	0.0	0.0	1.5%
OTHER VEGETATION	1,535.8	964.7	344.3	157.9	7.1	0.0	0.0	1.1%
KRUMMHOLZ	0.0	0.0	190.8	5,896.4	2,291.7	0.0	0.0	3.1%
NON-VEGETATION	173.5	699.2	1,746.9	14,261.2	25,227.0	6,676.6	442.3	18.5%
TUNDRA	0.0	0.0	88.1	7,652.2	21,256.7	4,209.0	218.4	12.5%
WATER	13.3	142.1	211.5	470.4	279.5	6.2	0.0	0.4%
Total	4.6%	17.3%	23.6%	30.8%	19.4%	4.1%	0.2%	100.0%

Figure 4.8: Area distribution of the cover types in relation to their elevation in the Rocky Mountain National Park study area.

slope, and stand density all have significant influence on the spectral response of the various forest cover types. According to Blackard and Dean (1999) elevation should be an excellent predictor of forest cover type, although not a perfect one without accounting for the complementary influence of aspect upon cover type. Figures 4.7 and 4.8 show the area distribution of the cover types in relation to their elevation in both study areas.

After appending the 16 and 20 DEM quadrangles in both study areas respectively, but before the DEMs were clipped to the exact boundaries of the study areas, the predictive variables of aspect, slope, vertical distance to the nearest water surface feature, as well as three relative measures of incident sunlight were developed from the DEMs.

3) ***Aspect*** (degrees): The aspect maps were developed from the DEMs using standard GIS surface analysis. The aspect variable for the Roosevelt National Forest Wilderness Areas is presented in Figure 4.9. (Note: for simplicity, not all the maps of both areas are shown, but simply the illustration of one or the other area used in the study.)

4) ***Slope*** (degrees): In a similar way as the aspect, slope maps in degrees were produced using standard GIS surface analysis procedures. The slope variable for Rocky Mountain National Park study area is presented in Figure 4.10.

The distribution of many cover types is strongly correlated to the topographic characteristics of the terrain, making them more likely to occur on a particular slope or aspect. The fact that this parameters influence temperature and amount of moisture

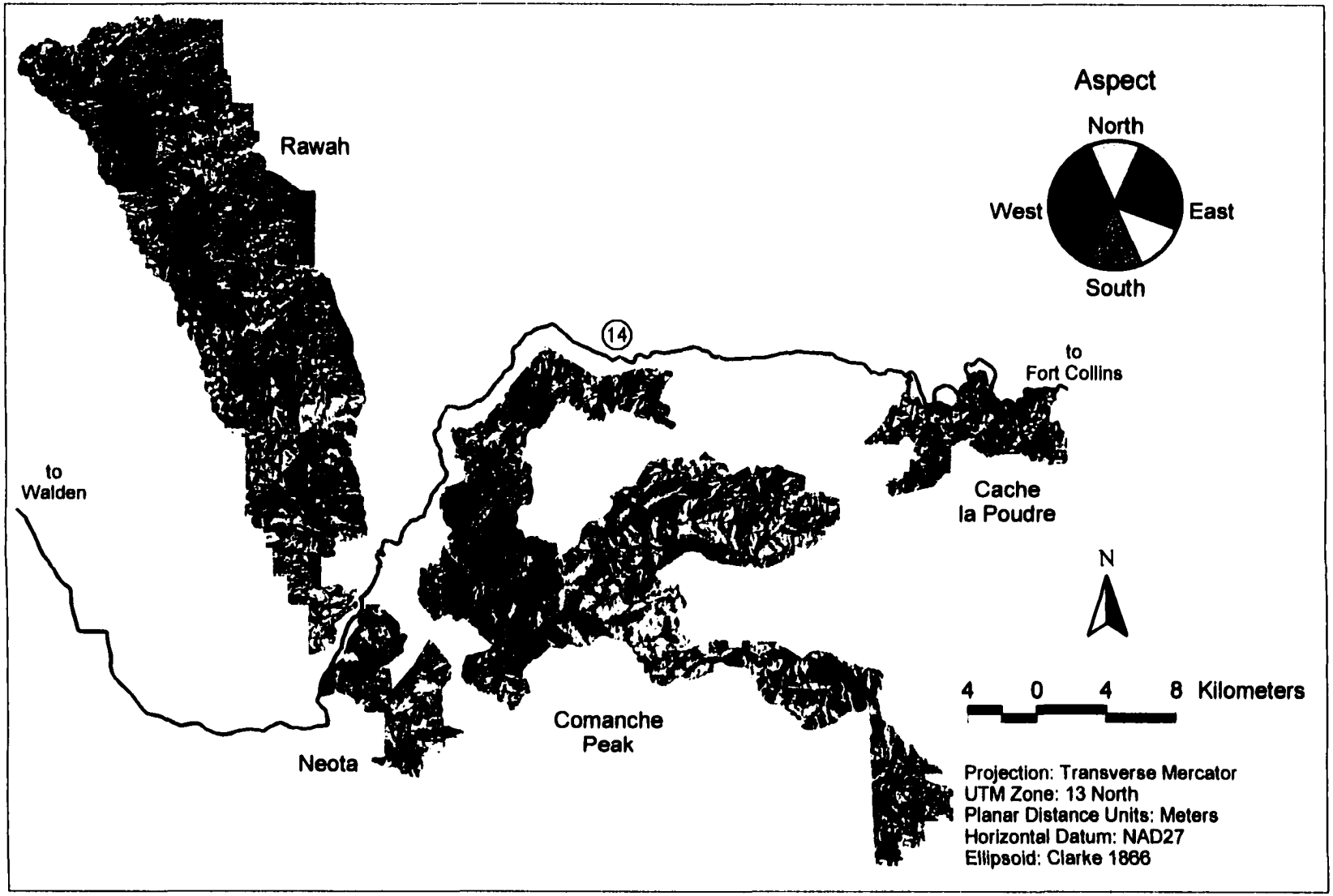


Figure 4.9: Aspect values of the Roosevelt National Forest Wilderness areas

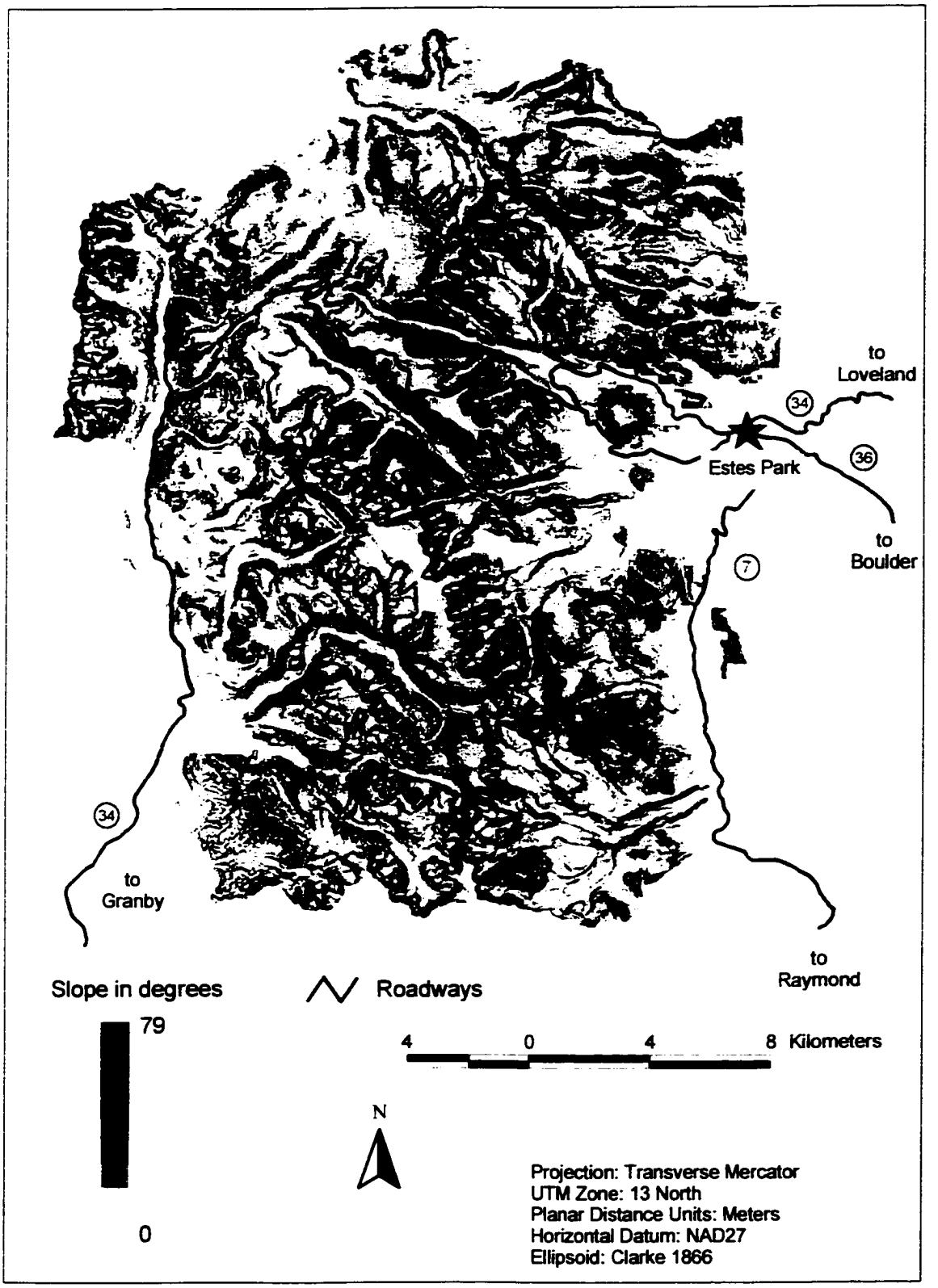


Figure 4.10: Slope values in the Rocky Mountain National Park study area

available to forest stands should make them important as predictive variables Blackard (1998).

5) Relative measure of incident sunlight

The amount of sunlight received by the vegetation is determined by the topography and time of the day. Therefore, a relative measure of incident sunlight should be especially useful in areas with steep terrain, where the complex topography can produce long periods of non-exposure to direct sunlight. Since the study areas are generally rolling to mountainous terrain, according to Blackard (1998), three incident sunlight indices (rather than one) were used to provide a better indication of the overall radiation in each cell:

a. ***Relative measure of incident sunlight at 9 a.m. on the summer solstice*** (index):

The relative measure of incident sunlight at 9 a.m was calculated by determining an approximate sun position (altitude and azimuth) in relation to a centrally located ground position for both study areas. This ground position was arbitrarily selected as N40°40' latitude and W105° 40' longitude, which lies within the Comanche Peak wilderness area (Blackard 1998). The sun position (altitude and azimuth) at 9 a.m. as determined by Blackard (1998) was 114° azimuth and 59° altitude. These sun angle values were then used as inputs into a GIS hill shading procedure along with the DEMs of the study areas, to calculate the relative measure of incident sunlight values received by

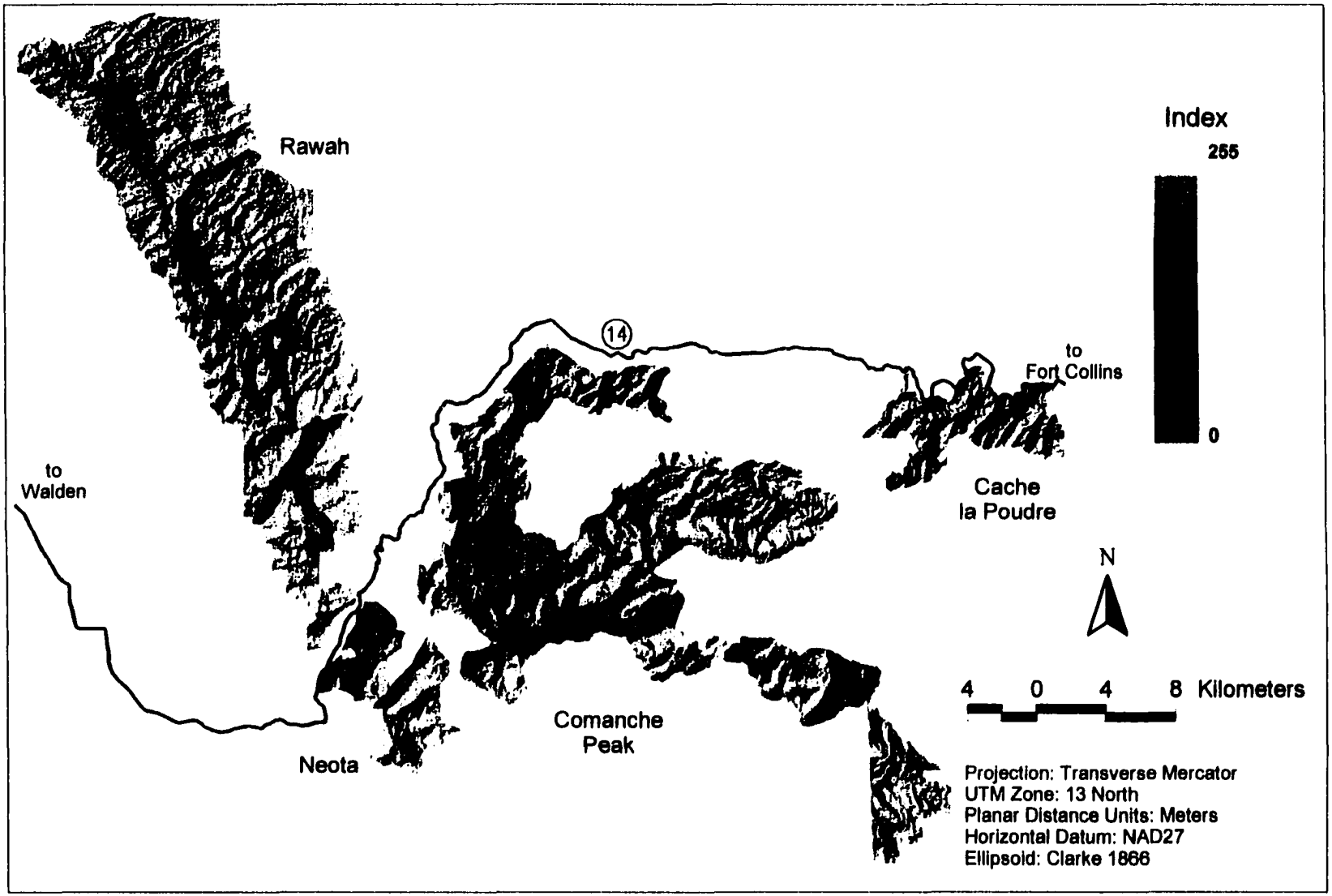


Figure 4.11: Relative measure of incident sunlight for the Roosevelt National Forest Wilderness areas at 9 a.m. on the summer solstice.

each raster cell. Figure 4.11 shows the incident sunlight variable at 9 a.m. for the Roosevelt National Forest wilderness areas.

b. ***Relative measure of incident sunlight at noon on the summer solstice*** (index):

To generate this variable the sun position (altitude and azimuth) at noon used was 218° azimuth and 69° altitude. As described in the relative measure of incident sunlight at 9 a.m., these sun angle values were the used as inputs into a GIS hill shading procedure along with the DEMs of the study areas, to calculate the relative measure of incident sunlight values received by each raster cell. Figure 4.12 shows the incident sunlight variable at noon for the Rocky Mountain National Park study area.

c. ***Relative measure of incident sunlight at 3 p.m. on the summer solstice*** (index):

To produce this variable the sun position (altitude and azimuth) at 3 p.m. used was 269° azimuth and 38° altitude. As described in the previous two independent variables, these sun angle values were the used as inputs into a GIS hill shading procedure along with the DEMs of the study areas, to calculate the relative measure of incident sunlight values received by each raster cell. Figure 4.13 shows the incident sunlight variable at 3 p.m. for the Roosevelt National Forest wilderness areas.

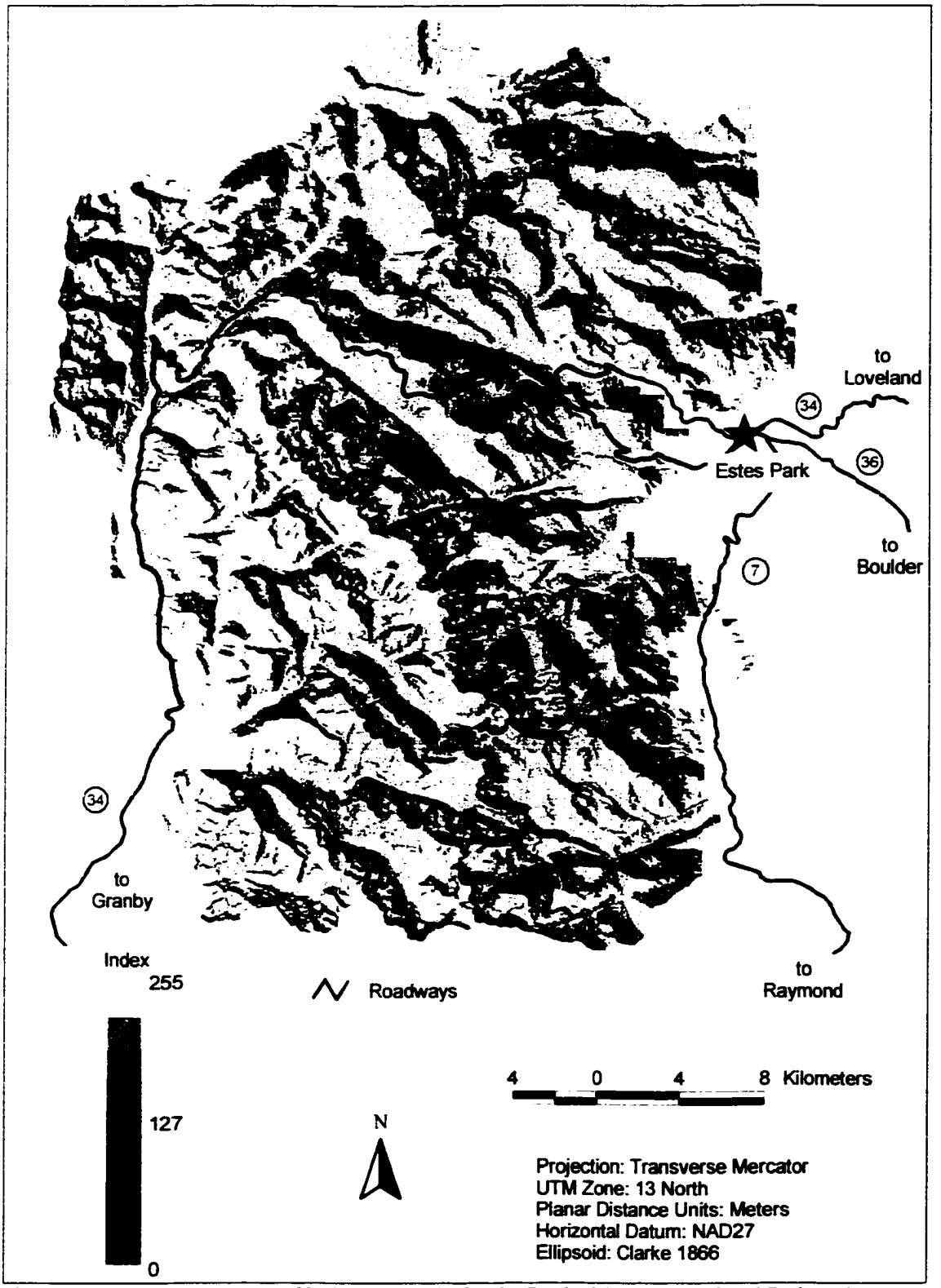


Figure 4.12: Relative measure of incident sunlight for the Rocky Mountain National Park study area at noon on the summer solstice.

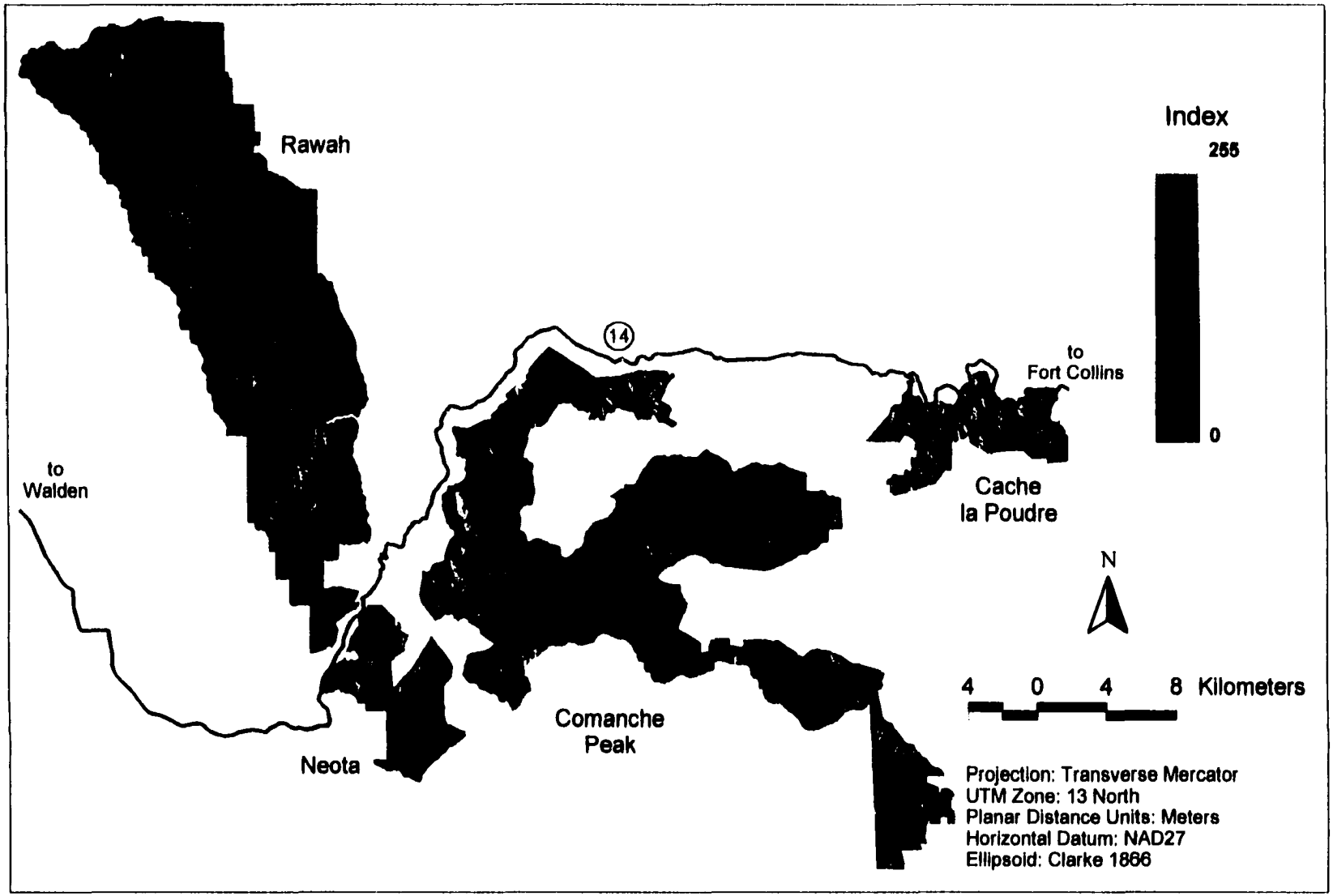


Figure 4.13: Relative measure of incident sunlight for the Roosevelt National Forest Wilderness areas at 3 p.m. on the summer solstice.

6) ***Horizontal distance to the nearest surface water feature*** (meters): The horizontal distance to the nearest surface water feature variable was obtained by applying a Euclidean distance analysis to USGS hydrologic data. Figure 4.14 shows horizontal distance to the nearest surface water feature variable in the Rocky Mountain National Park study area.

7) ***Vertical distance to the nearest surface water feature*** (meters): This distance was calculated by using a combination of the DEM, hydrologic data, and a custom-built analysis function (Blackard, 1998). Figure 4.15 shows the vertical distance to the nearest surface water feature in the Roosevelt National Forest wilderness areas.

   The horizontal and vertical distances to the nearest water feature are particularly useful in the identification of cover types that have a tendency to be located along watercourses. According to Blackard (1998) the additional vertical distance measure may assist in this task for areas of complex or steep terrain, where a particular cell may be horizontally near but vertically distant to a surface water feature.

8) ***Horizontal distance to nearest roadway*** (meters): Using the same procedure applied to the nearest surface water feature, the horizontal distance to the nearest roadway variable was produced using a Euclidean distance analysis to roadway data. Proximity to roadways can provide a good indication of human caused disturbances to otherwise undisturbed forest stands, such as intentional or unintentional ignition of forest fires. . Figure 4.16 shows horizontal distance to the nearest roadway variable in the Rocky Mountain National Park study area.

9) ***Horizontal distance to the nearest wildfire ignition point*** (meters): This variable was generated in a similar procedure as the other horizontal distances from a USFS

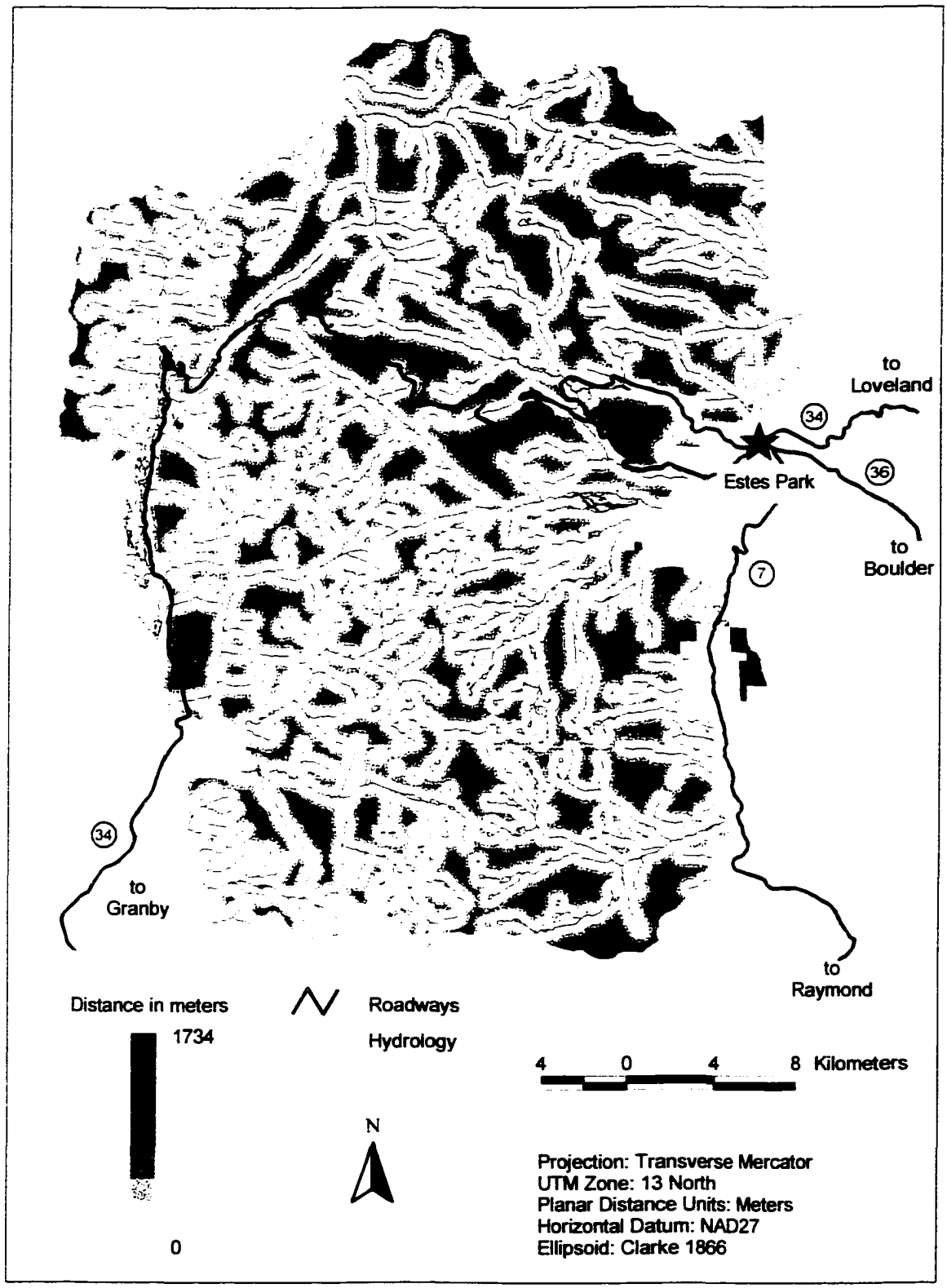


Figure 4.14: Horizontal distance to the nearest surface water feature in the Rocky Mountain National Park study area

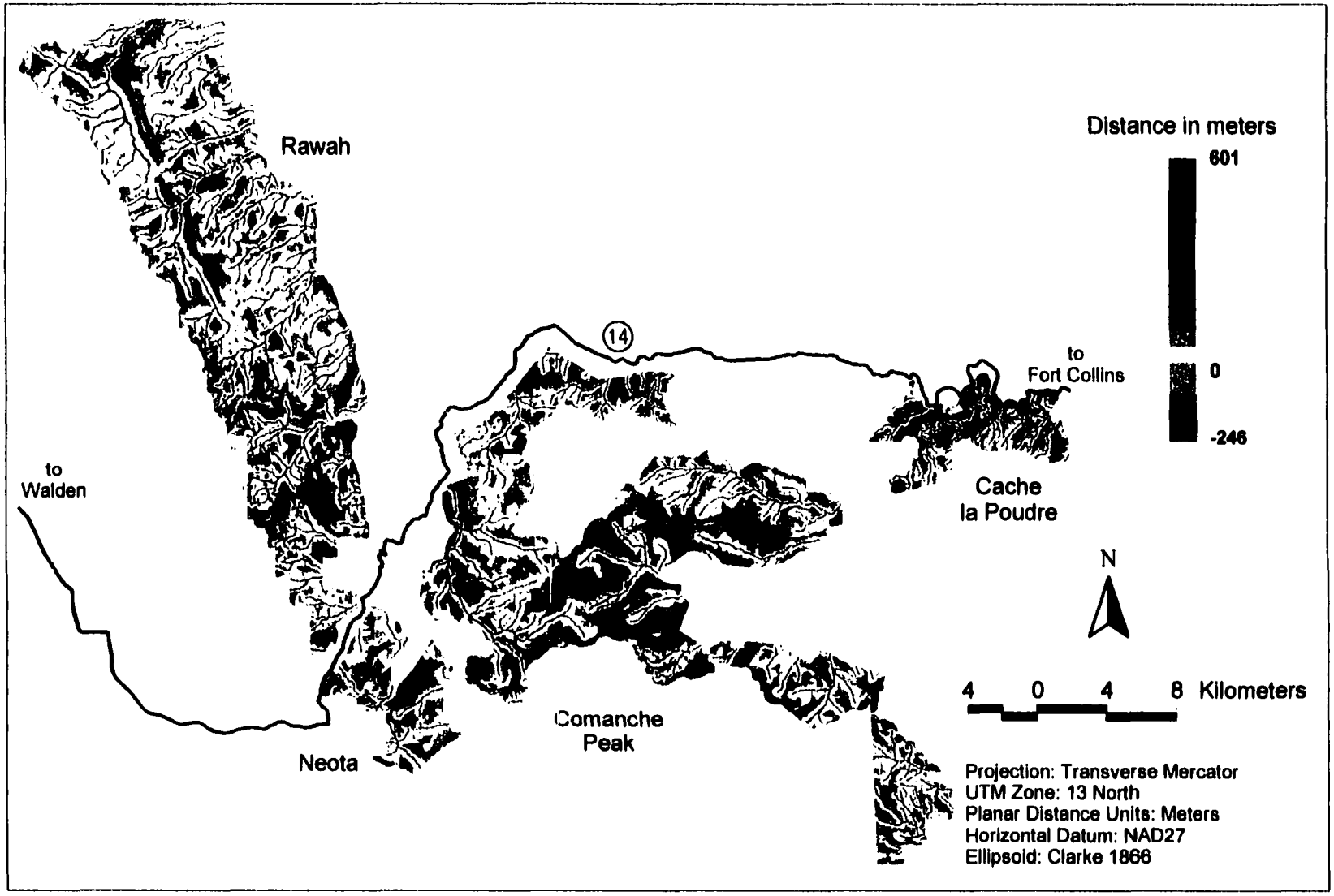


Figure 4.15: Vertical distance to the nearest surface water feature for the Roosevelt National Forest Wilderness areas.

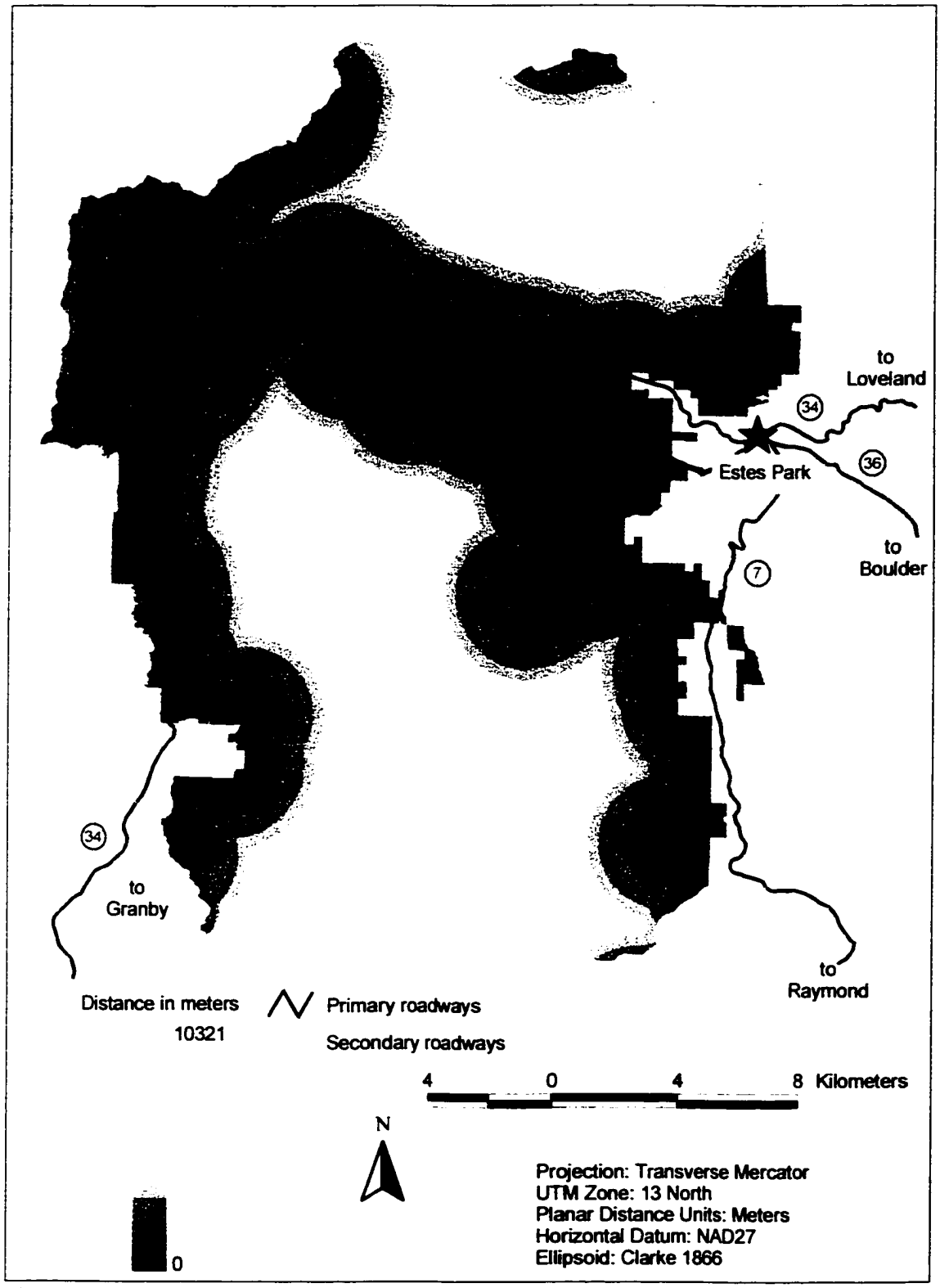


Figure 4.16: Horizontal distance to the nearest roadway in the Rocky Mountain National Park study area

dataset showing fire ignition points recorded in the last 20 years. As in the case of the distance to the nearest roadway its purpose is to model possible disturbance to the forest. However, this data set presents limitations that need to be described. Figure 4.17 shows the horizontal distance to the nearest wildfire ignition point in the Roosevelt National Forest wilderness areas. According to Blackard (1998), although this data set does provide an indication of ignition point locations in the recent past, it does not contain information of historic fire disturbances or conflagrations. This type of information could be very useful, since large fires occurring up to four hundred years ago could have an impact upon present day forest cover types. It also lacks information of the actual extend of the fire disturbances that could allow the identification of geographic areas having possible forest stand-altering disturbances.

10) ***Soil type designation*** (categorical data, binary values): The soil type designation for the Roosevelt National Forest Wilderness areas was obtained from a 1:24,000 scale USFS ecological land type units database. In order to satisfy the requirements of the artificial neural network modeling process, this qualitative variable was transformed to a binary format, such that an observation with a value of 0 would represent an absence, while a value of 1 would represent a presence of a specific soil type. A total of forty-five different soil types characterize the Roosevelt National Forest Wilderness areas. In the case of the Rocky Mountain National Park study area, the soil type designation was obtained from the Soil Survey Geographic (SSURGO) Data produced by the USDA Natural Resources Conservation Service. A total of forty-six different soil types characterize this area. Figure 4.18 shows the soil type designation variable in the Rocky Mountain National Park study area.

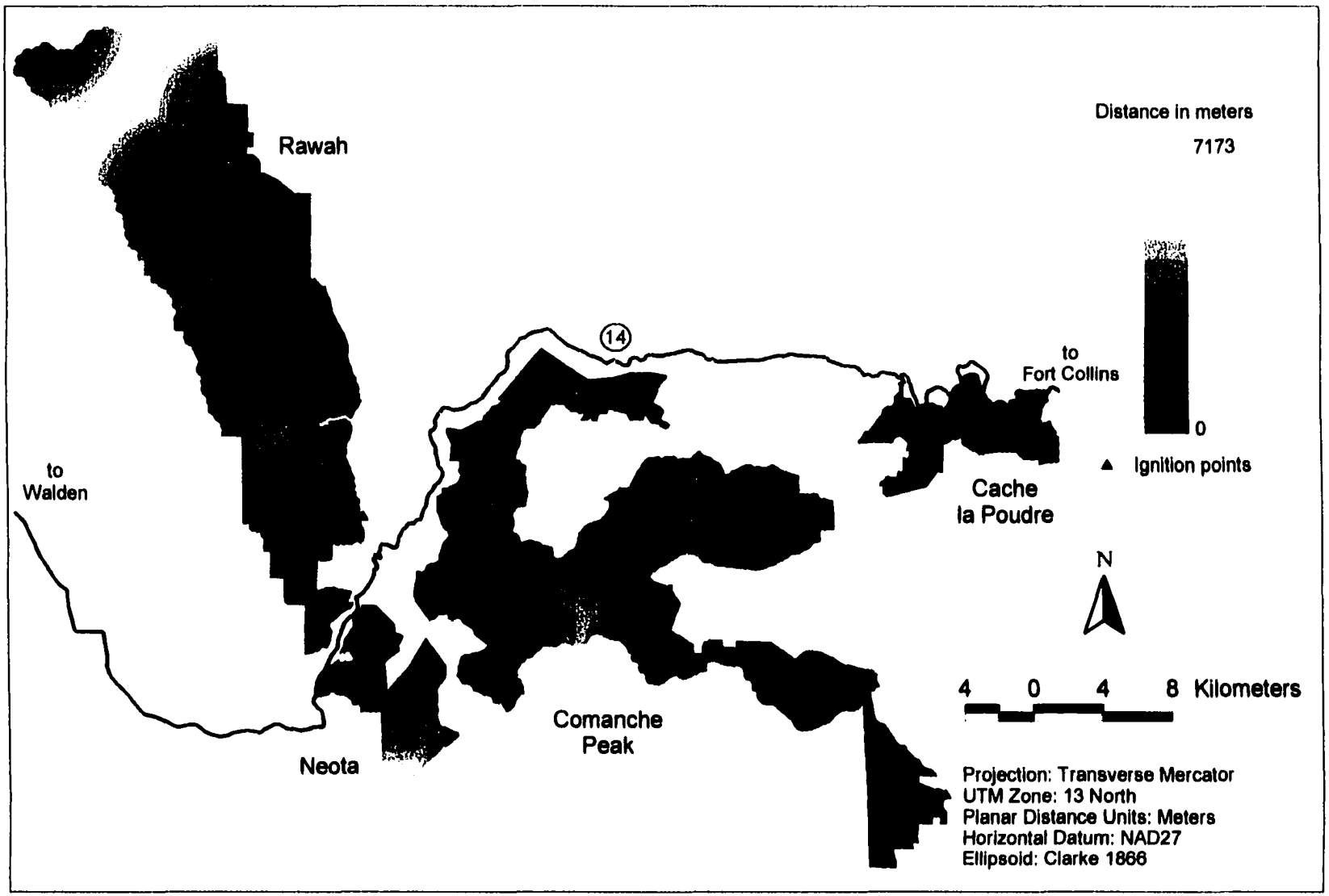


Figure 4.17: Horizontal distance to the nearest wildfire ignition point for the Roosevelt National Forest Wilderness areas.

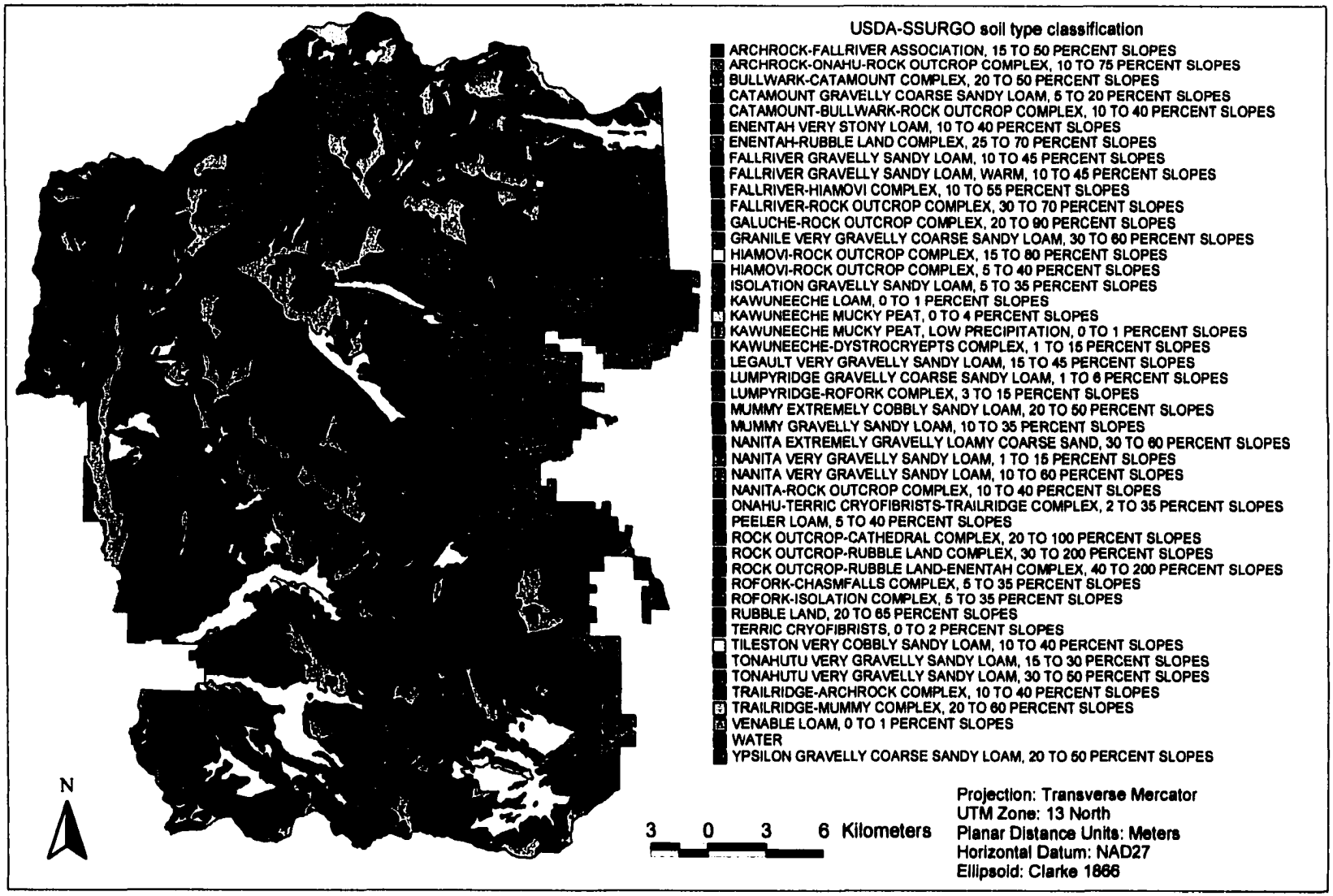


Figure 4.18: USDA-SSURGO soil type classification for the Rocky Mountain National Park study area

The soil type variables were included in the model to assist in the prediction of cover types that might correlate well with characteristics of specific soil types (Blackard 1998).

4.2.2 Satellite data

The satellite imagery consisted of a seven-band Landsat 5 TM scene acquired in July 5th, 1992. The time of acquisition was at 9:15 a.m. local time with a sun elevation of 59 degrees and an azimuth of 115 degrees. The scene, centered over Estes Park (Landsat TM Pathfinder path 34, row 32) was completely cloud free.

The 1992 Landsat image was preferred over a more recent Landsat TM7 scene due to ideal environmental conditions, as well as the considerably smaller amount of snow at that particular point in time. These conditions allowed the exposure of more cover types at higher elevations making the satellite data more consistent with the reference data. In addition to this, the date of acquisition of the selected image is closer to the time when the reference data was produced, which reduces the chance of possible disturbances that might have caused cover type changes in the meantime. The seven bands of the 1992 Landsat TM scene are presented in Figure 4.19.

4.2.3 Aerial-photo index

An aerial photo index in digital format was obtained from the Larimer County GIS Division. This index corresponds to a project that acquired color aerial photographs at a 15,480 scale of the entire county in July and August of the year 2000. This dataset was used to develop the sampling methodology (described in a later chapter) and to

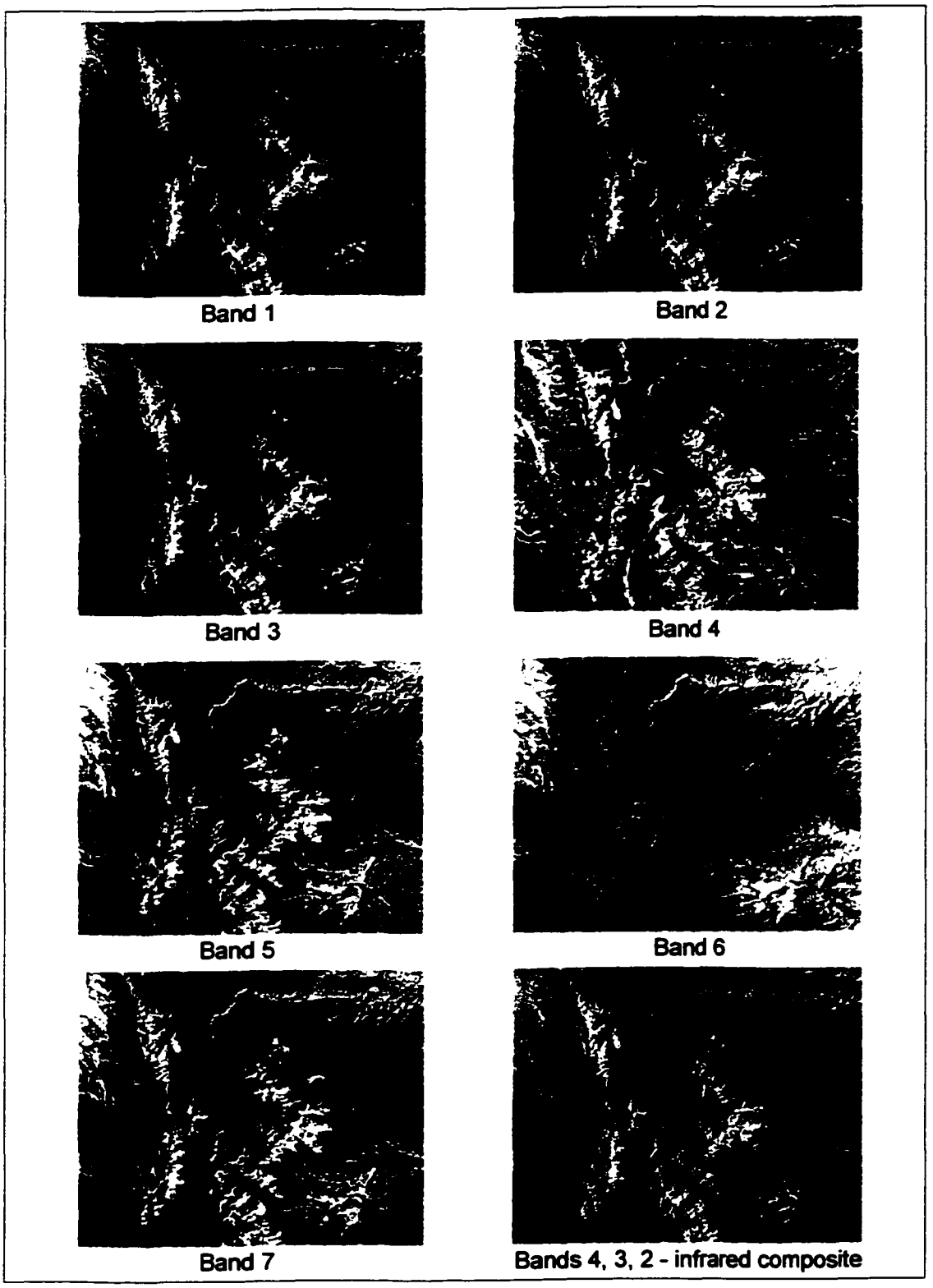


Figure 4.19: Subset of the 1992 Landsat TM scene of the study areas showing the seven spectral bands and 4-3-2 infrared composite.

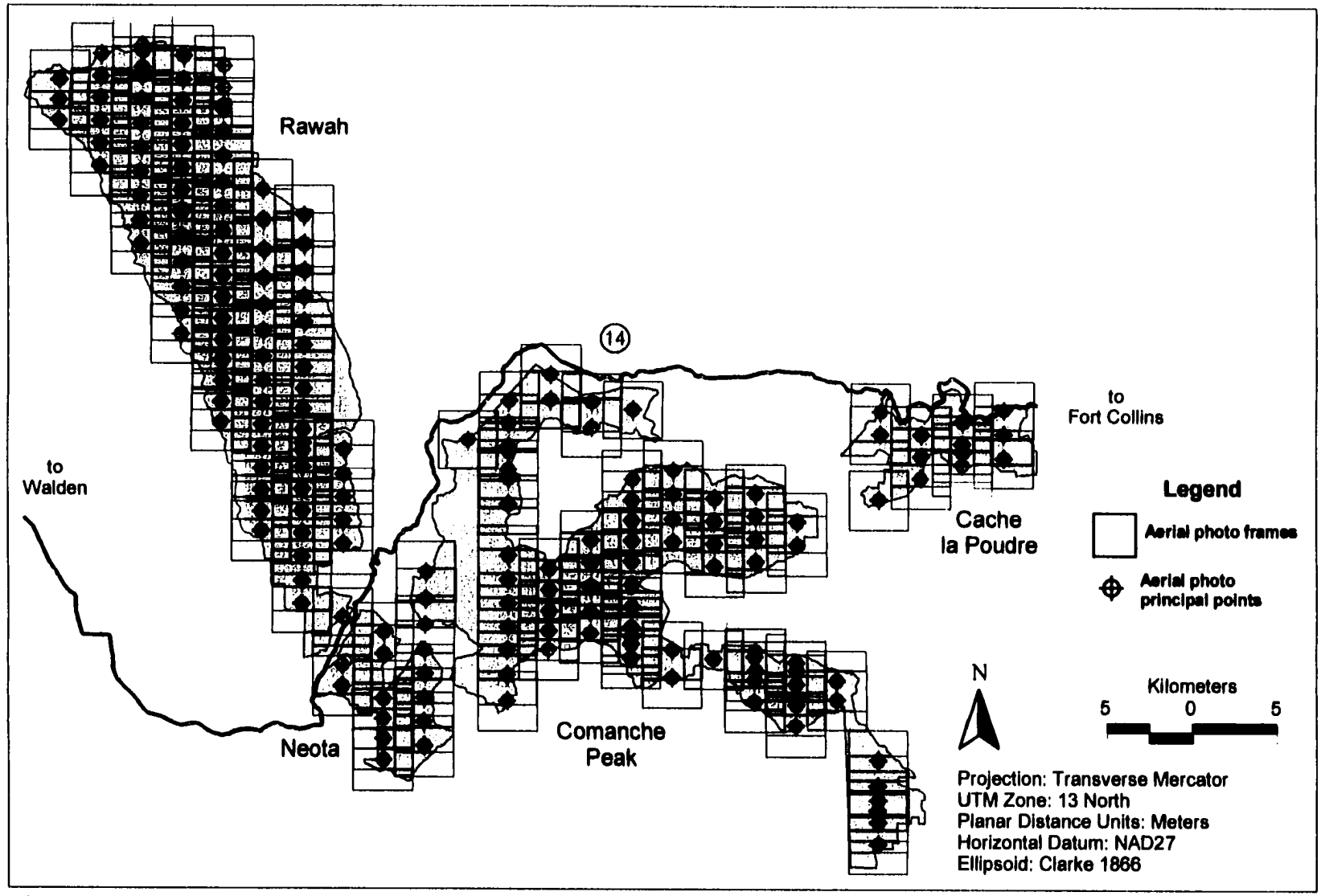


Figure 4.20: Aerial photo index of the Roosevelt National Forest Wilderness areas

provide a reference of ancillary data for the evaluation of the classification. The aerial photo index for the Roosevelt National Forest Wilderness Areas is presented in Figure 4.20.

4.2.4 Additional data preparation and preprocessing

4.2.4.1 GIS data

Besides the particular procedures used in the development of each of the GIS data sets explained above in the GIS data description section, the data sets were geo-referenced to the following standard coordinate system parameters:

Projection: Universal Transverse Mercator (UTM),

UTM zone: 13 North,

Planar distance units: meters,

Horizontal Datum: North American Datum (NAD) 27.

4.2.4.2 Satellite imagery

- ***Radiometric correction***: The Landsat TM5 scene was inspected for data errors such as line dropouts, stripping, and line start problems. Nevertheless, the scene presented no errors making any rectifications unnecessary.
- ***Geometric correction***: The Landsat TM image was already geometrically rectified to the exact same parameters as the GIS data (i.e., Universal Transverse Mercator coordinate system; UTM Zone: 13 North; datum: NAD27; spheroid: Clarke 1866). However, it was necessary to resample the image to a 30 m pixel size in order for its pixels to be congruent with the grid cells of the GIS data.

- ***Image enhancement***: Several image enhancement techniques such as linear contrast stretch, histogram equalization, and filtering were applied to the image to facilitate visual interpretation. This was important for the familiarization of the interpreter with the distribution and characterization of the cover types on the satellite image, as well as to compare the image to the existing reference cover type maps in both study areas. However, none of these enhanced images were used in the actual image classification procedure, as the enhancement procedures alter radiometric characteristics of the data, and therefore are generally considered to be inappropriate as input to the classification algorithms.

4.2.4.3 Satellite imagery and GIS data

- ***Data reduction:*** Once the seven Landsat TM bands and the GIS data sets were co-registered, all the data sets were clipped to the boundaries of both study areas (i.e. to the boundaries of the Roosevelt National Forest Wilderness areas and Rocky Mountain National Park) using GIS masking procedure in order to reduce computer-processing time. In addition to this, the data was carefully inspection to ensure they have the same number of grid-cells and/or pixels.

- ***Data transformation:*** After the data size was reduced, it was necessary to convert it to text format (i.e., ASCII) in order to be incorporated to the neural network modeling process. This was performed using a commonly used GIS function. Each of the variables was then parsed from a two-dimensional text matrix to a single column of data using a simple C-code program created for this purpose.

- ***Data scaling***: In order to incorporate the data to the neural network, it needs to be scaled according to the form of the activation function used (e.g., a sigmoid function

or an hyperbolic tangent function). Feature values (e.g., 8-bit digital data scaled from 0 to 255) should be centered and scaled to the activation function's range (usually 0 to 1 or −1 to 1) in order to avoid early saturation effects and local minima. This was performed using the *Data Transformation* commands in the case of the NeuralSIM artificial neural network modeling procedure, and by applying a normalization sequence in the case of the MATLAB modeling (Anderson, 1998).

4.3 Experimental design

4.3.1 Data selection

Many studies conducted over the years have indicated that identifying an effective, representative set of training data is one of the most critical aspects of computer analysis of remotely sensed data (Hoffer 1986, Campbell 1996). In an ideal statistical sampling the data is selected in an absolute random fashion. However, in practice the geographic characteristics of the terrain make such an approach economically unfeasible, more so when working with very large areas, as in the case of this study. In any sampling procedure the distribution of the sample should be proportional to the distribution of the original population. Nevertheless, in the process of training an artificial neural network, very large or numerous classes can overshadow very small classes, especially when working with noisy data, where the variation of noise can be larger than some very small classes (Dean 2001, personal communication). One of the most important parts of this study was to develop a sampling methodology compatible with both statistical and neural network requirements, but which also allows for a practical and economical way of field sampling and error-checking. Having this in mind, a stratified systematic random

sampling approach was developed. For this purpose, an area equivalent to 20 aerial photos was selected in each of the study areas.

4.3.1.1 Data selection in Roosevelt National Forest Wilderness Areas

In the case of the Roosevelt National Forest Wilderness areas, 20 principal points where selected from a total of 202. For the selection, the area was stratified in 4 strata representing the boundaries of the four wilderness areas (i.e., Rawah, Neota, Comanche Peak and Cache la Poudre) in order to include all of them in the sample. Then, a second stratification was performed using the DEM to generate seven elevation strata of approximately 1000 feet (300 meters) to ensure that samples covering the entire range of elevation were obtained. The starting point of the sampling was selected randomly and the spacing varied within each stratum according to its size.

In order to smooth the progress of the study and given the availability of complete reference datasets, no photo-interpretation, and thus no aerial photos were needed to obtain the training, testing and validation data. Instead, the corresponding information was extracted from the reference data by delineating blocks that represented an area equivalent to the effective areas of aerial photos. Once the principal points were selected, a 6 by 6-inch sample block was defined around each point using a customized GIS function. These polygons were equivalent to an area of 79 by 79 grid-cells and represented the effective area of the aerial photos. Under regular circumstances, in absence of reference data, the data to train and evaluate the classification would have been obtained through photo-interpretation of twenty 1:15,480 color infrared aerial photos. Since the purpose of this study was to develop a widely applicable classification

technique, an approach was developed to simulate the use of aerial photos. A diagram of a block representing an aerial photo and its effective area is presented in Figure 4.21.

After the blocks were systematically distributed, the cover type information was extracted from the Roosevelt National Forest Wilderness areas reference map using a simple GIS procedure. Figure 4.22 shows the spatial distribution of the sampling blocks containing cover type information in the Roosevelt National Forest Wilderness areas. The statistical distribution of the cover types in the sample versus their distribution in the original population can be compared in Figure 4.23.

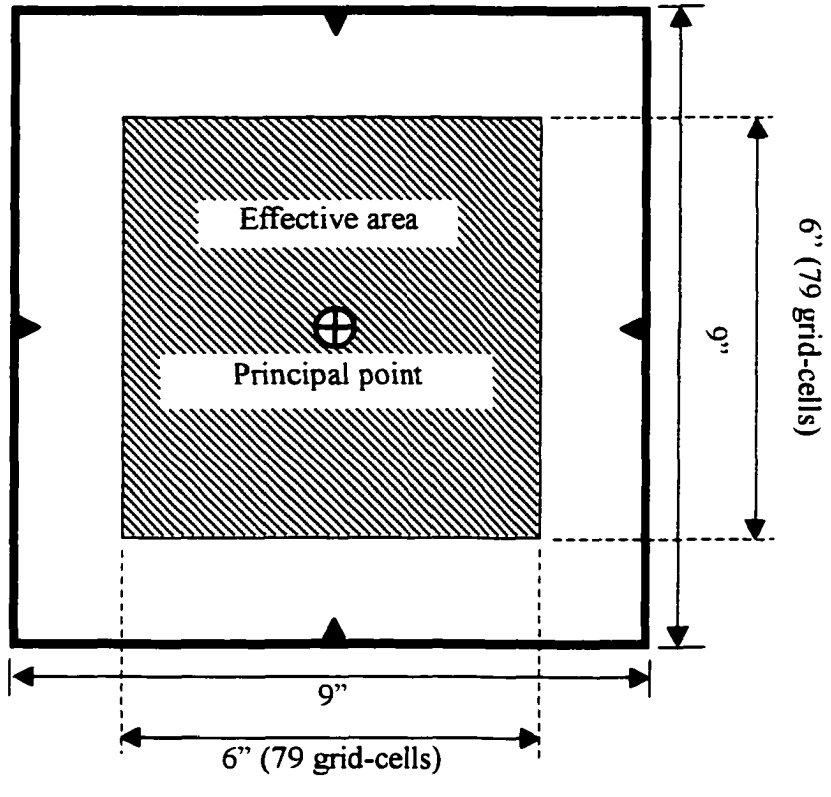


Figure 4.21: Diagram of a simulated aerial photo and its effective area

Figure 4.22: Spatial distribution of the sample blocks containing cover type information in the Roosevelt National Forest Wilderness areas

In order to comply with the requirements of the artificial neural network, a second stage sampling was performed using the sampling material obtained in the systematic random sampling. Within this sampling material, a stratification of the cover types distribution was performed using the following criteria to select a predetermined number of observations (i.e. raster cells or pixels corresponding to a particular cover type) for the training, testing and validation datasets:

(1) Vegetation cover types (highest classification priority): Initially the selection of the sampling material for all vegetation cover types was based on the data available for the least numerous cover type (riparian), which totaled 703 observations. According to Blackard (1998) utilizing 60 percent of the available data for training is an effective use of data. Following this condition, 60 percent (421 observations) of all the sample material available for riparian, was assigned for training, 20 percent (141 observations) for testing and 20 percent (141 observations) for validation. The other seven vegetation cover types were going to be sampled using this exact same size and proportions.

Nevertheless, due to the reduced size of the riparian cover type this sample size turned out to be very small to obtain enough sampling material to classify the entire Roosevelt National Forest Wilderness areas, and was increased 60 percent to 674 observations for training, 225 for testing and 225 for validation for the remaining 7 vegetation cover types, so that in the end the total sample size would represent approximately 1% of the study area.

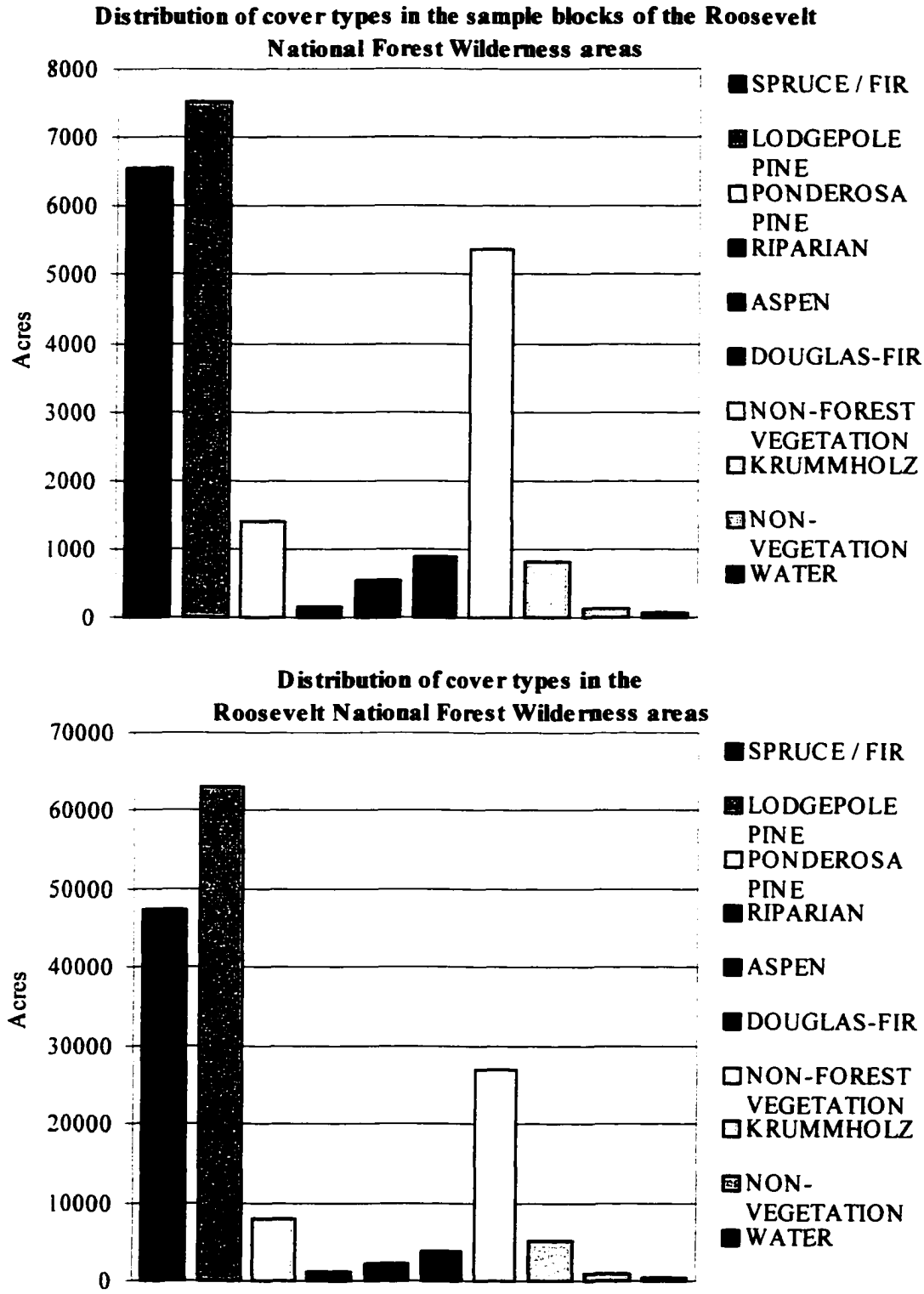


Figure 4.23: Comparison of distribution of the cover types in the sample blocks versus the their distribution in the original population in the Roosevelt National Forest Wilderness Areas.

(2) Non-vegetation cover type except water: As in the case of the vegetation cover types, the selection of Non-vegetation cover types was based on the availability of sampling material (606 observations), of which 60 percent (364 observations) was assigned for training, 20 percent (121 observations) for testing and 20 percent (121 observations) for validation.

(3) Water: In a similar way, the extraction of water sample data was based on the availability of sampling material (318 observations) of which of which 60 percent (190 observations) was assigned for training, 20 percent (64 observations) for testing and 20 percent (64 observations) for validation.

The total number of observations sampled for the Roosevelt National Forest Wilderness areas was 9495 observations or 1.3 percent of the original population size. Figure 4.25 shows the distribution of the cover types in the final sample.

4.3.1.2 Data selection in the Rocky Mountain National Park study area

In the case of the Rocky Mountain National Park study area, another 20 principal points where selected from a total of 85 covering the area, as displayed in the aerial photo index. Only the area of the Park corresponding to Larimer County was sampled because the aerial photo index did not cover the area of the park in Boulder and Grand Counties. For the selection, the DEM of the area was stratified in seven elevation strata of approximately 1000 feet (300 meters) to cover the entire elevation range of the park.

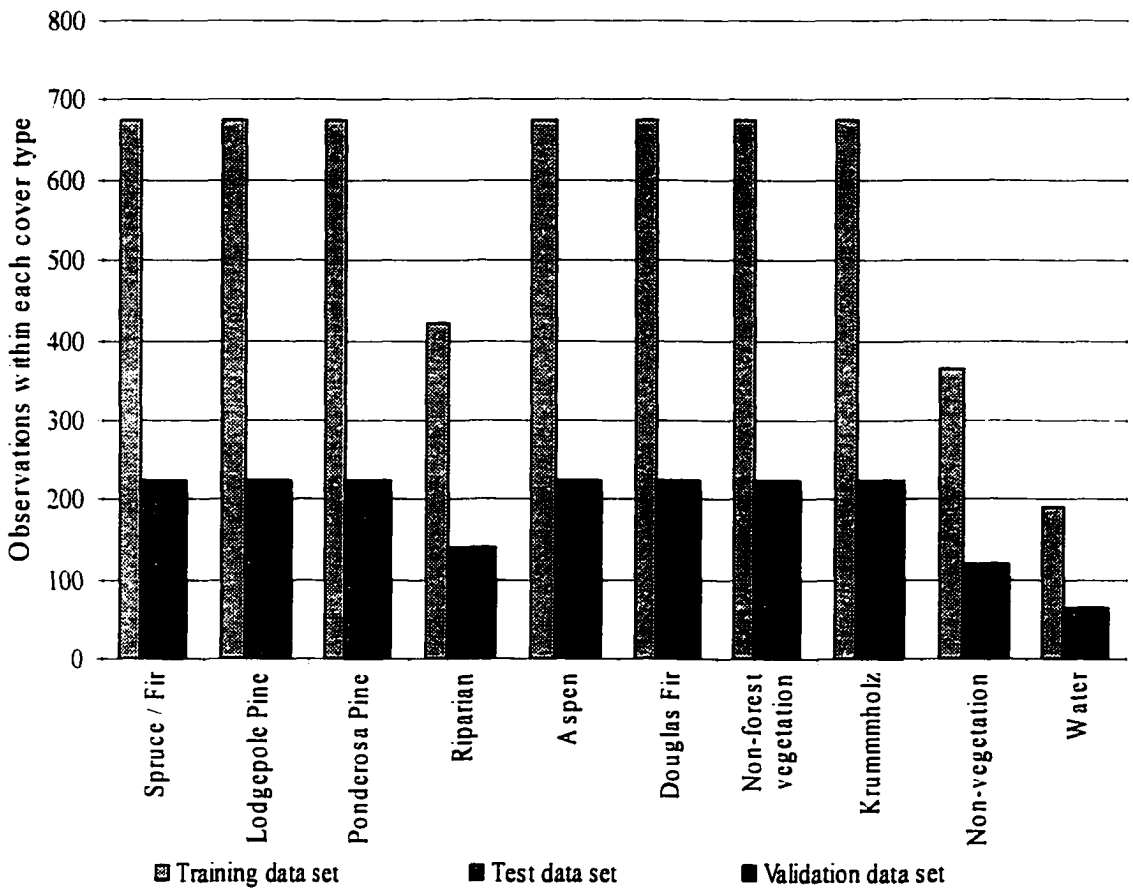


Figure 4.24: Distribution of the cover types for each data set in the final sample for the Roosevelt National Forest Wilderness areas.

Since the area of the park is encompassed within a single boundary unit, there was no need to perform the boundary stratification used in the case of the Roosevelt National Forest Wilderness areas. As described before, the starting point of the systematic sampling blocks was selected randomly and the spacing between blocks varied within each elevation stratum according to its size.

After the blocks were systematically distributed, the cover type information was extracted from the Rocky Mountain National Park reference map using a simple GIS procedure. Figure 4.25 shows the sampling blocks containing cover type information in the Rocky Mountain National Park study area. The distribution of the cover types in the sample and in the original population for the Roosevelt National Forest Wilderness areas can be compared in Figure 4.26

As in the case of the Roosevelt National Forest Wilderness areas, a second sampling was performed within the initial systematic sampling in order to comply with the requirements of the artificial neural network classification. However, based on the initial experience, the stratification of the cover types was slightly modified to improve the classification of this area. The following criteria were used to select the training, testing and validation datasets:

The distribution of the training, testing and validation data sets followed the 60 – 20 - 20 percent rule used before for all cover types. However, the stratification of the cover types was performed by multiplying each cover type in the available sampling data by a weight determined empirically so that the less numerous cover types were proportionally increased in size, but at the same time keeping the distribution of the cover types in the final sample proportionally closer to the distribution of the cover types in the original population. The total number of observations sampled for the Roosevelt National Forest Wilderness areas was 14830 or 1.2 percent of the original population size. Figure 4.27 shows the distribution of the cover types in the final sample for the Rocky Mountain National Park study area.

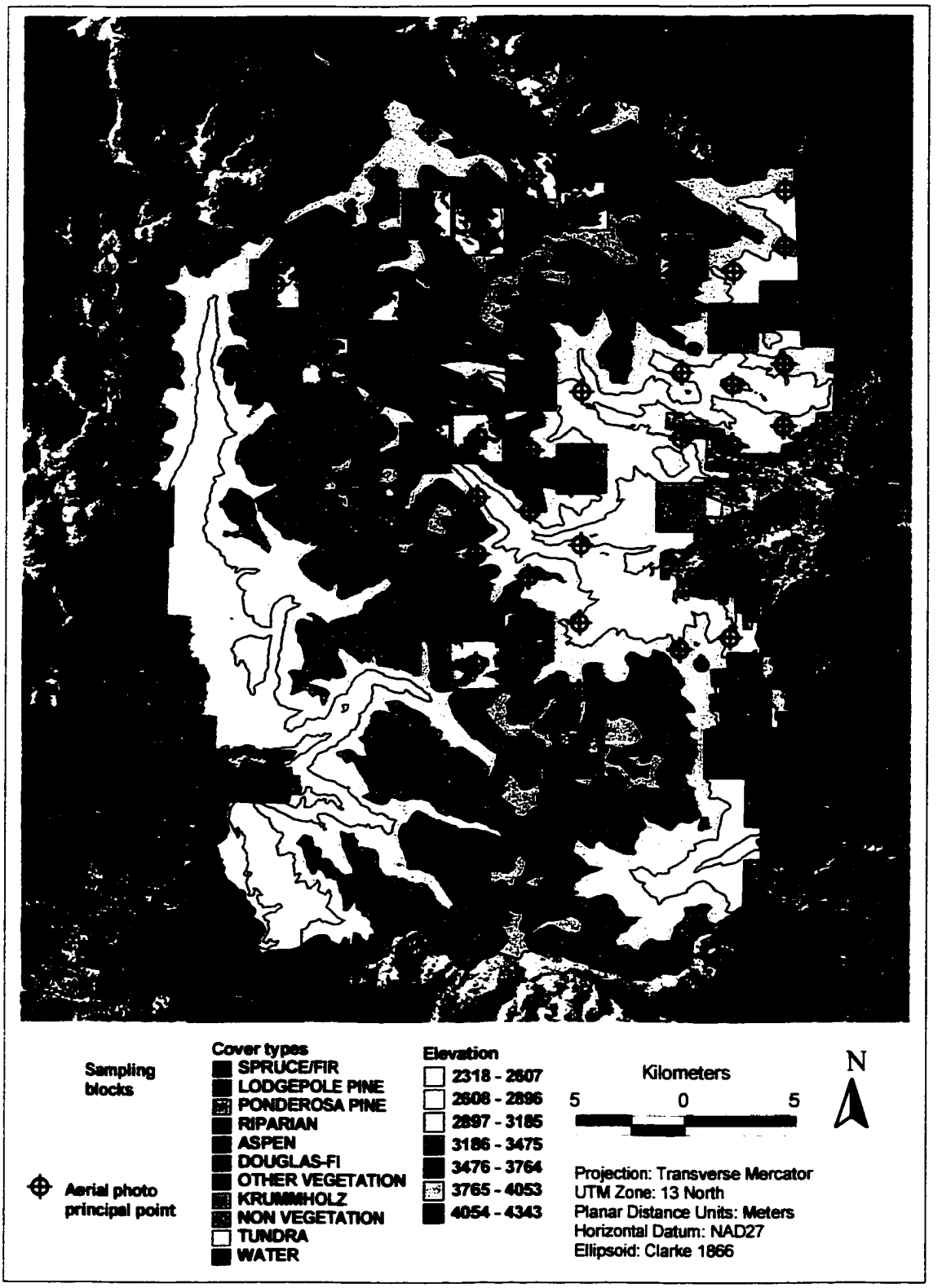


Figure 4.25: Spatial distribution of the sample blocks containing cover type information in the Rocky Mountain National Park area

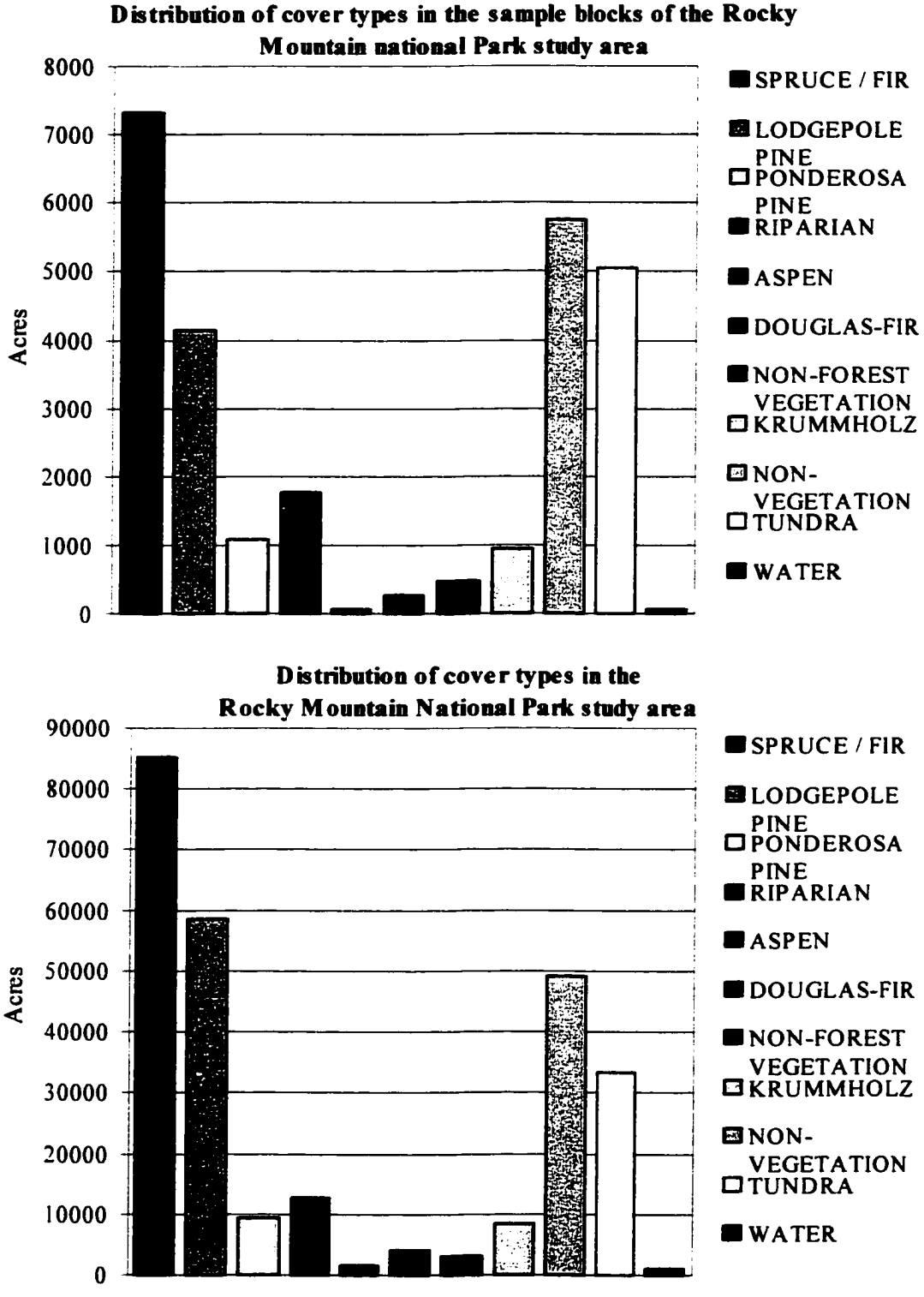


Figure 4.26: Comparison of distribution of the cover types in the sample blocks versus the their actual distribution in the original population in the Rocky Mountain National Park study area.

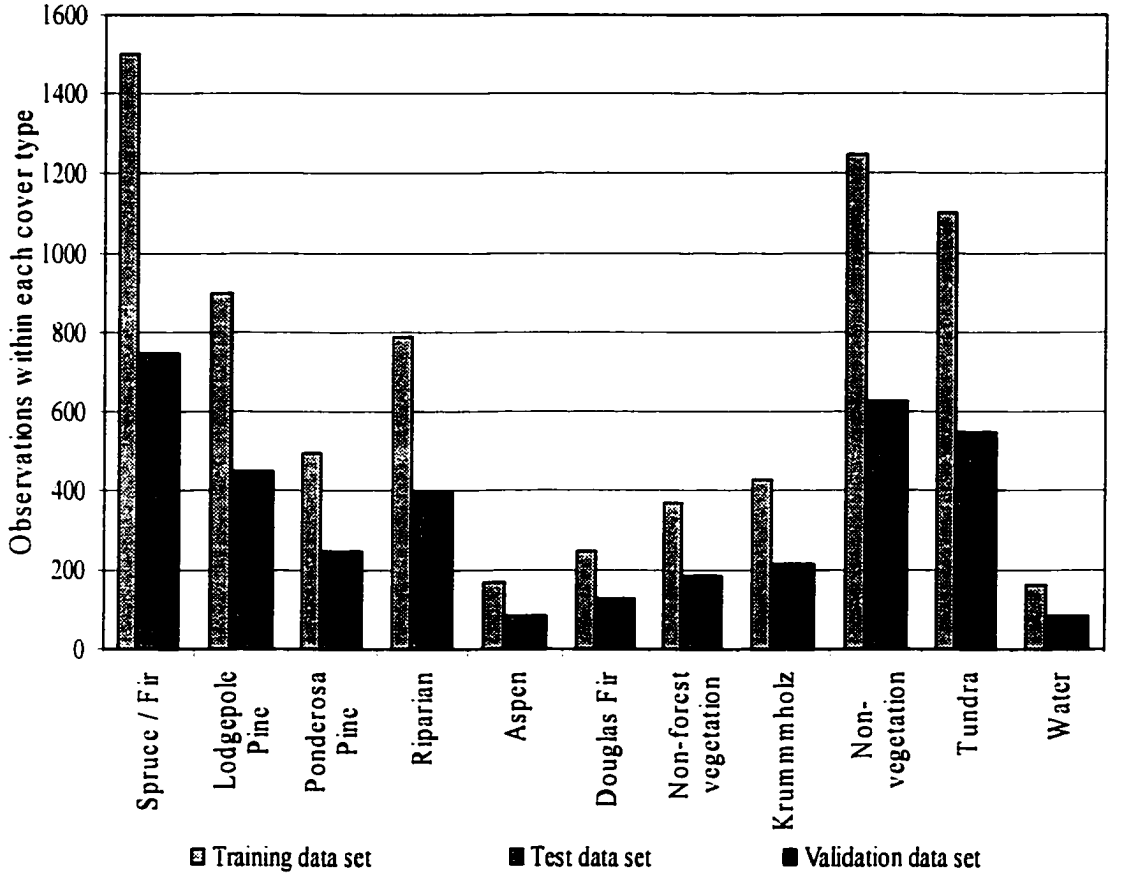


Figure 4.27: Distribution of the cover types for each data set in the final sample for the Rocky Mountain National Park study area.

4.3.2 Development of the Artificial Neural Network model

Once the GIS data to be used in the neural network was generated, the neural network model itself was developed. The model development (or training) used both a subset of the cartographic data derived from the GIS (for the neural network's

independent variables) and a subset of the reference or "truth" data (for the neural network's dependent variables).

As described in the previous section, the subset of cartographic and field reference data was subdivided in 3 independent parts, consisting of training, test, and validation data. In accordance with standard neural network development procedures, the first two datasets were used to train the network, while the latter (validation data) was used to ensure the generalizability of the network's solution.

Exact network parameters (i.e., number of hidden layers, number of nodes per hidden layer, learning rate, momentum rate, etc.) were derived through experimentation and varied in the different models. As recommended by Kanellopoulos and Wilkinson (1997), geometrical arguments and heuristics were applied to define the network architecture. The total number of input features and output classes was carefully examined to define a network size appropriate for the classification problem. To this regard, classification performance was checked during training, as well as the sufficiency of the accuracy achieved with the validation data, to ensure that the classifier generalized well to new, different data. In addition to this, results obtained by Blackard (1998), for a similar modeling experiment in the Roosevelt National Forest Wilderness areas, showed that a model containing 54 input variables obtained a considerably better classification accuracy result than models developed with fewer variables, indicating the benefit to use all the available variables.

Two parallel approaches were undertaken to develop the artificial neural network models. The first approach involved the use of MATLAB. In the second approach, the NeuralSIM software package developed by Aspen Tech was utilized. Since MATLAB

and NeuralSIM operate in very different ways, this comparative experiment provided an additional reference point to evaluate behavior of the model ([1]).

4.3.2.1 Artificial Neural Network Model development using MATLAB

For the development of the artificial neural network model with MATLAB, customized programs written by Dr. Charles Anderson of the Computer Science Department at Colorado State University were applied. The type of network utilized in the MATLAB models was the *multi-layer perceptron* trained with the *backpropagation* algorithm, in which the input, hidden and output layer nodes were fully connected. This type of network is the most widely applied in the classification of remotely sensed data and has proved to be very effective (Paola and Schowengerdt 1993, Wilkinson 1996, Atkinson and Tatnall 1997, Benediksson and Sveinsson 1997, Blackard and Dean 1999). The *generalized delta rule* with gradient descent was used in the network training, and the activation function for the hidden and output layers was the *hyperbolic tangent* (*tanh(z)* = sinh(z) / cosh(z)).

The neural network architecture and learning parameters that give the best results for a particular problem can only be determined experimentally, and this can be a lengthy process, especially for large classification tasks (Kanellopoulos and Wilkinson 1997). For that reason, a number of trial-and- error experiments were performed to determine the architectural and training parameters required by the network.

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[1] ***Note***: the results of the derivation of the neural network parameters and training development, using both MATLAB and NeuralSIM, are presented in the following sections because they were a necessary previous step to the classification procedure.

The first two of these parameters were the optimal learning rate (η) and momentum rate (α). These are two parameters required to initialize the backpropagation algorithm that must also be determined by trial-and-error. The learning rate is a parameter that controls the amount by which weights are changed during training (Fausett 1994). The smaller the learning rate magnitude, the smaller the changes in the weights from one iteration to the next. Smaller changes produce a smoother trajectory in weights space, but also a slow rate of learning. Alternatively if the learning rate is very large, the risk of oscillatory weight changes fluctuating around an optimum increases (Blackard 1998). The momentum rate is a common modification to the standard backpropagation training by which, at each step, weight adjustments are based on a combination of the current weight adjustment (as found in standard backpropagation) and the weight change from a previous step (Fausett 1994). In other words, the momentum rate is a modification of the generalized delta rule in which the equivalent of physical momentum is added to the system to keep the network on its downward path on the energy surface (Caudill and Butler 1992). The generalized delta rule is presented in Eq. (4.1)

$$\Delta w_{kj}(n) = \alpha\Delta\, w_{kj}(n-1) + \eta\delta_k(n)y_{kj}(n) \qquad (4.1)$$

where:

$\Delta w_{kj}(n)$ is the weight adjustment

α is the momentum rate parameter

$\alpha\Delta w_{kj}(n-1)$ the amount of weight change in the previous iteration

η is the learning rate parameter

$\delta_k(n)$ is the local error gradient

$y_{kj}(n)$ output signal from node j into node k

The experiment was designed using the best network parameters obtained by Blackard (1998), and then modifying the learning and momentum rate magnitudes in different combinations to try to improve the performance of the model. The factors evaluated in the experiment were the root mean square error (MSE) of training and validation gradient descent curve, as well as the oscillatory changes of the validation gradient descent curve. Figure 4.28 shows five error gradient descent curves for a neural network with a 55-110-10 configuration using the following learning rates (LR) and momentum rates (MR) combinations: (a) LR = 0.5, MR=0.5; (b) LR = 0.5, MR =0.0;(c) LR = 0.5, MR=0.9; (d) LR = 0.1, MR = 0.1; (e) LR = 0.9, MR = 0.1. Best results were obtained with a learning rate and momentum rates of 0.1. Although a network with these parameters can take more time to train, as shown by the slope of the training and validation gradient descent curves in the 500 epochs experiment, the oscillation of the validation gradient descent curve is minimal, indicating a more stable model. Furthermore, although the difference of the mean square errors between the best candidate, case (d), and the second best candidate, case (b), is very small, the slope of the curve shows a clear downward tendency, indicating that the error can be reduced with further training.

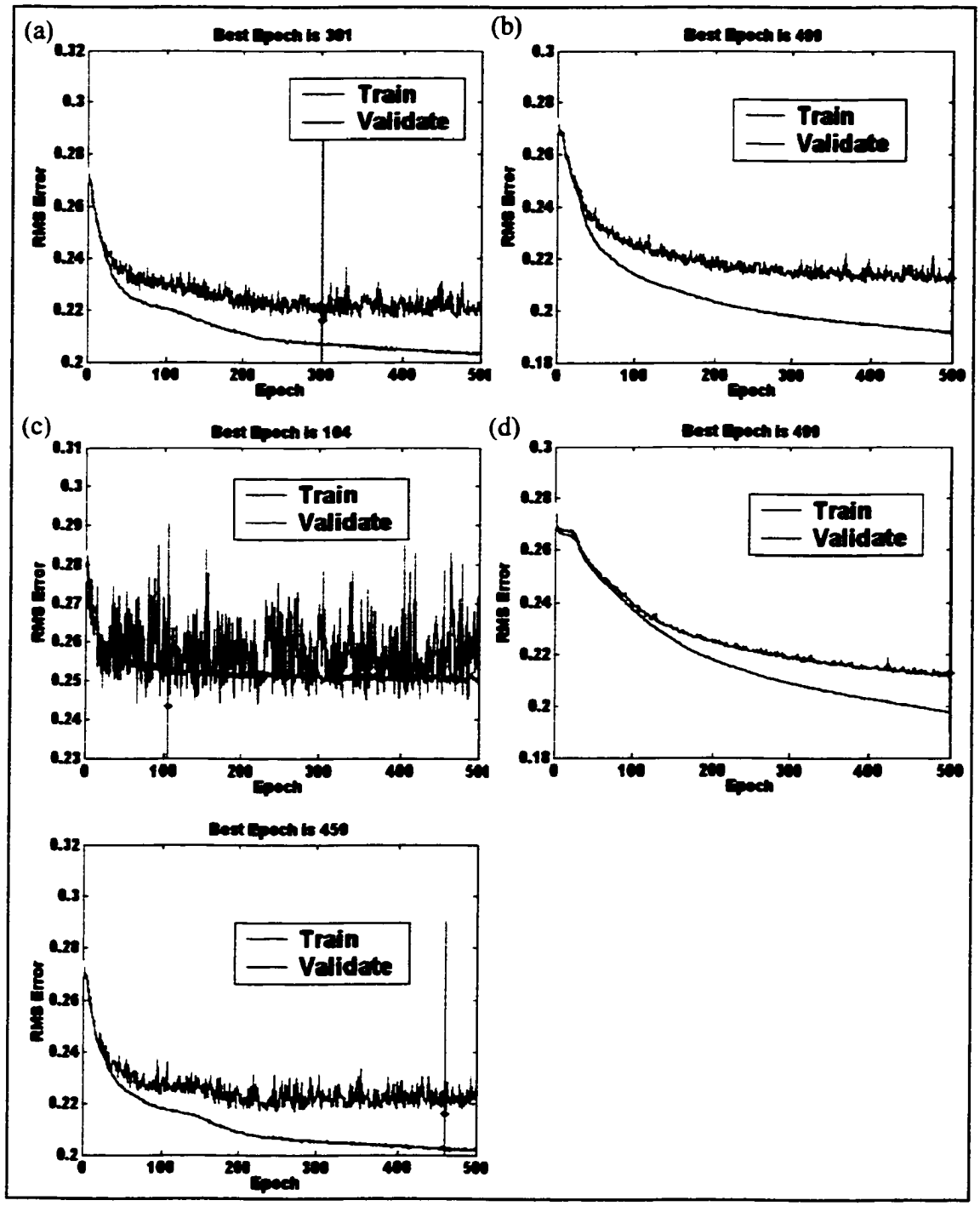
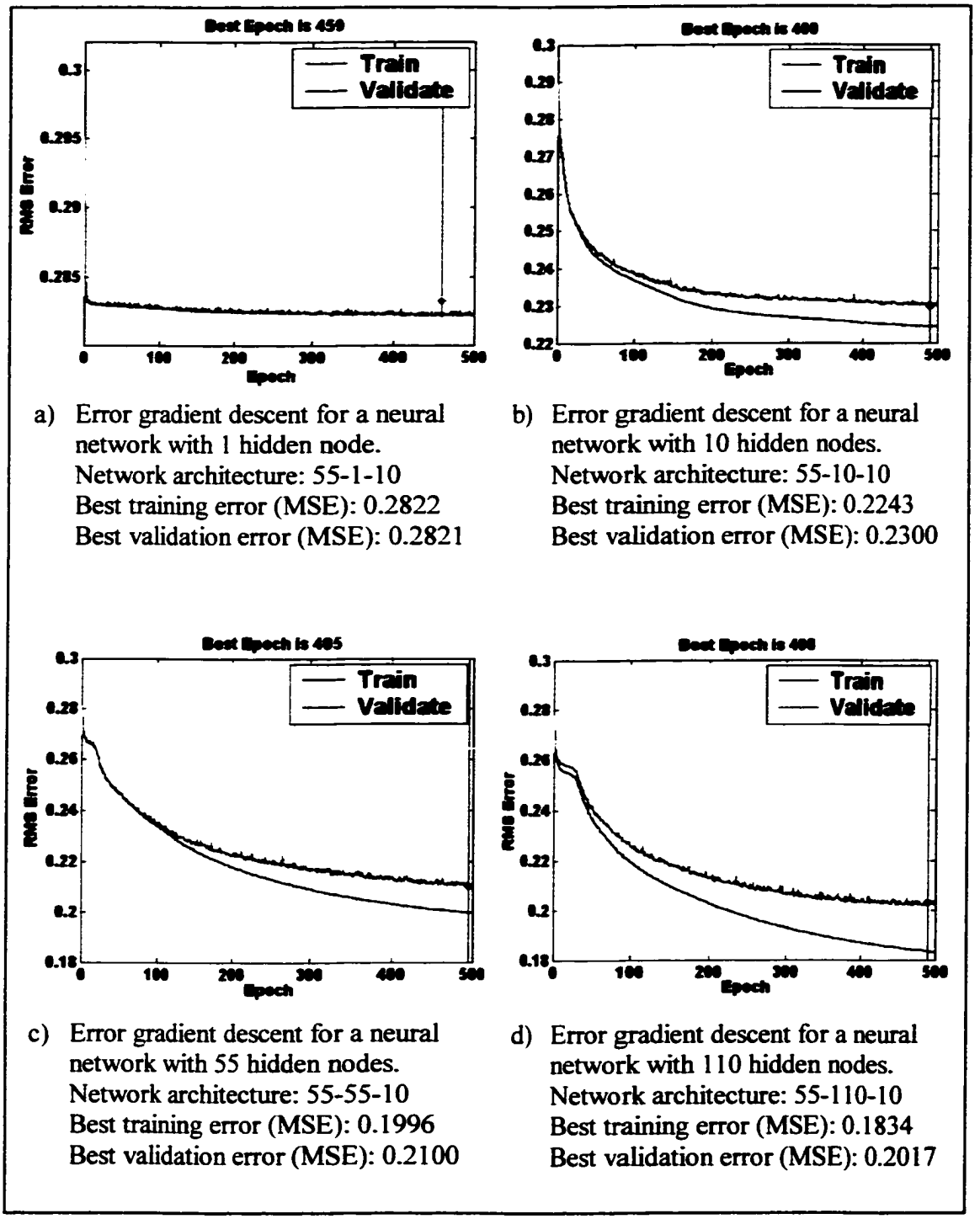


Figure 4.28: Error gradient descent curves of different learning (LR) and momentum rates (MR) for a neural network with a 55-110-10 configuration: (a) LR = 0.5, MR=0.5; (b) LR = 0.5, MR =0.0;(c) LR = 0.5, MR=0.9; (d) LR = 0.1, MR = 0.1; (e) LR = 0.9, MR = 0.1.

Once the best learning and momentum rates were determined, a second experiment was performed to determine number of hidden layers, and the number of nodes per layer. Based on the number of output classes to be classified in this study (ten for the Roosevelt National Forest Wilderness areas, and eleven for the Rocky Mountain National Park study area), it was determined that only one hidden layer was required. Extensive research by Kanellopoulos and Wilkinson (1997) on neural network classification of remotely sensed data has shown that in general, a single hidden layer is suitable for most classifications with less than twenty classes, while the additional flexibility provided by a second hidden layer is required if the number of classes is bigger.

To determine the number of nodes within the hidden layer a small experiment was performed to find the best possible fit in both study areas. Four possible numbers of hidden nodes were investigated: (1) One node, (2) ten nodes, (3) a number nodes equal to number of the input nodes, (4) a number of nodes double the number of input nodes, and (5) a number of nodes three-times the number of input nodes. According to the recommendations of Kanellopoulos and Wilkinson (1997), ideally the first hidden layer of a network with two hidden layers should contain two to three times the number of inputs such that a sufficient number of hyper-planes can be formed to define hyper-regions. The number of hidden nodes that produced the minimum classification error (as measured by mean square error or MSE) of the training/test and validation data sets was generally selected as the best value. A graphic description of this experiment is presented in Figure 4.29. The best results were obtained with a number of hidden nodes



a) Error gradient descent for a neural network with 1 hidden node.
Network architecture: 55-1-10
Best training error (MSE): 0.2822
Best validation error (MSE): 0.2821

b) Error gradient descent for a neural network with 10 hidden nodes.
Network architecture: 55-10-10
Best training error (MSE): 0.2243
Best validation error (MSE): 0.2300

c) Error gradient descent for a neural network with 55 hidden nodes.
Network architecture: 55-55-10
Best training error (MSE): 0.1996
Best validation error (MSE): 0.2100

d) Error gradient descent for a neural network with 110 hidden nodes.
Network architecture: 55-110-10
Best training error (MSE): 0.1834
Best validation error (MSE): 0.2017

Figure 4.29: Comparison of error gradient descent curves in the neural network trainings of the Roosevelt National Forest Wilderness areas using 1, 10, 55 and 110 hidden nodes.

double the number of input nodes. This was consistent with results found in the literature (Kanellopoulos and Wilkinson 1997, Blackard and Dean 1999).

A neural network architecture with three times the number of input nodes (not shown in Figure 29), demonstrated no further reduction of the root mean square error. On the other hand, such a large number of hidden nodes increased the network training time considerably, making the model impractical. Based on these results, it was confirmed that the size of the hidden layer should be around twice the size of the input layer.

The next step in the development of the model was to further train the networks with the previously determined best network parameters until the best number of iterations or epochs was achieved. The best number of iterations corresponds to the point in the training when the validation gradient descent curve "levels off". In other words, no further reduction of the validation root mean square error is attained. This refers to the ability of a neural net to interpolate and extrapolate to a new set of data (Atkinson and Tatnall 1997). If the network is trained too well on the training data it might not perform accurately on the rest of the image; conversely, if the training is deficient it will not be able to discriminate between classes, even in the training data, to an acceptable level (Paola and Schowengerdt 1993). For this training process, another experiment was performed to determine the optimal number of iterations or epochs, in which maximum number of iterations was set to 2000. This number was determined based on the previous experiments and was sufficient to obtain the best number of iterations. Figure 4.30 shows the training process performed to determine the optimal number of iterations or best

epoch in the Roosevelt National Forest Wilderness Areas. The best epoch for this model was 1797 with a best training (MSE) of 0.1744 and a best validation (MSE) of 0.2004.

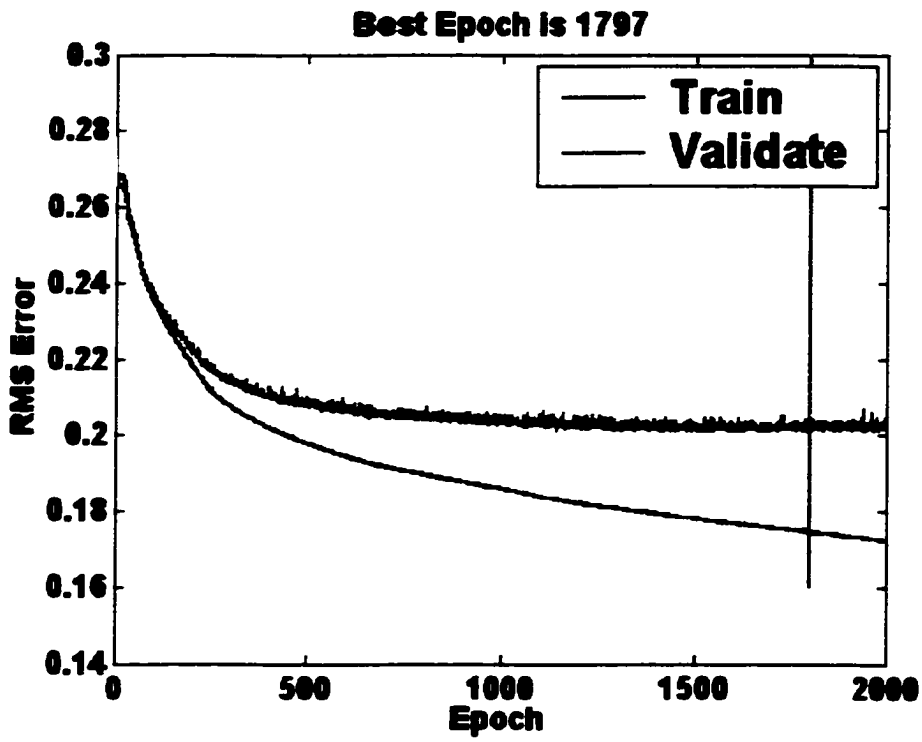


Figure 4.30: Training process performed to determine the optimal number of iterations or best epoch in the Roosevelt National Forest Wilderness Areas. The best epoch for this model was 1797 with a best training (MSE) of 0.1744 and a best validation (MSE) of 0.2004.

After the best number of iterations was determined, the networks were trained using all the previously described best values. This completed the model development and training process. As a result, the trained networks were ready to compute probability values using the entire datasets of the study areas. The outcome of this computation was a

series of binary values (ten for the Roosevelt National Forest Wilderness areas, and eleven in the case of the Rocky Mountain National Park study area) for each observation. Each of these values corresponded to the posterior probability of a specific cover type to occur. However, before they were transformed to probability maps, standardized, so that their sum for a particular observation equaled one. These posterior probabilities later became prior probabilities in the Bayesian / Maximum Likelihood classification algorithm (to be described in a later section).

4.3.2.2 Artificial Neural Network Model development using NeuralSIM

Although some of the general principles of the model development using NeuralSIM were similar to the ones described in the MATLAB modeling process (e.g., the use of a *multilayer perceptron* type of network), there were important differences caused by inherent characteristics of the software. NeuralSIM comes with several predefined options to serve a variety of applications, making it a very easy to use neural network modeling software. One of the main advantages of NeuralSIM is the capability to manipulate and transform raw data, making previously required data transformations (e.g. scaling, transformations to binary format, etc.) unnecessary. However, its algorithms differ from "conventional" neural network modeling procedures. For instance, NeuralSIM is based on a constructive approach to building networks developed by Scott Fahlman of Carnegie Mellon University. In its original form, this technique was referred to as Cascade Correlation. The "Cascade" part of this title refers to the architecture and its mode of construction, which entails adding hidden units (network nodes lying between the input and output) one at a time, and always connecting all the previous units to the

current unit. The "Correlation" part of the title refers to the way hidden units were trained by trying to maximize the correlation between output of the hidden unit and the desired output of the network across the training data (NeuralSIM manual 1998). Consequently, NeuralSIM does not provide the flexibility of a manual construction of the network architecture. In other words, although it allows you to place restrictions on how many hidden processing elements are added at a time and on the maximum number of processing elements, NeuralSIM builds the network itself, based on the characteristics of the data. In this process, each hidden node created by NeuralSIM is established by testing several candidates. A list of transfer functions can be specified corresponding to successive candidates. The list can be biased in favor of certain transfer functions. However, in this study, only the hyperbolic tangent (*tanh*) transfer function was used, as recommended for most problems. According to NeuralSIM manual (1998), it is advisable to select hidden candidates using only the *tanh* function before attempting to use the other transfer functions.

NeuralSIM uses the cascade method of network construction together with a choice of two learning rules. An *Adaptive Gradient* learning rule, which is widely applicable, and a *Kalman learning rule*, which is applicable to regression type problems in which the number of inputs is not too large. In this study the first type of learning rule was used. The *Adaptive Gradient* learning rule uses back-propagated gradient information to guide an iterative line search algorithm. This is a very general learning rule and is used by default for most of the levels and modes within NeuralSIM (NeuralSIM manual 1998). The *Adaptive Gradient* learning features a *weight decay* factor. This factor is meant to prevent overfitting of the training data (i.e., to preserve the

ability of the neural network to generalize). The weights in a neural net form a highly condensed representation of your training data. During training, the learning rule modifies the weights in response to the training data. If left unchecked, the weights for a processing element can latch onto spurious information in the training data, such as data that does not represent a general trend in the input data. By slowly decaying the weights during the course of the training, only the general trends remain encoded in the weights. Values for the weight decay parameters should be kept small (typically less than 0.05). Otherwise any useful information in the data is completely washed out. In practice, weight decay is usually more effective if the weight decay for the output layer is an order of magnitude less than the weight decay for the hidden layer. So, for example, you should couple a value of 0.01 for the hidden weight decay with a value of 0.001 for the output weight decay (NeuralSIMmanual 1998).

Another of NeuralSIM *'s* specially developed features is the *SoftMax* output transfer function. Although no specific details are provided on the algorithm and mechanics of this function, it is automatically used for problems where the transformed output data is probabilistic. In other words, it is used where for each output record, the sum of values is equal to 1 and each individual output value is between 0 and 1, like in the case of this study. The *SoftMax* function is set up by default for classification problems in conjunction with a *relative entropy* objective function. The *relative entropy* measure maximizes the probability of successful classification by internally considering each category in the classification output to be mutually exclusive and assigning it to an output node in the neural net. The *SoftMax* function ensures that the outputs of the neural net enforce the mutual dependence of the outputs (NeuralSIMmanual 1998).

As a result of the way it operates, NeuralSIM does not provide an option to plot the error gradient descent curves. Thus, there is no way to analyze the behavior of the network training process and visually determine when is the best time to stop the training (i.e. best epoch), as is the case with MATLAB. Conversely, NeuralSIM will automatically resolve when to stop the training based on the characteristics of the data and predefined parameters (e.g., the *patience* and *tolerance*). *Patience* is a mechanism that is used to control convergence of the algorithm. Each time the population's average fitness does not improve by more than a certain *tolerance*, the patience factor is incremented by 1. When the patience exceeds a certain number (6 by default), the algorithm is terminated. The *Tolerance* parameter is used to indicate what is a meaningful improvement at each stage of model building (NeuralSIMmanual 1998).

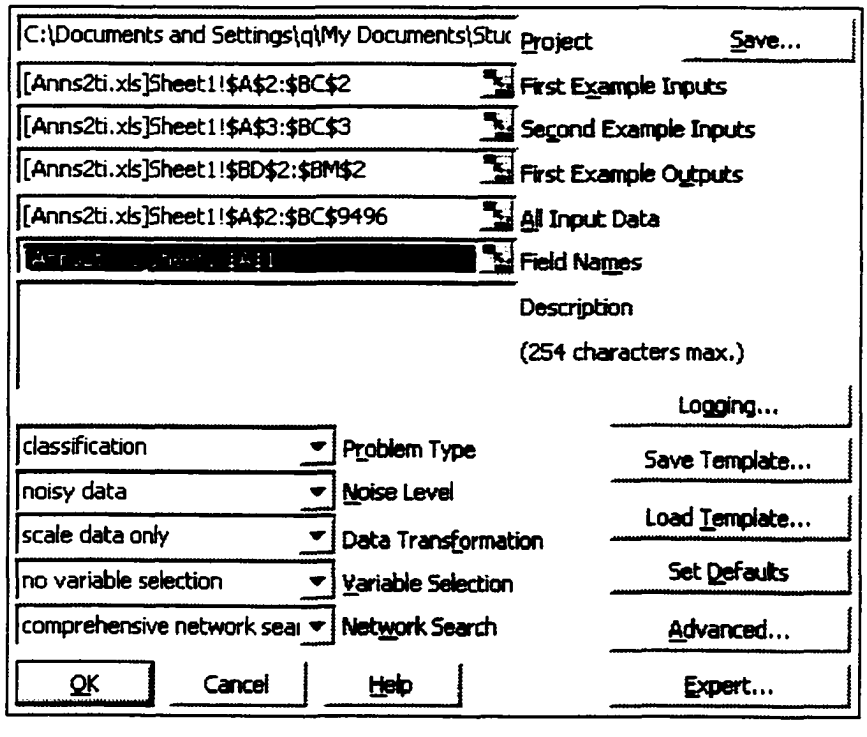


Figure 4.31: General settings of the NeuralSIM modeling of the Roosevelt Forest Wilderness areas data obtained using the *Wizards* option.

The neural network modeling process with NeuralSIM was initialized using the *Wizards* option, which is available via the NeuralSIM *'s* Microsoft *Excel* user interface. The wizard mode provided the best general settings for the model (see Figure 4.31). Then the *Expert Level Parameters* menu was used to specify the exact size and location of the training, test, and validation data sets, and to modify the critical parameters, described above, required for the construction of the neural network architecture and the training development.

The model development and training was completed after obtaining the smallest possible root mean square error for the validation data sets. The best results for the neural network training in the Roosevelt National Forest Wilderness and Rocky Mountain National Park study areas are presented in Tables 4.1 and 4.2 respectively.

Data set	**Observations**	**Accuracy (MSE)**
Train data set	4747	0.1236
Test data set	2374	0.2194
Validation data set	2374	0.2166
All	9495	0.1708

Table 4.1: Mean Root Square Error (MSE) for the best training results of the NeuralSIM neural network modeling in the Roosevelt National Forest Wilderness areas.

Data set	Observations	Accuracy (MSE)
Train data set	7415	0.1101
Test data set	3707	0.2088
Validation data set	3708	0.2185
All	14830	0.1618

Table 4.2: Mean Root Square Error (MSE) for the best training results of the NeuralSIM neural network modeling in the Rocky Mountain National Park study area.

Once the networks were trained, probability values were computed using the entire datasets of the study areas. As a consequence of the size of the data sets, the application of the trained networks on the entire datasets was performed using the batch mode of NeuralSIM. As in the case of the MATLAB neural models, the outcome of this computation was a series of values (ten for the Roosevelt National Forest Wilderness areas, and eleven in the case of the Rocky Mountain National Park study area) for each observation. Each of these values corresponded to the posterior probability of a specific cover type to occur. The outcome of NeuralSIM, however, was different from the one of *Mat Lab* in that they did not require the posterior scaling and standardizing. This was done by default by NeuralSIM. As in the case with MATLAB, the probabilities were then input into the Bayesian / Maximum Likelihood classification procedure.

4.3.3 Supervised Bayesian / Maximum Likelihood classification procedure

The output of the neural network modeling consists of values that can be interpreted as probabilities, indicating the likelihood that each portion of the region of

interest belongs in each of the possible information categories. Such an approach could therefore provide a Bayesian classifier with the required *a priori* information to minimize the cost of misclassification, resulting in a theoretically optimum classification (Lillesand and Kiefer 2000). According to Campbell (1996), for remote sensing classification, application of Bayes rule is especially effective when classes are indistinct or overlap in spectral data space, as is the case in this study. It can also form a convenient vehicle for incorporating ancillary data into the classification, as the added information can be expressed as a conditional probability. The Bayesian / Maximum Likelihood classifier rule is presented in Eq. 4.2 (Jensen 1996).

$$\mathbf{P(x\,|C)_{P(c)} = \log_e(P(C)) - \{0.5\log_e[\det(V_c)]\}} \\ \mathbf{-[0.5(M_x - M_c)^T (V_c^{-1})(M_x - M_c)]} \qquad \textbf{Eq. 4.2}$$

Where:

$P(x\,|C)_{P(c)}$ is the probability that a pixel x belongs to *class C* given the *a priori* probability of encountering *class C*.

$P(C)$ is the *a priori* probability of encountering *class C*.

$\det(V_c)$ is the determinant of the covariance matrix (Vc) of class C for bands k through l.

M_x is the measurement vector of digital values associated to pixel x

M_c is the mean measurement vector for *class C*

The effect of using the ***a priori*** probabilities in a Bayesian / Maximum Likelihood classification is presented in Figure 4.32. The graph on the right (B) shows the assignment of a greater weight to class 1, which implies a shift of the class limits to the right, reducing the extents of class 2 (Schowengerdt 1983). The consequence of this Maximum Likelihood boundary shift is a significant improvement in the assignment of the pixels in both classes to the correct informational category as compared to the traditional approach that would assume an equal prior probability for both classes.

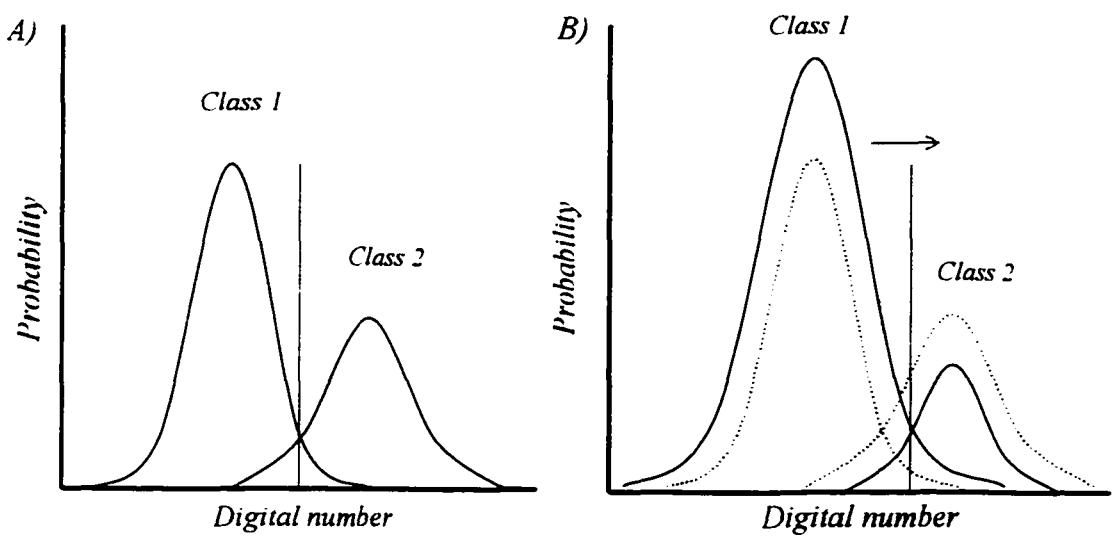


Figure 4.32: Effect of using priors in a Bayesian / Maximum Likelihood classification (Schowengerdt 1983).

With the neural network produced prior probabilities in hand, a Bayesian / Maximum Likelihood classification was conducted. Training statistics were obtained from the Landsat TM image using exact same locations of the observations obtained for the neural network modeling. For this purpose, the training, test, and validation datasets were combined into a single sample dataset and then signatures for each cover type were

developed. Once the signatures were produced, the classifier defined what informational category each pixel in the study areas should be classified into, based on the probability maps produced by the neural network models, as well as the information contained in the satellite data (see Figure 4.33).

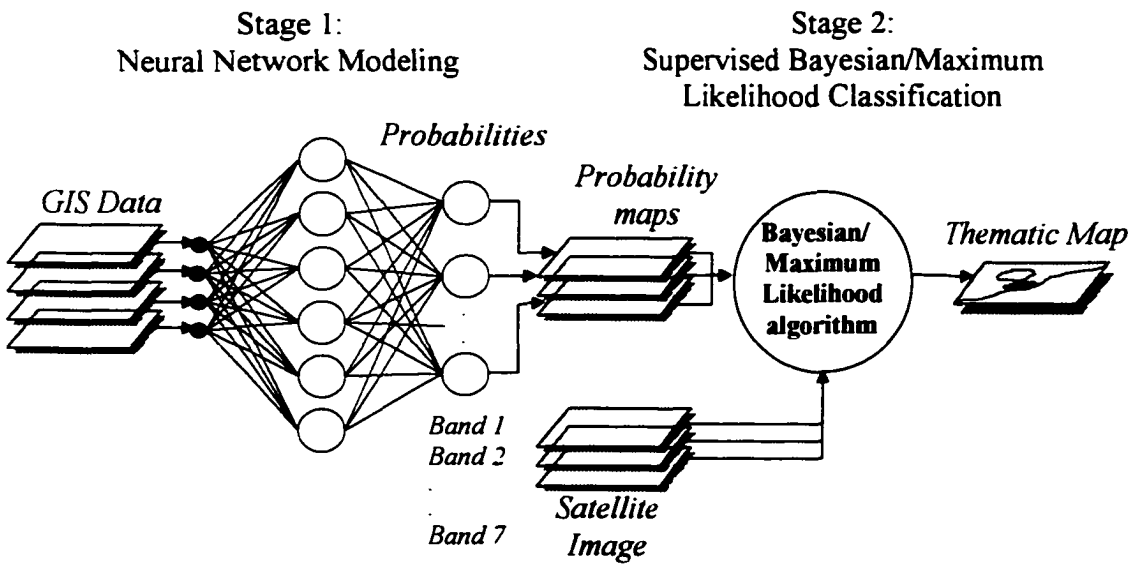


Figure 4.33: Diagram of the supervised Bayesian / Maximum Likelihood classification procedure.

The Bayesian / Maximum Likelihood classification was performed using *IDRISI32*. Traditionally, prior probabilities are incorporated manually in association with the spectral signature of each class and based on the expertise and knowledge of the area possessed by the image interpreter. In addition to this traditional way of introducing prior probabilities into the Maximum Likelihood classifier (available in the most common image classification software), *IDRISI32* also has the capability to fit raster data sets

containing probabilities for each single grid-cell for the different cover types into the Maximum Likelihood classifier. This has the additional advantage of including a spatial component to the classifier. Ten probability maps, one for each cover type, were used in the case of the Roosevelt National Forest Wilderness areas and eleven in the case of the Rocky Mountain National Park study area.

Initially two different classifications were carried out for each study area, one using the prior probabilities obtained with MATLAB, and another one with the probabilities obtained using NeuralSIM. Later on, three additional experiments were performed. The first two involved the use of two new sets of probability maps that were developed not only using GIS data but also the Landsat TM bands themselves. The third type of experiment consisted of a conventional Bayesian Maximum Likelihood classification, in which the area proportions of the cover types where used as prior probabilities. The proportion of this was obtained from the cover type reference data of both study area. For example, if Lodge pole pine occupied 50 percent of the area, Ponderosa pine 15 percent, and Aspen 35 percent, a probability of 0.5 and 0.15 and 0.35 was assigned to their corresponding spectral signatures.

4.3.4 Conventional supervised Maximum Likelihood classifier development

In addition to the supervised Bayesian / Maximum Likelihood classifier analysis described in the previous section, a conventional non-Bayesian classification was carried out for comparison purposes. This classification consisted of a conventional, supervised Maximum Likelihood classification technique (see Figure 4.34).

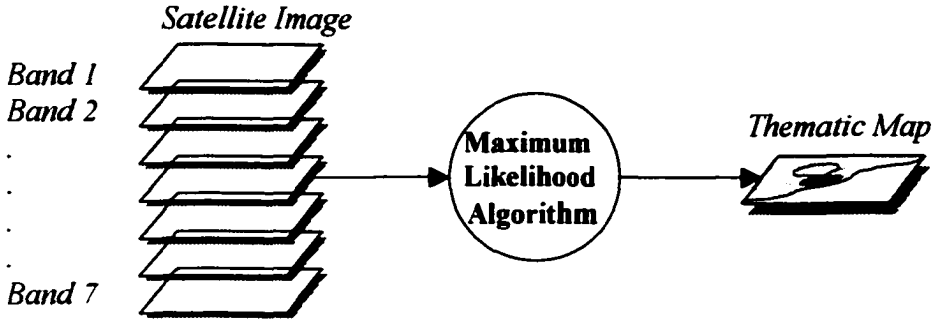


Figure 4.34: Diagram of the conventional Maximum Likelihood classification procedure.

As in the case of the previous classification the training statistics were developed from the Landsat TM image using the combination of the training, test, and validation observations obtained for the neural network modeling. In general terms, the development of the cover type signatures was identical to the one used in the Bayesian classifier. The only difference between the two procedures was that in the conventional Maximum Likelihood classification, the signatures associated with the cover types had an equal probability to be assigned to each of the possible information categories.

4.3.5 Conventional artificial neural network classification

A "conventional" neural network approach, in which Landsat TM bands were incorporated to the neural network together with the GIS variables, was also carried out for comparison purposes. A diagram of the conventional neural network classification

procedure is presented in Figure 4.35. This neural network models were also developed in MATLAB and NeuralSIM in a manner similar to that described previously for the neural network probability models.

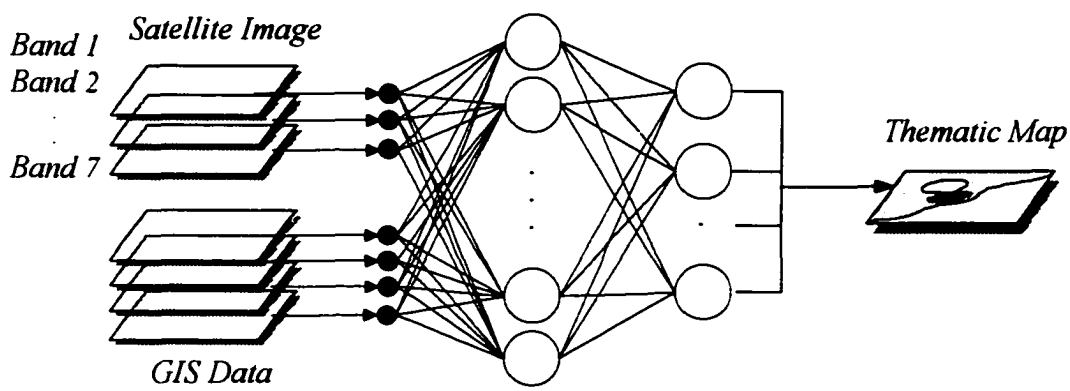


Figure 4.35: Diagram of the conventional neural network classification procedure.

4.3.5.1 Conventional artificial neural network classification using MATLAB

For the conventional artificial neural network classification using MATLAB, seven Landsat TM Bands, ten continuous GIS variables and forty-five binary GIS variables corresponding to the soil types were input to the model in the case of the Roosevelt National Forest Wilderness areas. Based on this number of inputs, the network architecture used was 62 input nodes, 124 hidden nodes and 10 output nodes. The error gradient-descent curves of the classification model training in the Roosevelt National Forest Wilderness areas are presented in Figure 4.36. The error gradient descent curves of

the classification model training in the Roosevelt National Forest Wilderness areas and Rocky Mountain National Park study area are presented in Figures 4.37.

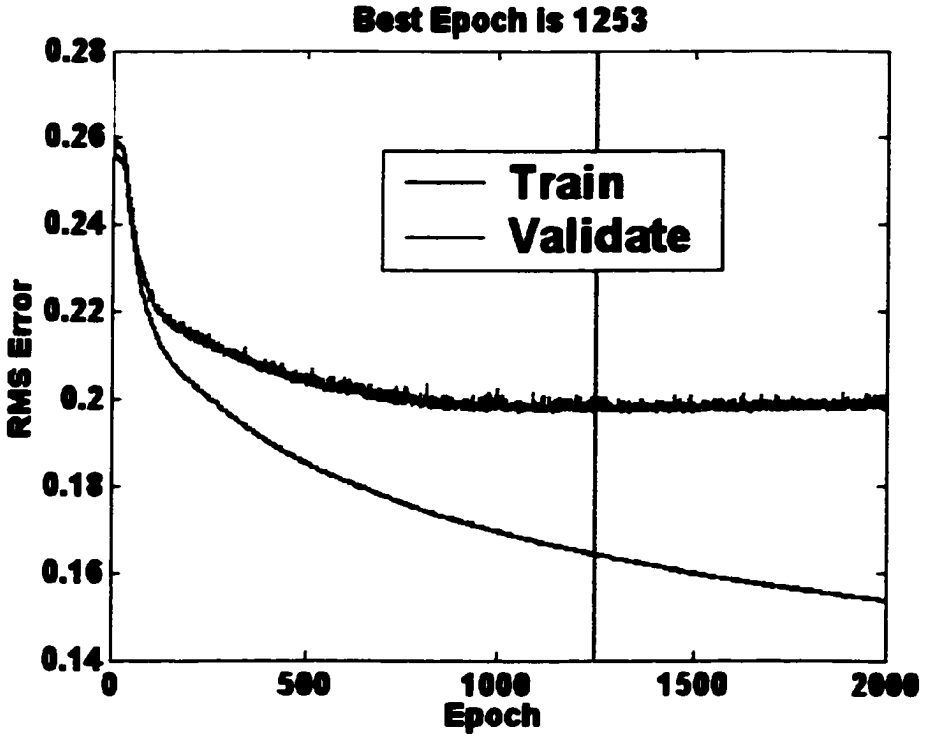


Figure 4.36: Training process performed to determine the optimal number of iterations for the neural network classification model in the Roosevelt National Forest Wilderness areas. The network architecture for this model was 62-124-10. The best epoch was 1253 iterations, with a best training (MSE) of 0.1639 and a best validation (MSE) of 0.1967.

In the case of Rocky Mountain National Park, seven Landsat TM bands, ten continuous GIS variables, and 46 binary variables corresponding to the soil type were used as input. Based on this number of inputs, the network architecture used for this

model consisted of 62 input nodes, 124 hidden nodes and 10 output nodes. For further details on how the neural network was trained please refer to Artificial Neural Network development using MATLAB (Section 4.3.2.1).

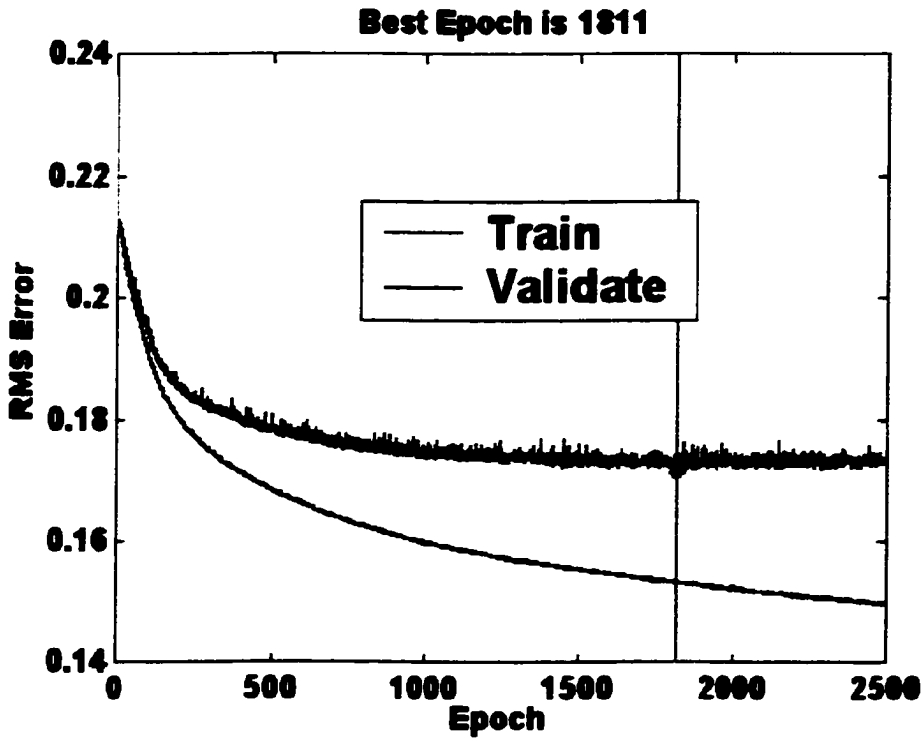


Figure 4.37: Training process performed to determine the optimal number of iterations for the neural network classification model in the Rocky Mountain National Park study area. The network architecture of this model was 63-126-11. The best epoch was 1811 iterations, with a best training (MSE) of 0.1533 and a best validation (MSE) of 0.1717.

After the parameters that produced the best models for each of the study areas were identified and the networks were trained using the test, training and validation data sets, the corresponding models were applied to the totality of the study areas. As in the case of the probability models, the outcome of the classification models was a series of values (ten for the Roosevelt National Forest Wilderness areas, and 11 in the case of the

Rocky Mountain National Park study area) corresponding to the posterior probability of a specific cover type to occur. Again the outputs of the MATLAB models were standardized, so that their sum for a particular observation equaled one.

Using a simple C program and the output posterior probabilities obtained from the classification models, each individual observation in the areas to be classified was assigned membership to the cover type exhibiting the highest probability value. This produced a dataset that was then transformed to the final thematic map with the classified cover types using a standard GIS text to raster format transformation.

Using this same procedure, two additional classifications were performed with the neural network models developed to produce only probabilities (i.e., the models trained without the seven Landsat TM bands, as described in Section 4.3.2.1). This was done for comparison purposes, to analyze the contribution of the satellite data to the classification accuracy, as compared to a model using only GIS variables.

4.3.5.2 Conventional artificial neural network classification using NeuralSIM

In a similar way, as previously described in Section 4.3.2.2 (Artificial Neural Network development using NeuralSIM), the neural network classification modeling process with NeuralSIM was initialized using the *Wizards* option, available in the NeuralSIM *'s* Microsoft *Excel* user interface. The wizard mode provided the best general settings for the model. Then the *Expert Level Parameters* menu was used to specify the exact size and location of the training, test, and validation data sets, and to modify the critical parameters, required for the construction of the neural network architecture and the training.

The model development was completed after obtaining the smallest possible root mean square error for the validation data sets. The best results for the neural network training in the Roosevelt National Forest Wilderness and Rocky Mountain National Park study areas are presented in Tables 4.3 and 4.4 respectively. For further details on the neural network training using NeuralSIM, please refer to Section 4.3.2.2.

Data set	Observations	Accuracy (MSE)
Train data set	4747	**0.0913**
Test data set	2374	**0.2060**
Validation data set	2374	**0.2153**
All	9495	**0.1509**

Table 4.3: Mean Root Square Error (MSE) for the best training results of the NeuralSIM neural network classification in the Roosevelt National Forest Wilderness areas.

Data set	Observations	Accuracy (MSE)
Train data set	7415	**0.1013**
Test data set	3707	**0.2023**
Validation data set	3708	**0.2143**
All	14830	**0.1548**

Table 4.4: Mean Root Square Error (MSE) for the best training results of the NeuralSIM neural network classification in the Rocky Mountain National Park study area.

4.3.6 Comparative evaluation of the classification techniques

Once the classification results produced by the different classification techniques described above were produced, a comparative evaluation was performed. The comparison of the neural network / Bayesian classification approach using GIS data in combination with satellite remote sensor data, to "conventional" neural network classification, and to traditional classification of satellite data sensor data, must provide clear documentation of the effectiveness and efficiency of the new approach. For this purpose, the evaluation was divided in three parts:

(1) a quantitative evaluation,

(2) a qualitative evaluation, and

(3) an evaluation of the technique efficiency.

Although more weight was given to the quantitative evaluation, all three factors played a significant role in the final selection of the best classification technique. A diagram of the evaluation procedure is presented in Figure 4.38.

4.3.6.1 Quantitative evaluation

In the quantitative evaluation, the accuracy of the classifications was assessed by comparing them to the totality of the reference data in the Roosevelt National Forest Wilderness areas. In the case of the Rocky Mountain National Park study area only the area of the park within Larimer County was used as a reference, due to the fact that this was the only area covered by the aerial photos used in the sampling procedure (see Section 4.3.1.2, Data selection in the Rocky Mountain National Park study area).

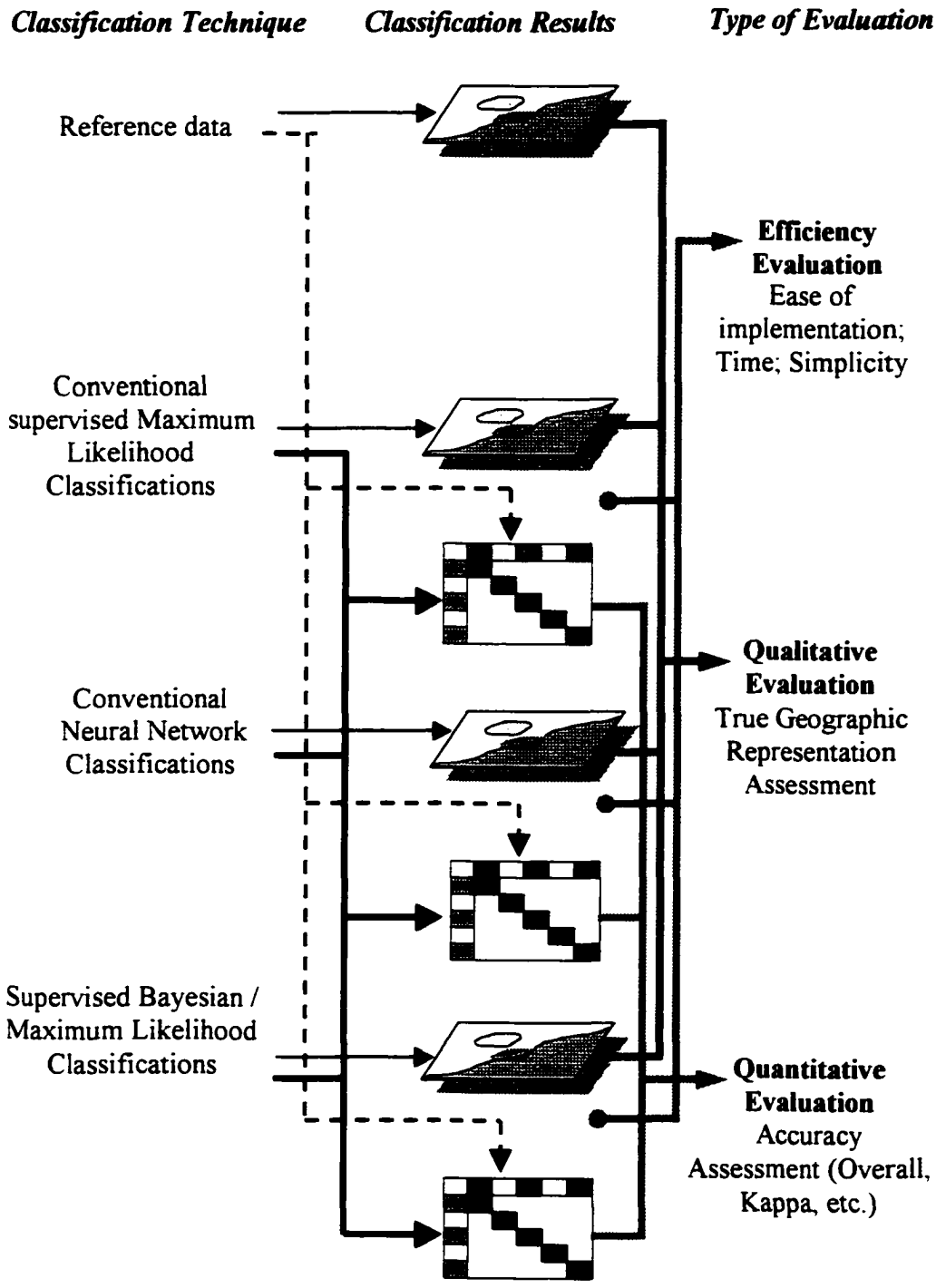


Figure 4.38: Comparative evaluation of the classification techniques.

The quantitative evaluation consisted of the analysis of the classification statistics generated in *IDRISI32* using the accuracy assessment commands provided by the software. The quantitative evaluation corresponded to a 100 percent, per pixel comparison between the reference and the classification data sets (i.e., every pixel in the Roosevelt National Forest Wilderness areas, and every pixel in the Larimer county portion of the Rocky Mountain National Park study area was compared to a corresponding pixel in their reference data). Thus, no sampling was necessary for evaluation purposes.

The classification statistics presented in the form of error matrices are the *overall accuracy*, the *producer's accuracy*, and the *user's accuracy*, as well as the individual and overall *Kappa* coefficients. The overall accuracy is obtained by dividing the sum of the correct pixels of every category along the major diagonal by the total number of pixels in the error matrix. According to Jensen (1996), the overall accuracy is a non-site specific measure that ignores locational accuracy. A non-site specific accuracy assessment can yield very high accuracy but misleading results when all the errors balance out in a region. The producer's accuracy is the total number of correct pixels in a category, divided by the total number of correct pixels in that category as derived from the reference data (i.e. the column total). This statistic indicates the probability of a reference pixel being correctly classified and is a measure of omission error. This statistic is called the producer's accuracy because the producer of the classification is interested in how well a certain area can be classified (Jensen, 1996). The *user's accuracy* is obtained by the division of the total number of correct pixels in a category by the total number of pixels that were actually classified into that category. This is a measure of commission

error and indicates the probability that a pixel classified on the map actually represents that category on the ground (Jensen 1996).

The *Kappa* coefficient is a measure of agreement, in which the off-diagonal elements are incorporated as a product of the row and column marginals (Jensen 1996). This statistic is a measure of the difference between the actual agreement between the reference data and an automated classifier and the chance agreement between the reference data and a random classifier. The Kappa statistic serves as an indicator of the extent to which the percentage correct values of an error matrix are due to "true" agreement versus "chance" agreement (Lillesand and Kiefer 2000).

4.3.6.2 Qualitative evaluation

The qualitative evaluation consisted of an assessment of true geographic representation. True geographic representation in this study was evaluated as a measure of how accurately a predictive model geographically classifies observations into their correct cover types (e.g. position, shape, size). Although this evaluation is subjective, it is a very important complement to the quantitative evaluation, since not only the number of correctly classified observations is important, but also how close these predictions are to the actual spatial distribution in the reference data. The assessment of true geographic representation was accomplished by visually comparing the cover type maps obtained from the different classification techniques to the cover types maps of the reference data.

4.3.6.3 Evaluation of the technique efficiency

Since one of the objectives of this study is the development of a widely applicable classification technique, a very important aspect of the evaluation was the efficiency of the classification models. This consisted of an assessment of the ease of implementation, as well as the simplicity of the procedures. The time and effort required for an interpreter to produce a classification map, from the preparation of suitable data sets, ready for input into the different models, to the production of the final output, passing through the time required in the main modeling and classification process, were taken into account in this evaluation. These factors were balanced to the improvement in classification accuracy.

CHAPTER 5. RESULTS AND DISCUSSION

The comparative results of all the classification techniques applied to both study areas are first presented in summary tables showing the overall accuracies and Kappa statistics in Sections 5.1 and 5.2. Tables containing the producer's and user's accuracies, as well as the individual Kappa values for the individual cover types across all the classification techniques are also presented in order to clarify classification patterns. A detailed discussion of the particular classification characteristics of each one of the classification techniques follows in Sections 5.3, 5.4 and 5.5. Specific details were obtained by analyzing the individual error matrices and classification statistics for each classification technique presented in Appendix 1. In addition to this, classification results are also presented in the form of thematic maps displaying the classified cover types versus the actual cover types in the reference data. Finally, a general discussion is presented in Section 5.6.

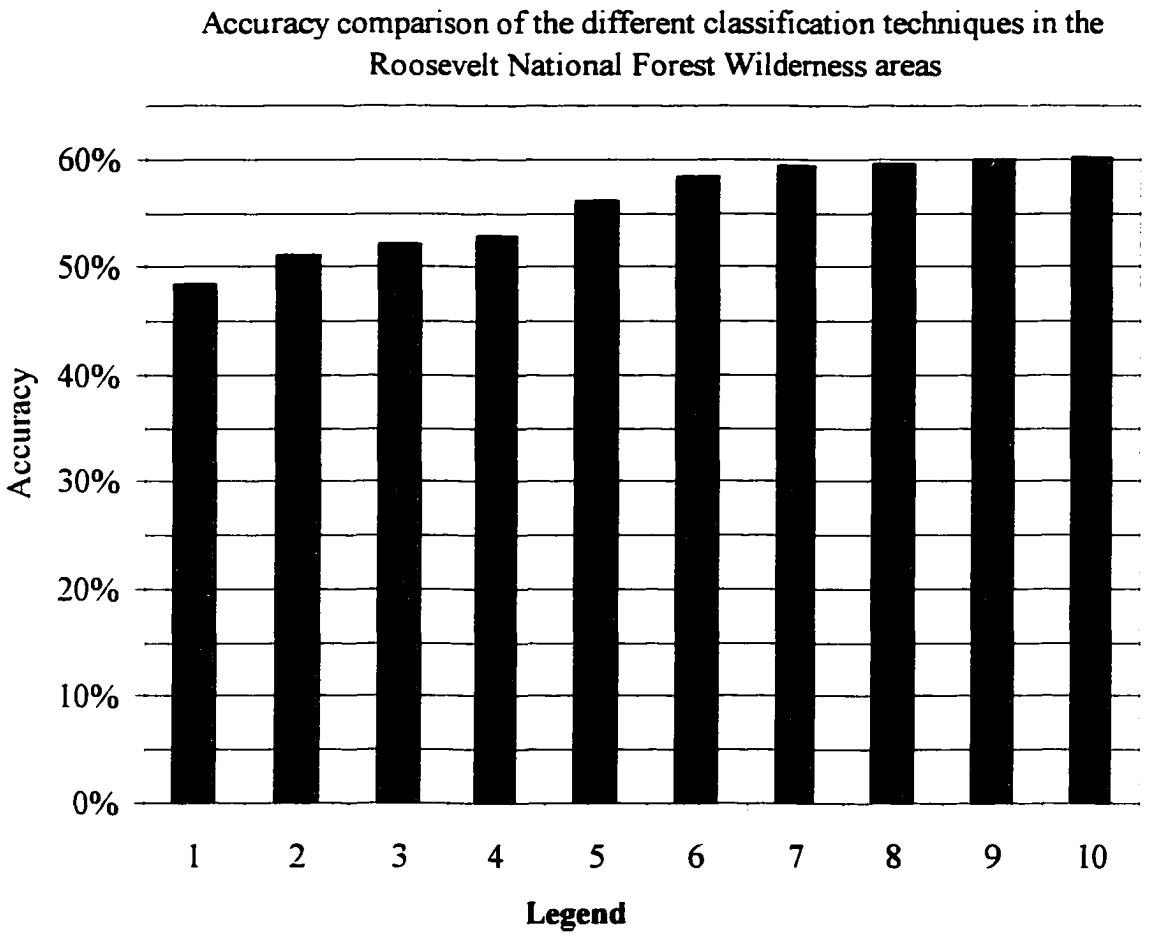
5.1 Comparative results of the classifications performed in the Roosevelt National Forest Wilderness areas

The results of the classifications performed in the Roosevelt National Forest Wilderness areas are presented in Table 5.1 and Figure 5.1. A comparison of the classification accuracies of all the classification techniques, ranked from lowest to highest shows that the overall accuracies range from 48.44 percent for the supervised Maximum Likelihood classification to 60.16 percent for the Bayesian/Maximum Likelihood

classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data. The use of this new technique represents an increase of 11.72 % over the conventional classification procedure. However, "conventional" neural networks classifications both with NeuralSIM and MATLAB also obtained classification overall accuracies around 60 percent (59.94 percent and 59.32 respectively).

Classification technique	Accuracy	Kappa
Supervised Maximum Likelihood classification	48.44%	0.33
"Conventional" Bayesian/Maximum Likelihood classification with probabilities obtained from area proportions of cover types	51.11%	0.35
"Conventional" neural network classification with MATLAB using GIS data	52.11%	0.39
"Conventional" neural network classification with NeuralSIM using GIS data	52.85%	0.38
Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using only GIS data	56.18%	0.42
Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using GIS data and Landsat TM data	58.28%	0.44
"Conventional" neural network classification with MATLAB using GIS and Landsat TM data	59.32%	0.46
Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using only GIS data	59.56%	0.46
"Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data	59.94%	0.46
Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data	60.16%	0.46

Table 5.1: Accuracy comparison of the different classification techniques applied to the Roosevelt National Forest Wilderness areas.



Nr. **Classification technique**

1 = Supervised Maximum Likelihood classification

2 = "Conventional" Bayesian/Maximum Likelihood classification with probabilities obtained from area proportions of cover types

3 = "Conventional" neural network classification with MATLAB using GIS data

4 = "Conventional" neural network classification with NeuralSIM using GIS data

5 = Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using only GIS data

6 = Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using GIS data and Landsat TM data

7 = "Conventional" neural network classification with MATLAB using GIS and Landsat TM data

8 = Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using only GIS data

9 = "Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data

10 = Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data

Figure 5.1: Accuracy comparison of the different classification techniques applied to the Roosevelt National Forest Wilderness areas.

An interesting result was achieved by the Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using only GIS data, which with 59.56 percent resulted in the third highest overall classification.

In addition to this, the producer's accuracy of the individual cover types across all the classifications techniques is presented in Table 5.2 and Figure 5.2. On average, the producer accuracies ranged from a minimum of 40.89 percent, attained by the "conventional" Bayesian/Maximum Likelihood classification with probabilities obtained from area proportions of cover types, to a maximum of 53.66 percent, attained by the neural network classification with MATLAB using GIS and Landsat TM data. In general the highest producer's accuracies were obtained by the techniques involving modeling with neural networks and a combination of GIS and Landsat TM data using both MATLAB and NeuralSIM. Cover type-wise the average producer's accuracy ranged from a minimum of 26.20 percent for *Riparian* to a maximum of 63.83 percent for *Water*.

In a similar way the user's accuracy of the individual cover types across all the classifications techniques are presented in Table 5.3 and Figure 5.3. On average the user's accuracies ranged from a minimum of 32.51 percent for the supervised Maximum Likelihood classification to a maximum of 45.34 percent for the Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using only GIS data. In this case the Bayesian classifications with prior probabilities obtained from NeuralSIM using only GIS data and a combination of GIS and Landsat data performed better than the other classification techniques. In regard to the cover types, the average user's accuracies ranged from 13.40 percent for the *Aspen* to 73.18 percent for the

Lodgepole pine. Cover types on the low range include *Riparian* (14.67 percent), Non-vegetation (15.27 percent), and *Krummholz* (19.11 percent). Cover types on the upper range include *Other Vegetation* (72.65 percent) and *Spruce/Fir* (59.06 percent).

Table 5.4 and Figure 5.4 display the Kappa values for the individual cover types in the Roosevelt National Forest Wilderness area. The overall Kappa values ranged from a minimum of 0.3264 for the supervised Maximum Likelihood classification to a maximum of 0.4642 percent for the Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat data. The "Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data, and the "Conventional" neural network classification with MATLAB using GIS and Landsat TM data scored also very high with overall Kappa values of 0.4641 and 0.4638 respectively, clearly indicating a better performance of the neural network models trained with GIS and spectral data. In regard to the cover types, the average Kappa values ranged from 0.2453 for the Riparian to 0.6361for Water. Cover types on the low range include Non-vegetation (0.34984) and *Krummholz* (0.3668). Cover types on the upper range include *Aspen* (0.5656) and Ponderosa pine (0.4751).

Classification technique	SPRUCE / FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	WATER	Average
"Conventional" Bayesian/Maximum Likelihood Classification with probabilities obtained from area proportions of cover types	62.80%	61.03%	30.81%	16.70%	46.54%	51.90%	19.79%	30.00%	23.06%	66.26%	40.89%
Supervised Maximum Likelihood Classification	60.39%	57.75%	30.94%	17.48%	52.57%	57.38%	14.14%	31.85%	25.64%	68.00%	41.61%
"Coneventional" neural network classification with NeuralSIM using only GIS data	50.08%	53.24%	63.33%	32.25%	44.95%	42.01%	58.69%	44.65%	41.70%	58.77%	48.97%
Bayesian/Maximum Likelihood Classification with probabilities obtained from MATLAB using only GIS data	66.39%	59.79%	44.88%	23.28%	68.35%	58.00%	37.76%	36.61%	32.71%	66.31%	49.41%
Bayesian/Maximum Likelihood Classification with probabilities obtained from MATLAB using GIS data and Landsat TM data	69.12%	63.69%	43.31%	22.58%	65.95%	54.30%	36.89%	39.13%	32.93%	68.83%	49.67%
"Conventional" neural network classification with MATLAB using only GIS data	56.15%	46.49%	59.19%	31.48%	66.42%	46.11%	57.59%	49.86%	41.26%	50.80%	50.54%
Bayesian/Maximum Likelihood Classification with probabilities obtained from NeuralSIM using only GIS data	60.75%	62.62%	60.47%	31.33%	58.35%	47.25%	57.12%	42.27%	39.92%	60.51%	52.06%
Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data	68.89%	59.81%	52.35%	29.09%	62.52%	52.31%	54.82%	39.48%	38.97%	67.52%	52.58%
"Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data	64.19%	60.45%	59.38%	30.30%	61.39%	47.71%	58.10%	43.69%	40.65%	65.01%	53.09%
"Conventional" neural network classification with MATLAB using GIS and Landsat TM data	66.77%	57.23%	54.87%	27.54%	64.64%	46.02%	56.75%	54.64%	41.85%	66.26%	53.66%
Average	62.55%	58.21%	49.95%	26.20%	59.17%	50.30%	45.17%	41.22%	35.87%	63.83%	49.25%

Table 5.2: Producers's accuracy for each cover type across all the classification techniques in the Roosevelt National Forest Wilderness areas.

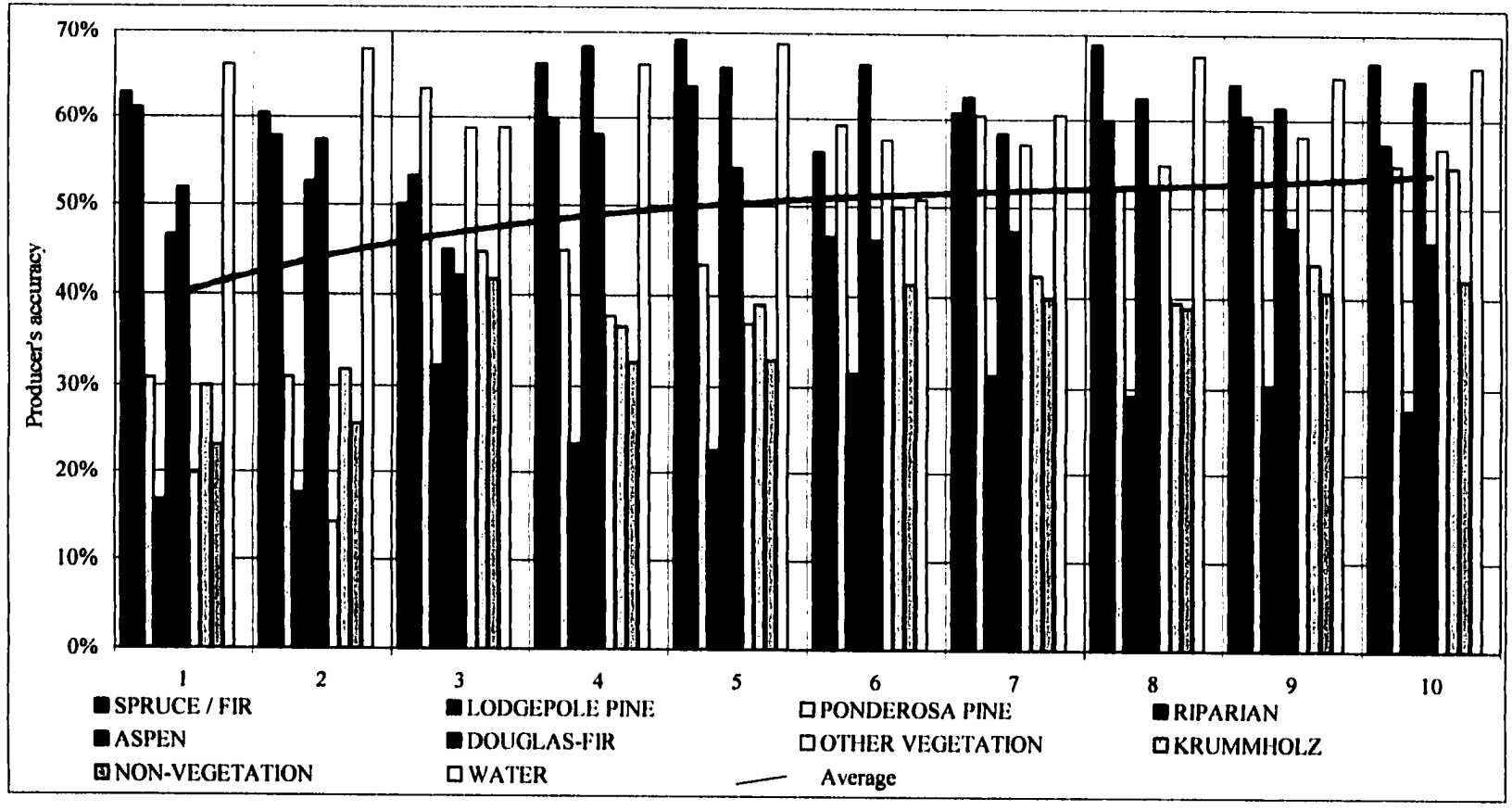


Figure 5.2: Producer's accuracy for the individual cover types across all the classification techniques in the Roosevelt National Forest Wilderness areas: (1) "Conventional" Bayesian/Maximum Likelihood classification with probabilities obtained from area proportions of cover types (2) Supervised Maximum Likelihood classification (3) "Coneventional" neural network classification with NeuralSIM using GIS data (4) Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using only GIS data (5) Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using GIS data and Landsat TM data (6) "Conventional" neural network classification with MATLAB using GIS data (7) Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using only GIS data (8) Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data (9) "Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data (10) "Coneventional" neural network classification with MATLAB using GIS and Landsat TM data.

Classification technique	SPRUCE / FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	WATER	Average
Supervised Maximum Likelihood Classification	57.52%	70.68%	45.18%	2.58%	10.08%	20.15%	76.32%	12.32%	11.34%	18.95%	32.51%
"Conventional" Bayesian/Maximum Likelihood Classification with probabilities obtained from area proportions of cover types	56.65%	70.20%	45.78%	3.10%	12.45%	21.99%	75.21%	12.39%	11.77%	21.92%	33.15%
"Conventional" neural network classification with NeuralSIM using only GIS data	54.57%	69.17%	52.69%	19.93%	10.97%	42.25%	64.22%	18.19%	8.22%	24.37%	36.46%
"Conventional" neural network classification with MATLAB using only GIS data	58.77%	73.64%	51.62%	24.34%	9.38%	38.46%	61.62%	17.32%	12.84%	31.19%	37.92%
Bayesian/Maximum Likelihood Classification with probabilities obtained from MATLAB using only GIS data	60.03%	74.20%	50.26%	7.06%	12.47%	30.09%	79.44%	18.49%	17.42%	31.88%	38.13%
Bayesian/Maximum Likelihood Classification with probabilities obtained from MATLAB using GIS data and Landsat TM data	62.02%	76.19%	50.78%	7.09%	14.39%	29.85%	78.10%	18.72%	17.23%	34.91%	38.93%
"Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data	60.01%	74.34%	55.62%	22.45%	18.11%	38.79%	70.43%	24.25%	14.37%	31.22%	40.96%
"Conventional" neural network classification with MATLAB using GIS and Landsat TM data	62.84%	77.56%	54.91%	17.71%	13.08%	37.62%	66.38%	24.80%	18.40%	42.42%	41.57%
Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data	59.07%	74.57%	50.93%	19.65%	18.75%	39.44%	75.91%	22.26%	19.79%	45.71%	42.61%
Bayesian/Maximum Likelihood Classification with probabilities obtained from NeuralSIM using only GIS data	59.16%	71.20%	53.32%	22.83%	14.31%	43.12%	78.85%	22.34%	21.30%	66.95%	45.34%
Average	59.06%	73.18%	51.11%	14.67%	13.40%	34.18%	72.65%	19.11%	15.27%	34.95%	38.76%

Table 5.3: Users's accuracy for each cover type across all the classification techniques in the Roosevelt National Forest Wilderness areas.

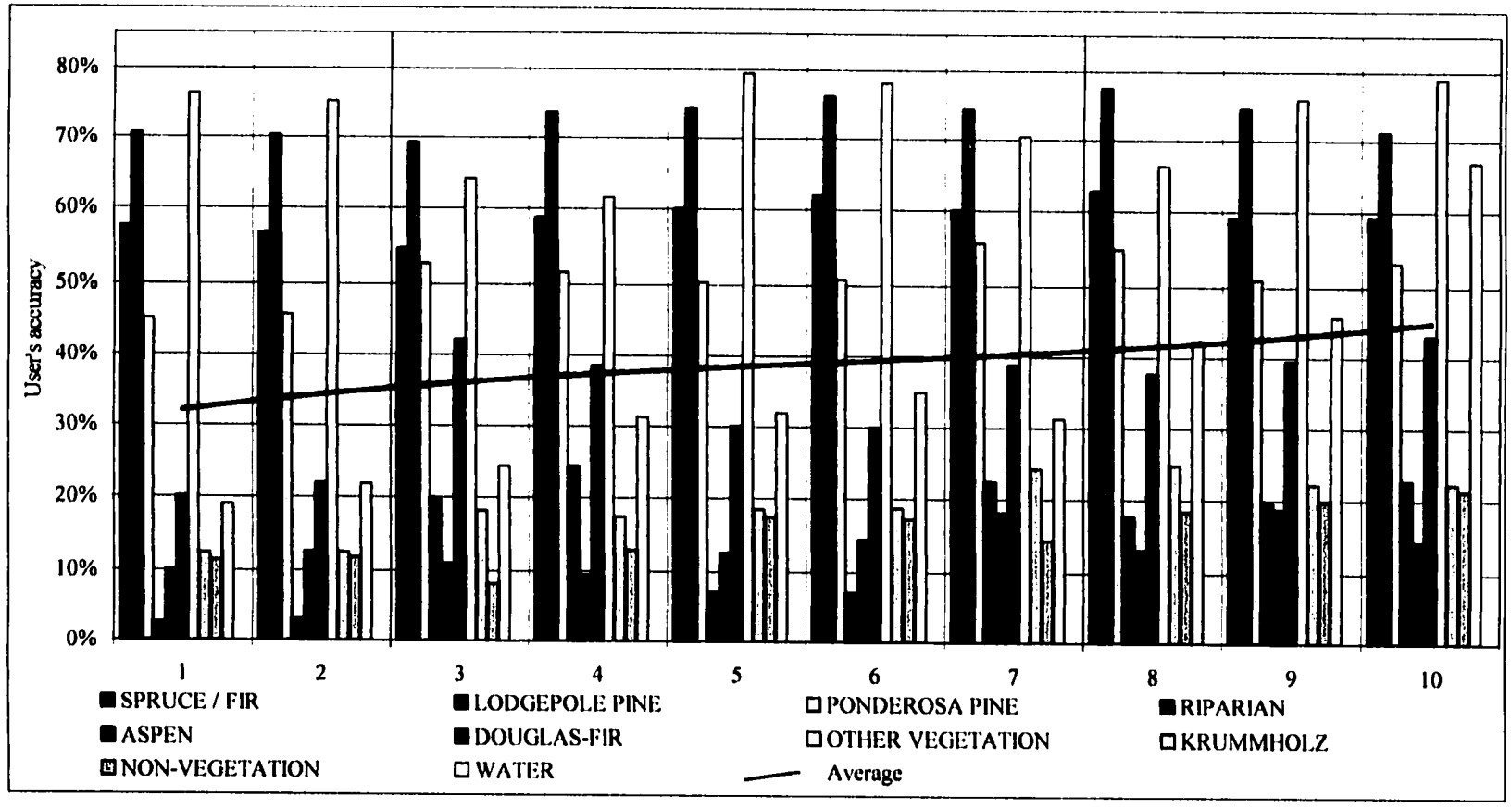


Figure 5.3: User's accuracy for the individual cover types accros all the classification techniques in the Roosevelt National Forest Wilderness areas: (1) Supervised Maximum Likelihood classification (2) "Conventional" Bayesian/Maximum Likelihood classification with probabilities obtained from area proportions of cover types (3) "Conventional" neural network classification with NeuralSIM using GIS data (4) "Coneventional" neural network classification with MATLAB using GIS data (5) Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using only GIS data (6) Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using GIS data and Landsat TM data (7) "Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data (8) "Conventional" neural network classification with MATLAB using GIS and Landsat TM data (9) Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data (10) Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using only GIS data.

Classification technique	SPRUCE / FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	WATER	Overall Kappa
Supervised Maximum Likelihood Classification	0.4238	0.3748	0.2849	0.1296	0.4904	0.5421	0.1136	0.2562	0.2466	0.6767	**0.3264**
"Conventional" Bayesian/Maximum Likelihood Classification with probabilities obtained from area proportions of cover types	0.4447	0.4050	0.2840	0.1311	0.4375	0.4897	0.1605	0.2403	0.2218	0.6597	**0.3486**
"Conventional" neural network classification with NeuralSIM using only GIS data	0.3131	0.3268	0.6099	0.3139	0.4178	0.4058	0.5114	0.3986	0.3995	0.5848	**0.3830**
"Conventional" neural network classification with MATLAB using only GIS data	0.3871	0.2860	0.5671	0.3079	0.6293	0.4449	0.4962	0.4470	0.4016	0.5056	**0.3869**
Bayesian/Maximum Likelihood Classification with probabilities obtained from MATLAB using only GIS data	0.4988	0.4089	0.4230	0.2129	0.6587	0.5594	0.3232	0.3227	0.3198	0.6611	**0.4195**
Bayesian/Maximum Likelihood Classification with probabilities obtained from MATLAB using GIS data and Landsat TM data	0.5378	0.4567	0.4078	0.2065	0.6375	0.5218	0.3141	0.3471	0.3218	0.6865	**0.4435**
Bayesian/Maximum Likelihood Classification with probabilities obtained from NeuralSIM using only GIS data	0.4346	0.4258	0.5810	0.3060	0.5597	0.4581	0.5113	0.3850	0.3927	0.6041	**0.4560**
"Conventional" neural network classification with MATLAB using GIS and Landsat TM data	0.5139	0.3952	0.5250	0.2667	0.6215	0.4437	0.4944	0.5116	0.4108	0.6611	**0.4638**
"Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data	0.4746	0.4161	0.5709	0.2957	0.5956	0.4610	0.5131	0.4020	0.3967	0.6480	**0.4641**
Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data	0.5234	0.4104	0.4977	0.2828	0.6078	0.5072	0.4853	0.3579	0.3827	0.6738	**0.4642**
Average	0.4552	0.3906	0.4751	0.2453	0.5656	0.4834	0.3923	0.3668	0.3494	0.6361	**0.4156**

Table 5.4: Kappa values for each cover type across all the classification techniques in the Roosevelt National Forest Wilderness areas.

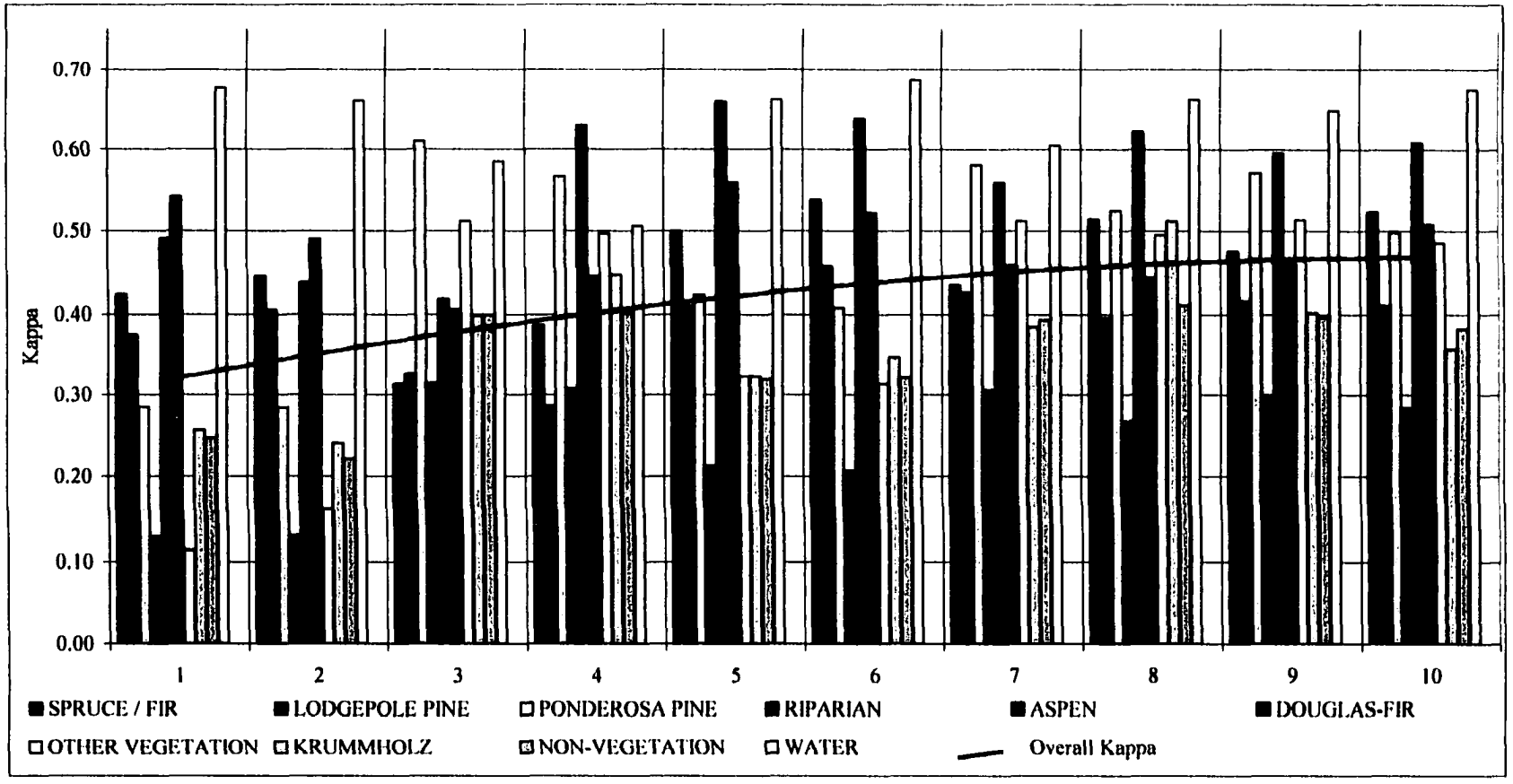


Figure 5.4: Kappa values for the individual cover types accros all the classification techniques in the Roosevelt National Forest Wilderness areas: (1) Supervised Maximum Likelihood classification (2) "Conventional" Bayesian/Maximum Likelihood classification with probabilities obtained from area proportions of cover types (3) "Conventional" neural network classification with NeuralSIM using GIS data (4) "Coneventional" neural network classification with MATLAB using GIS data (5) Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using only GIS data (6) Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using GIS data and Landsat TM data (7) Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using only GIS data (8) "Conventional" neural network classification with MATLAB using GIS and Landsat TM data (9) "Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data (10) Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using

5.2 Comparative results of the classifications performed in the Rocky Mountain National Park study area

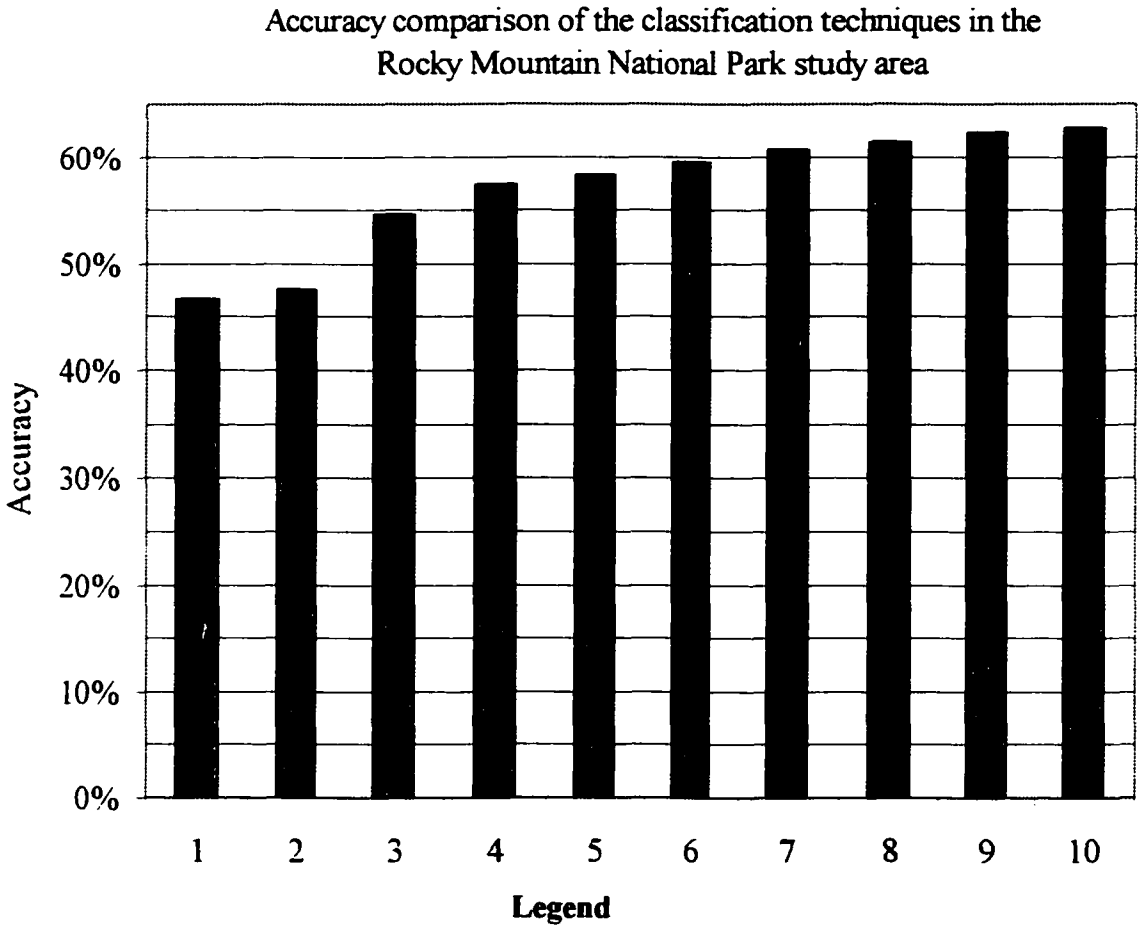
The results of the classifications performed in the Rocky Mountain National Park area are presented in Table 5.5 and Figure 5.5. A comparison of the classification accuracies of all the classification techniques, ranked from lowest to highest shows that the overall accuracies range from 46.77 percent for the supervised Maximum Likelihood classification to 62.61 percent for the Neural Network Classification with MATLAB using GIS and Landsat TM data. The use of the neural network classification represents an increase of 15.84 percent over the conventional classification procedure. The second highest accuracy was obtained by the Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data (62.28 percent), followed by the neural network classification with NeuralSIM using GIS and Landsat TM data in the third place (61.41 percent). As is the case of the Roosevelt National Forest Wilderness areas, "conventional" neural networks classifications both with NeuralSIM and MATLAB were among the classification techniques with highest overall accuracies. Also, very similar to the results in the Roosevelt National Forests study area was the accuracy achieved by the Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using only GIS data, which with 60.61 percent obtained the fourth highest overall classification.

The producer's accuracies of the individual cover types across all the classifications techniques are presented in Table 5.6 and Figure 5.6. On average, the producer accuracies ranged from a minimum of 47.40 percent, attained by the "conventional" Bayesian/Maximum Likelihood classification with probabilities obtained from area proportions of cover types, to a maximum of 58.00 percent, attained by the

Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data.

Classification technique	Accuracy	Kappa
Supervised Maximum Likelihood classification	46.77%	0.38
"Conventional" Bayesian/Maximum Likelihood classification with probabilities obtained from area proportions of cover types	47.63%	0.38
"Conventional" neural network classification with NeuralSIM using GIS data	54.60%	0.46
Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using only GIS data	57.34%	0.49
Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using GIS data and Landsat TM data	58.35%	0.50
"Conventional" neural network classification with MATLAB using GIS data	59.43%	0.50
Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using only GIS data	60.71%	0.53
"Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data	61.41%	0.54
Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data	62.28%	0.55
"Conventional" neural network classification with MATLAB using GIS and Landsat TM data	62.71%	0.54

Table 5.5: Accuracy comparison of the different classification techniques applied to the Rocky Mountain National Park study area.



Nr. **Classification technique**

1 =Supervised Maximum Likelihood classification

2 ="Conventional" Bayesian/Maximum Likelihood classification with probabilities obtained from area proportions of cover types

3 ="Conventional" neural network classification with NeuralSIM using GIS data

4 =Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using only GIS data

5 =Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using GIS data and Landsat TM data

6 ="Conventional" neural network classification with MATLAB using GIS data

7 =Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using only GIS data

8 ="Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data

9 =Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data

10 ="Conventional" neural network classification with MATLAB using GIS and Landsat TM data

Figure 5.5: Accuracy comparison of the different classification techniques applied to the Rocky Mountain National Park study area.

The highest producer's accuracies were obtained by the Bayesian/Maximum Likelihood classification with probabilities obtained from neural network using GIS data and Landsat TM data, using both NeuralSIM and MATLAB, followed very closely by "conventional" classification with neural networks using a combination of GIS and Landsat TM data using NeuralSIM and MATLAB.In regard to the cover types, the average producer's accuracies ranged from 34.96 percent for the *Aspen* to 69.39 percent for the *Lodgepole pine*. On the lower range of producer's accuracies was also *Riparian* with 34.99 percent.

The user's accuracy of the individual cover types across all the classifications techniques is presented in Table 5.7 and Figure 5.7. On average the user's accuracies ranged from a minimum of 39.47 percent for the supervised Maximum Likelihood classification to a maximum of 53.03 percent for the Neural Network Classification with NeuralSIM using GIS and Landsat TM data. As in the case of the Roosevelt National Forest Wilderness areas, the Bayesian classifications with prior obtained from NeuralSIM using both, only GIS data, and a combination of GIS and Landsat data performed better than the other classification techniques. In regard to the cover types, the average user's accuracies ranged from 13.55 percent for the *Aspen* to 74.14 percent for the *Non-vegetation*. Among the cover types on the lower user's accuracy range was also *Krummholz* (20.59 percent), and on the upper range was also *Spruce/Fir* (71.10 percent).

Table 5.8 and Figure 5.8 display the Kappa values for the individual cover types in the Rocky Mountain National Park study area. In this area, the overall Kappa values ranged from a minimum of 0.3752 for the supervised Maximum Likelihood classification to a maximum of 0.4642 percent for the Bayesian/Maximum Likelihood classification

with probabilities obtained from NeuralSIM using GIS data and Landsat data. As in the case of previous study area, the neural network models trained with GIS and spectral data obtained the overall performances. The "Conventional" neural network classification with MATLAB using GIS and Landsat TM data, and the "Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data ranked second and third with overall Kappa values of 0.5447 and 0.5356 respectively. The analysis of the average cover types Kappa values shows that values ranged from 0.3314 percent for Douglas-fir to 0.6858 for Water. Cover types on the low Kappa range include *Krummholz* (0.33391) and Aspen (0.3403). Cover types on the upper Kappa range include Spruce/Fir (0.5715), Riparian (0.5667) and Ponderosa pine (0.5662).

Classification technique	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	TUNDRA	WATER	Average
"Conventional" Bayesian/Maximum Likelihood Classification with probabilities obtained from area proportions of cover types	64.33%	59.46%	51.08%	58.28%	59.25%	25.71%	56.64%	51.08%	22.81%	19.16%	53.62%	47.40%
"Conventional" neural network classification with MATLAB using only GIS data	73.43%	47.81%	51.51%	59.89%	5.14%	26.83%	44.62%	16.24%	63.21%	65.48%	70.15%	47.66%
"Conventional" neural network classification with NeuralSIM using only GIS data	60.71%	48.77%	49.60%	47.93%	11.68%	38.72%	44.77%	25.60%	57.56%	64.05%	76.47%	47.81%
Supervised Maximum Likelihood Classification	62.05%	57.93%	51.84%	58.28%	60.85%	33.47%	57.04%	53.70%	22.57%	17.96%	50.69%	47.85%
Bayesian/Maximum Likelihood Classification with probabilities obtained from MATLAB using only GIS data	71.08%	61.13%	56.34%	63.97%	53.71%	30.68%	57.55%	45.75%	36.32%	52.05%	62.13%	53.70%
Bayesian/Maximum Likelihood Classification with probabilities obtained from NeuralSIM using only GIS data	72.74%	53.83%	57.46%	58.97%	23.59%	41.85%	51.54%	36.00%	52.53%	68.07%	76.18%	53.89%
"Conventional" neural network classification with MATLAB using GIS and Landsat TM data	74.53%	50.74%	63.90%	65.56%	21.05%	32.38%	54.35%	25.53%	63.49%	68.67%	74.76%	54.09%
"Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data	68.38%	52.34%	75.37%	60.32%	21.32%	41.97%	43.41%	34.06%	62.99%	64.91%	82.41%	55.23%
Bayesian/Maximum Likelihood Classification with probabilities obtained from MATLAB using GIS data and Landsat TM data	74.76%	52.23%	60.65%	64.47%	54.48%	35.54%	59.28%	55.48%	39.77%	53.61%	66.33%	56.05%
Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data	71.91%	56.60%	74.50%	64.11%	38.52%	42.73%	48.03%	47.24%	53.66%	62.44%	78.22%	58.00%
Average	69.39%	54.08%	59.23%	60.18%	34.96%	34.99%	51.72%	39.07%	47.49%	53.64%	69.10%	52.17%

Table 5.6: Producer's accuracy for each cover type across all the classification techniques in the Rocky Mountain National Park study area.

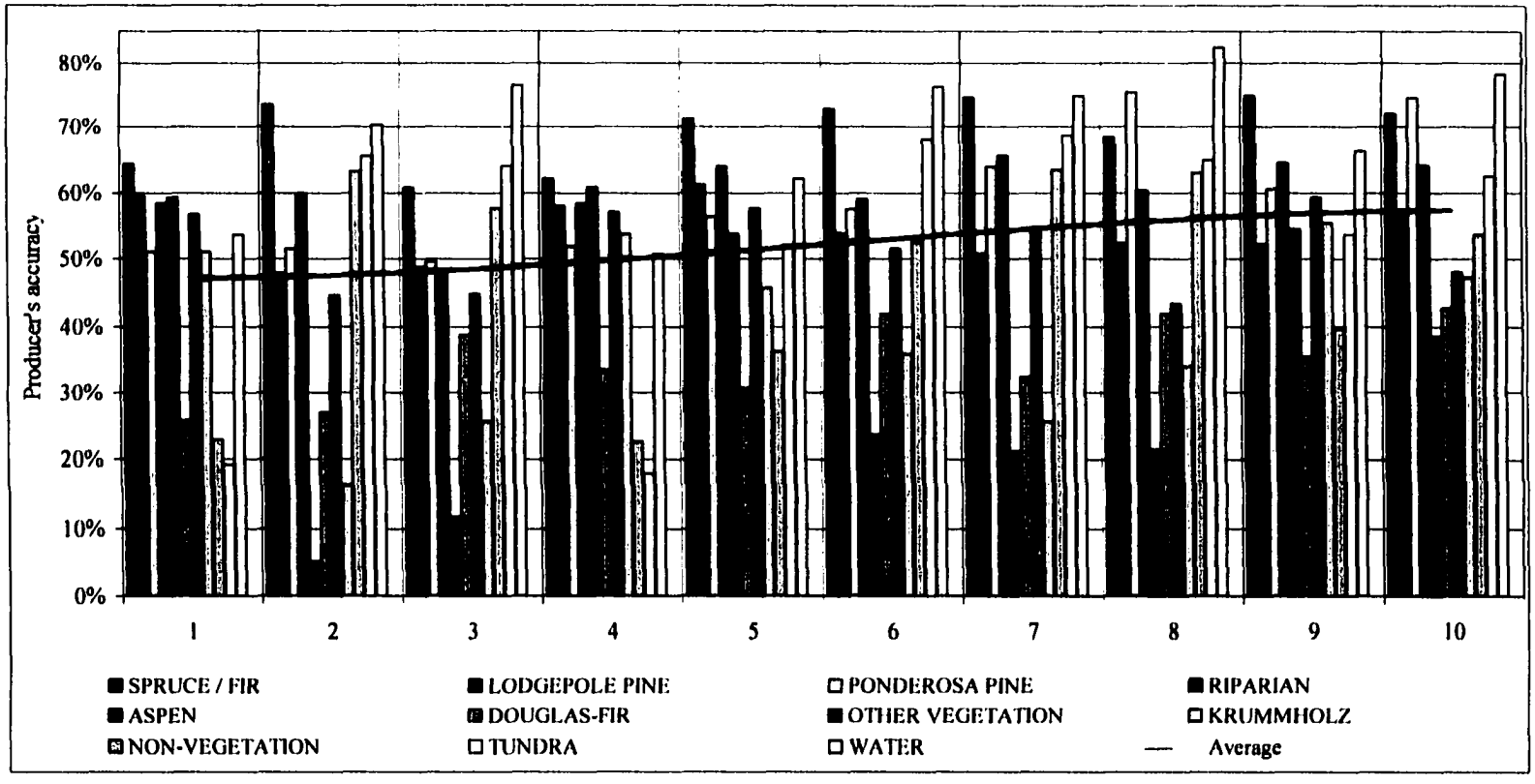


Figure 5.6: Producer's accuracy for the individual cover types across all the classification techniques in the Rocky Mountain National Park study area: (1) "Conventional" Bayesian/Maximum Likelihood classification with probabilities obtained from area proportions of cover types (2) "Conventional" neural network nlassification with MATLAB using GIS data (3) "Conventional" neural network classification with NeuralSIM using GIS data (4) Supervised Maximum Likelihood classification (5) Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using only GIS data (6) Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using only GIS data (7) "Conventional" neural network classification with MATLAB using GIS and Landsat TM data. (8) "Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data (9) Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using GIS data and Landsat TM data (10) Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data

Classification technique	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	TUNDRA	WATER	Average
Supervised Maximum Likelihood Classification	72.57%	54.23%	65.18%	38.12%	11.92%	19.00%	35.84%	12.13%	75.12%	42.88%	7.17%	39.47%
"Conventional" Bayesian/Maximum Likelihood Classification with probabilities obtained from area proportions of cover types	71.53%	54.20%	65.70%	38.05%	12.57%	20.73%	36.00%	12.31%	74.72%	43.92%	6.71%	39.68%
"Conventional" neural network classification with NeuralSIM using only GIS data	70.29%	56.67%	50.55%	33.21%	5.12%	28.54%	26.07%	20.46%	62.58%	58.44%	30.56%	40.23%
Bayesian/Maximum Likelihood Classification with probabilities obtained from MATLAB using only GIS data	74.74%	60.25%	68.78%	40.75%	15.94%	24.95%	37.55%	17.93%	83.04%	60.48%	14.25%	45.33%
Bayesian/Maximum Likelihood Classification with probabilities obtained from MATLAB using GIS data and Landsat TM data	73.49%	62.94%	69.70%	42.89%	16.45%	20.24%	44.17%	19.89%	83.11%	64.16%	19.84%	46.99%
"Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data	74.14%	59.68%	60.00%	42.37%	11.77%	32.69%	42.04%	24.76%	73.67%	66.22%	31.28%	47.15%
"Conventional" neural network classification with MATLAB using only GIS data	65.34%	61.47%	61.44%	40.95%	6.39%	30.18%	39.51%	25.99%	63.58%	62.34%	65.39%	47.51%
Bayesian/Maximum Likelihood Classification with probabilities obtained from NeuralSIM using only GIS data	74.01%	60.53%	61.26%	43.76%	10.29%	30.83%	33.35%	23.28%	80.86%	59.92%	50.24%	48.03%
Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data	74.26%	61.67%	65.46%	45.16%	16.67%	34.74%	49.09%	23.10%	81.68%	65.69%	55.28%	52.07%
"Conventional" neural network classification with MATLAB using GIS and Landsat TM data	70.62%	64.15%	66.72%	53.58%	28.41%	28.44%	52.97%	26.05%	63.05%	63.59%	65.74%	53.03%
Average	72.10%	59.58%	63.48%	41.88%	13.55%	27.03%	39.66%	20.59%	74.14%	58.76%	34.65%	45.95%

Table 5.7: User's accuracy for each cover type across all the classification techniques in the Rocky Mountain National Park study area.

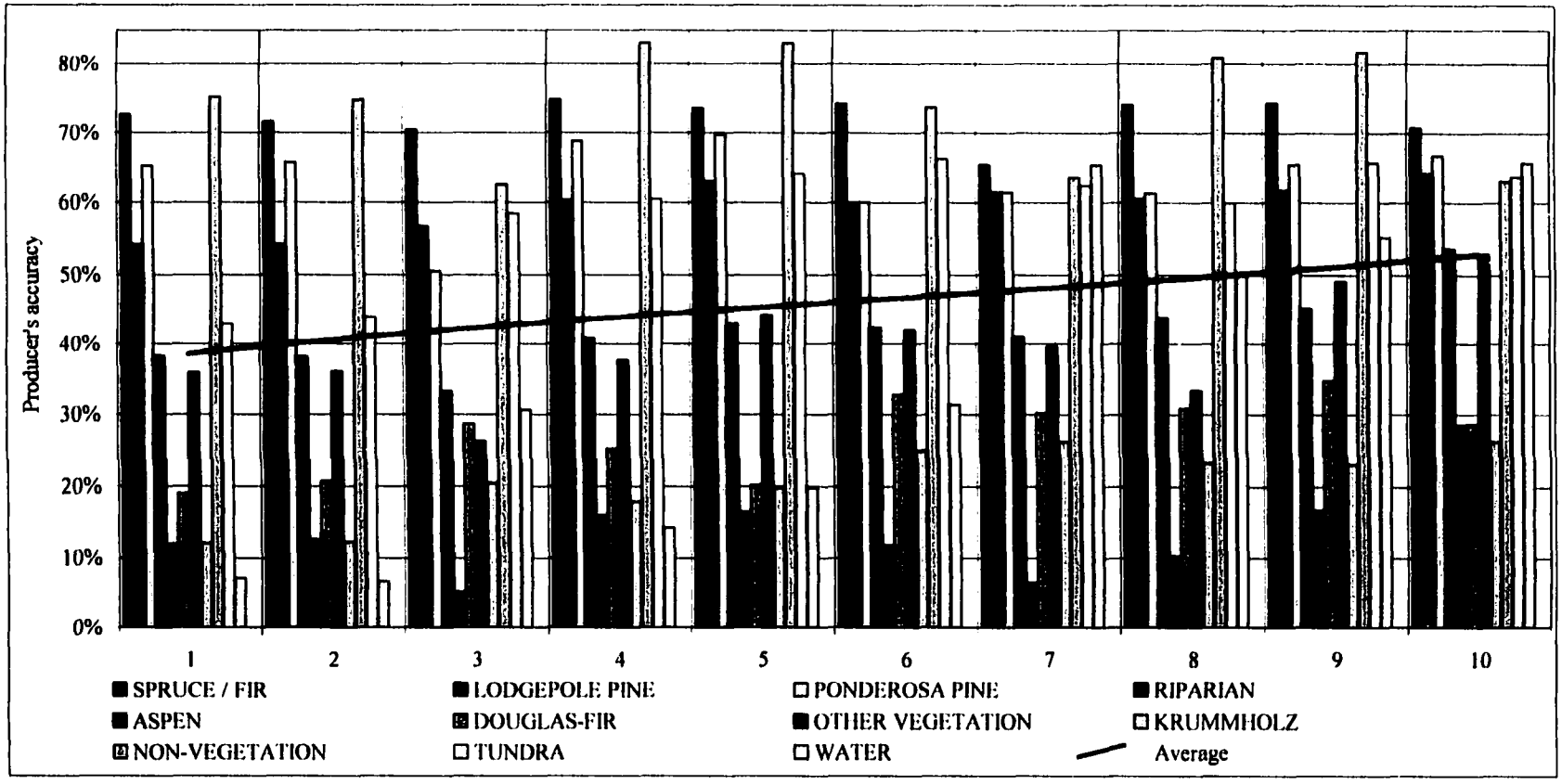


Figure 5.7: User's accuracy for the individual cover types accros all the classification techniques in the Rocky Mountain National Park study area: (1) Supervised Maximum Likelihood classification (2) "Conventional" Bayesian/Maximum Likelihood classification with probabilities obtained from area proportions of cover types (3) "Conventional" neural network classification with NeuralSIM using GIS data (4) Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using only GIS data (5) Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using GIS data and Landsat TM data (6) "Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data (7) "Conventional" neural network classification with MATLAB using GIS data (8) Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using only GIS data (9) Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data (10) "Conventional" neural network classification with MATLAB using GIS and Landsat TM

Classification technique	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	TUNDRA	WATER	Overall Kappa
Supervised Maximum Likelihood Classification	0.4900	0.4700	0.4900	0.5400	0.6000	0.3100	0.5600	0.4400	0.1900	0.1300	0.4900	**0.3752**
"Conventional" Bayesian/Maximum Likelihood Classification with probabilities obtained from area proportions of cover types	0.5121	0.4869	0.4845	0.5442	0.5798	0.2372	0.5544	0.4169	0.1883	0.1387	0.5216	**0.3819**
"Conventional" neural network classification with NeuralSIM using only GIS data	0.4703	0.3867	0.4613	0.4341	0.1036	0.3692	0.4309	0.2181	0.5019	0.5749	0.7624	**0.4557**
Bayesian/Maximum Likelihood Classification with probabilities obtained from MATLAB using only GIS data	0.5958	0.5176	0.5386	0.6054	0.5268	0.2884	0.5641	0.3979	0.3150	0.4544	0.6149	**0.4897**
Bayesian/Maximum Likelihood Classification with probabilities obtained from MATLAB using GIS data and Landsat TM data	0.6373	0.4321	0.5827	0.6125	0.5349	0.3307	0.5833	0.5008	0.3475	0.4743	0.6589	**0.5017**
"Conventional" neural network classification with MATLAB using only GIS data	0.5998	0.3869	0.4869	0.5636	0.0464	0.2543	0.4353	0.1416	0.5621	0.5949	0.7003	**0.5021**
Bayesian/Maximum Likelihood Classification with probabilities obtained from NeuralSIM using only GIS data	0.6140	0.4436	0.5467	0.5567	0.2245	0.4014	0.5022	0.3191	0.4700	0.6199	0.7604	**0.5258**
"Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data	0.5634	0.4273	0.7316	0.5692	0.2039	0.4035	0.4239	0.3034	0.5710	0.5929	0.8223	**0.5356**
"Conventional" neural network classification with MATLAB using GIS and Landsat TM data	0.6278	0.4195	0.6148	0.6305	0.2067	0.3071	0.5353	0.2259	0.5644	0.6305	0.7465	**0.5447**
Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data	0.6046	0.4736	0.7245	0.6105	0.3759	0.4121	0.4714	0.4269	0.4819	0.5664	0.7810	**0.5460**
Average	0.5715	0.4444	0.5662	0.5667	0.3403	0.3314	0.5061	0.3391	0.4192	0.4777	0.6858	**0.4858**

Table 5.8: Kappa values for each cover type across all the classification techniques in the Rocky Mountain National Park study area.

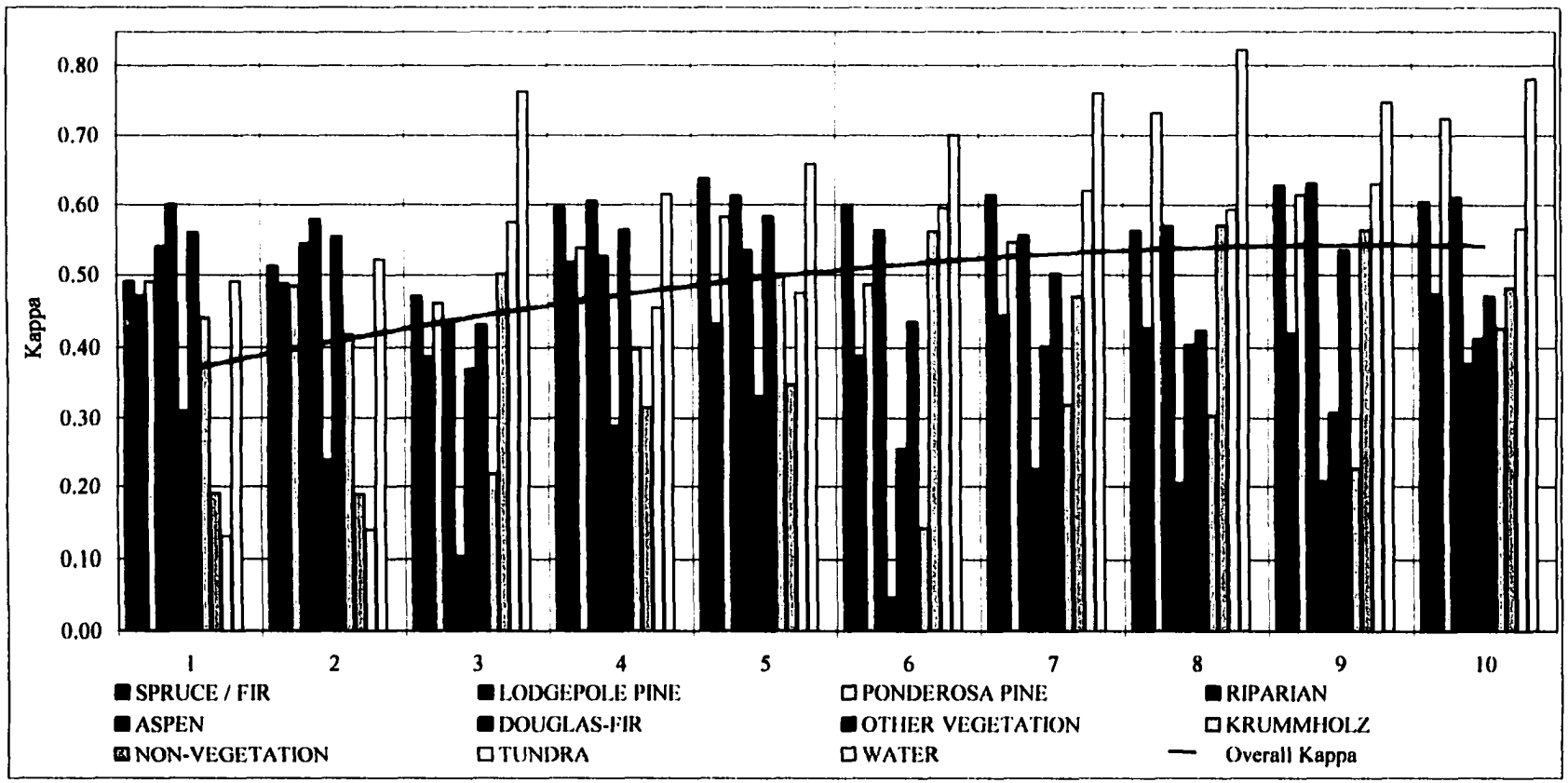


Figure 5.8: Kappa values for the individual cover types accros all the classification techniques in the Rocky Mountain National Park study area: (1) Supervised Maximum Likelihood classification (2) "Conventional" Bayesian/Maximum Likelihood classification with probabilities obtained from area proportions of cover types (3) "Conventional" neural network classification with NeuralSIM using GIS data (4) Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using only GIS data (5) Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using GIS data and Landsat TM data (6) "Conventional" neural network classification with MATLAB using GIS data (7) Bayesian/Maximum Likelihood Classification with probabilities obtained from NeuralSIM using only GIS data (8) "Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data (9) "Conventional" neural network classification with MATLAB using GIS and Landsat TM data (10) Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data.

5.3 Results of the supervised Maximum Likelihood classification

The supervised Maximum Likelihood classification technique only made use of the Landsat TM5 data and was the standard to which all the other techniques were compared. Although the easiest to apply and fastest to produce results, it was the least accurate of all the techniques evaluated, with an overall accuracy of 48.44 percent and an overall Kappa of 0.3264 in the Roosevelt National Forest Wilderness areas (see Table A1 in Appendix 1), and overall accuracy of 46.77 percent and overall Kappa of 0.37 in the Rocky Mountain National Park Study area (see Table A11 in Appendix 1).

The major factor contributing to the low classification performance in the Roosevelt National Forest Wilderness areas was a general overestimation of all the less numerous cover types. Among the most remarkable errors of commission was the one caused by the classification of the Riparian and Krummholz categories as the Other-vegetation category (i.e., tundra, shrubs and grass). Also very important was the confusion of Aspen with Lodgepole pine and Spruce/Fir. This may have been caused by the spectral variability present along the water streams in the Landsat image but absent in the reference data that was often classified as Aspen. The Water category was confused with Lodgepole pine and Spruce/Fir mainly because of shadows caused by the topographic effect, similarly to results obtained by Hoffer in 1979. There was also a considerable amount of error caused by the classification of Douglas fir as Lodgepole pine and Ponderosa pine in the lower elevation ranges that can be also attributed to shadows. Not of lesser importance is the confusion between the two largest categories, Spruce/ Fir and Lodgepole pine caused by the spectral similarities of these cover types.

In the case of the Rocky Mountain National Park study area, the overestimation of the less numerous cover types is also very evident. A similar pattern of confusion between the Riparian and Krummholz categories with the Tundra, and Other-vegetation categories is present in this area too. However the Riparian vegetation displays a higher accuracy than the one obtained in the Roosevelt National Forest Wilderness areas, probably due to the higher quality of the reference data and higher occurrence of this cover type. Another difference between the two areas is the confusion of the Water and Non-vegetation categories present in the Rocky Mountain National Park study area. The confusion can be explained by the presence of shadows in highly steep terrain. The difference between the two areas can be attributed by the large proportion of non-vegetated areas present in the Rocky Mountain National Park as compared to the Roosevelt National Forest Wilderness areas.

The cover type stratification performed in the sampling procedure in order to improve the performance of the artificial neural network (described in Section 4.3.4) might have been detrimental for the supervised Maximum Likelihood classification procedure, probably causing the overestimation of the less numerous categories.

An analysis of the Kappa coefficient of the individual cover types in the Roosevelt National Forest Wilderness areas (see Table 5.4 and Figure 5.4) indicates that overall there is a considerable amount of randomness present in the classification of the all cover types. This is particularly evident in the case of the Riparian, Other-vegetation, Krummholz, and Non-vegetation categories. The classification results of Rocky Mountain National Park, although displaying higher Kappa values, show consistency in this regard (see Table 5.8 and Figure 5.8), particularly in the Non-vegetation and

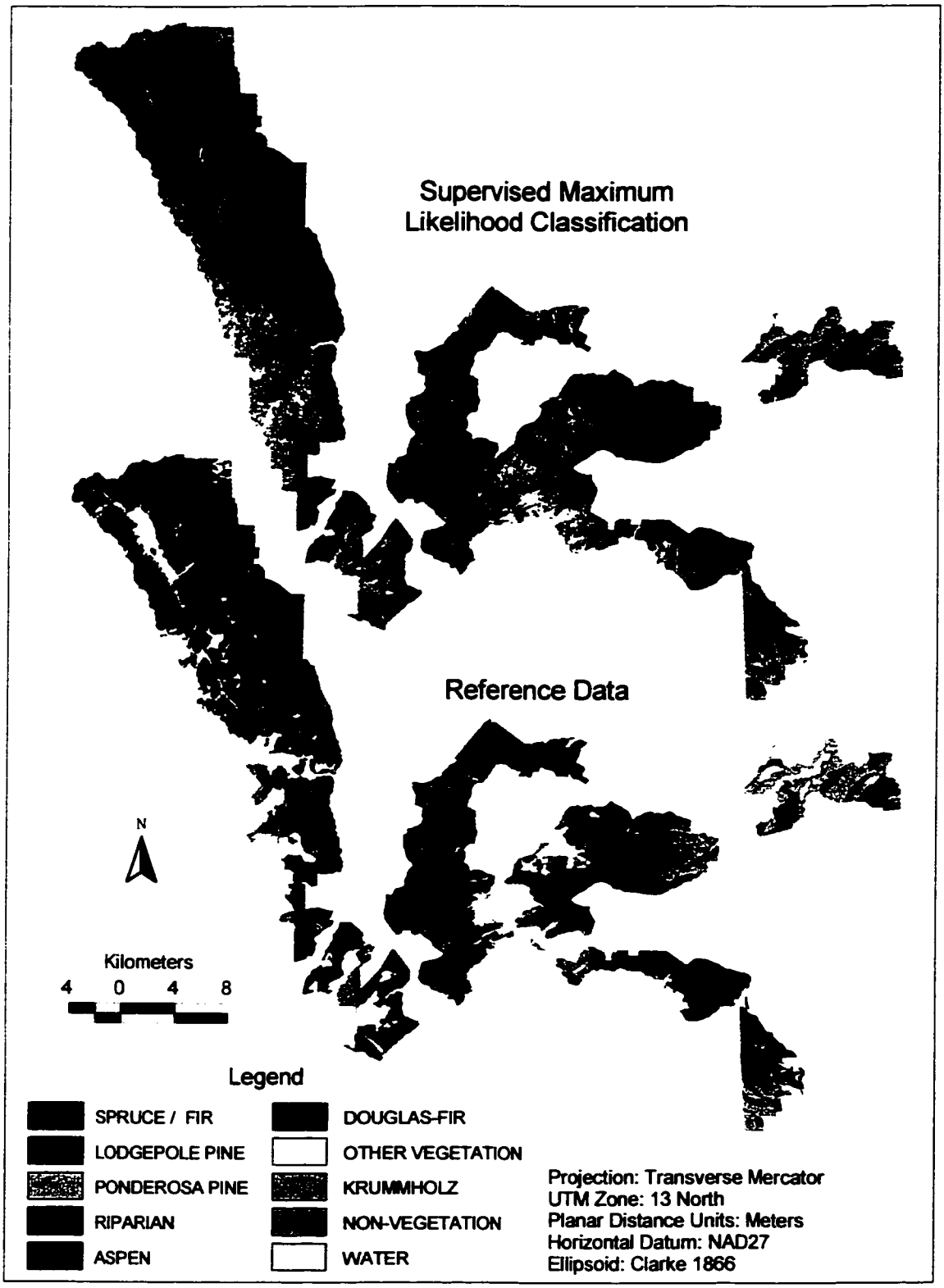


Figure 5.9: Supervised Maximum Likelihood classification in the Roosevelt National Forest Wilderness areas.

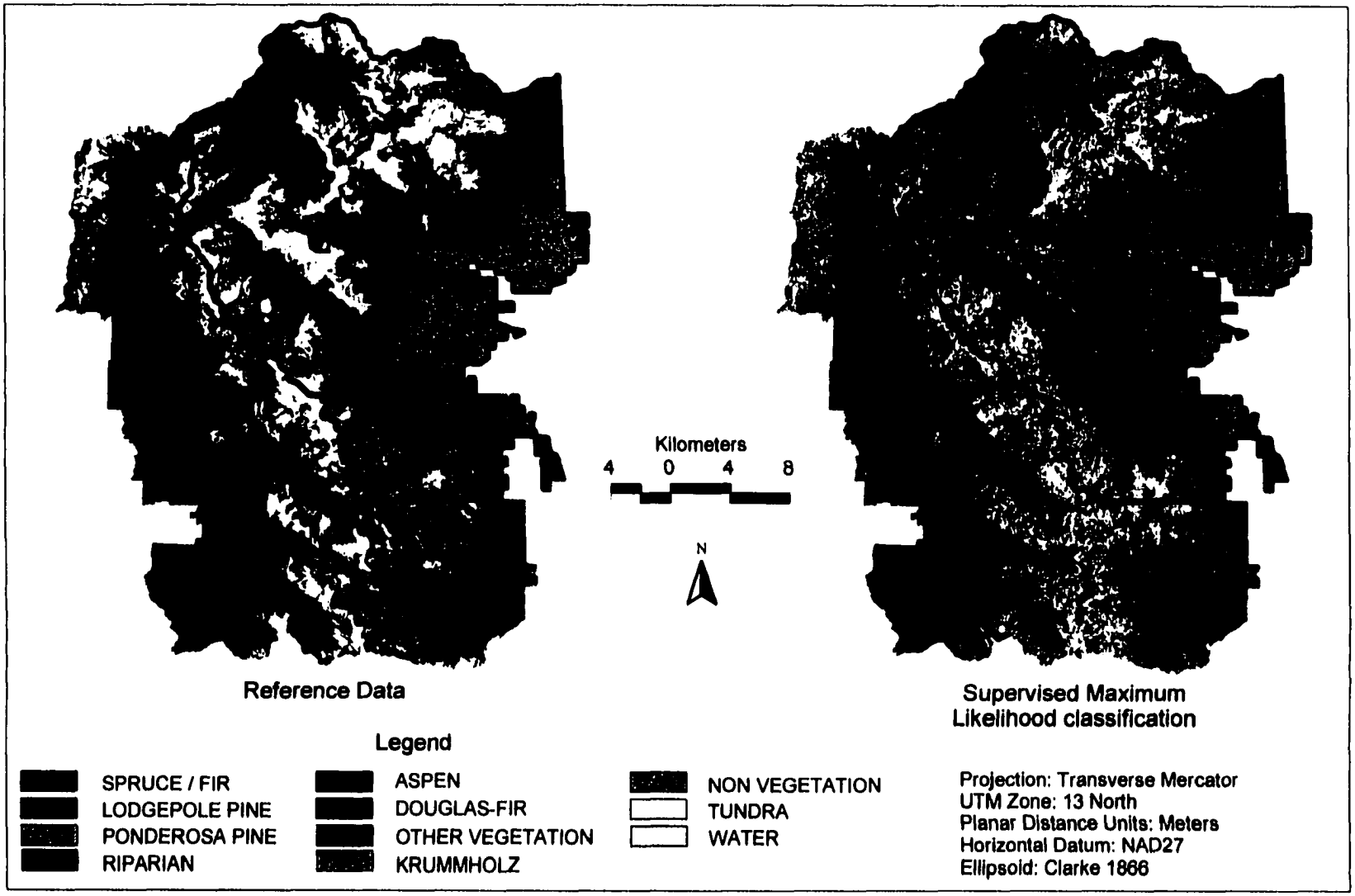


Figure 5.10: Supervised Maximum Likelihood classification in the Rocky Mountain National Park study area.

Tundra categories. This could be the result of the tremendous amount of spectral overlap among all the categories used in the classification, described later in Section 5.6.

Although very broad, general similarities exist between the supervised Maximum Likelihood classification maps of both study areas and their corresponding reference data sets. The true geographic representation of this classification technique can be graded as very poor. As evidenced in Figures 5.9 and 5.10, overall there is a considerable amount of variability present in the supervised Maximum Likelihood classification maps as compared to the reference maps of both study areas.

Due to the use of only satellite imagery, once the training data was extracted (as described in Section 4.3.1.1), the supervised Maximum Likelihood algorithm required only a few minutes to produce results. In general, the entire classification process with the supervised Maximum Likelihood classification required three to four hours (i.e., the time needed to produce a suitable set of training data). This makes it the simplest and easiest of all the different classification techniques used in this study.

5.4 Results of the Bayesian classification techniques

5.4.1 Results of the "conventional" Bayesian/Maximum Likelihood classification with probabilities obtained from area proportions of cover types

The inclusion of prior probabilities obtained from area proportions of cover types into a Bayesian Maximum Likelihood classifier showed a very slight improvement over results obtained with the Maximum Likelihood classifications described previously. Overall accuracy in the Roosevelt National Forest Wilderness areas increased from 48.44 percent to 51.11 percent, and 46.77 percent to 47.63 in the case of Rocky Mountain National Park (see Tables A2 and A12 in Appendix 1). However, these improvements

are not very meaningful in a practical sense, and a detailed inspection of the error matrices reveals that the exact same confusion patterns present in the Maximum Likelihood classification are also present here. This is also confirmed by analyzing the Kappa coefficients for the individual cover types in Tables 5.4 and 5.8 and Figures 5.4 and 5.8, respectively, for each study area.

The results are consistent for both study areas and are also evident in the classification maps presented in Figures 5.11 and 5.12. Furthermore, when compared to the maps of the Maximum Likelihood classifications, the Bayesian classifier maps demonstrate comparable levels of true geographic representation.

A possible explanation for this outcome may rest in the fact that the priors used in this conventional Bayesian classification procedure are completely deprived of spatial information. In other words, while containing information on what cover types are more likely to occur based on their proportions in the area of interest, they do not provide information on where this cover type is most likely to occur. In addition to this, a per pixel classification approach is not taking into consideration the spatial auto-correlation of the cover types, which could be very significant and can provide additional benefits to the classification (e.g., an observation 30 meters away from a group of Lodgepole pine pixels is more likely to be Lodgepole pine than another observation located 200 meters away)

Since the prior probabilities were calculated based on the area proportions of the cover types in the reference data sets, the time required to perform this classification did not increase to a great extent over the supervised Maximum Likelihood classification (around four hours). However, in a 'real life' situation, the time to estimate priors could

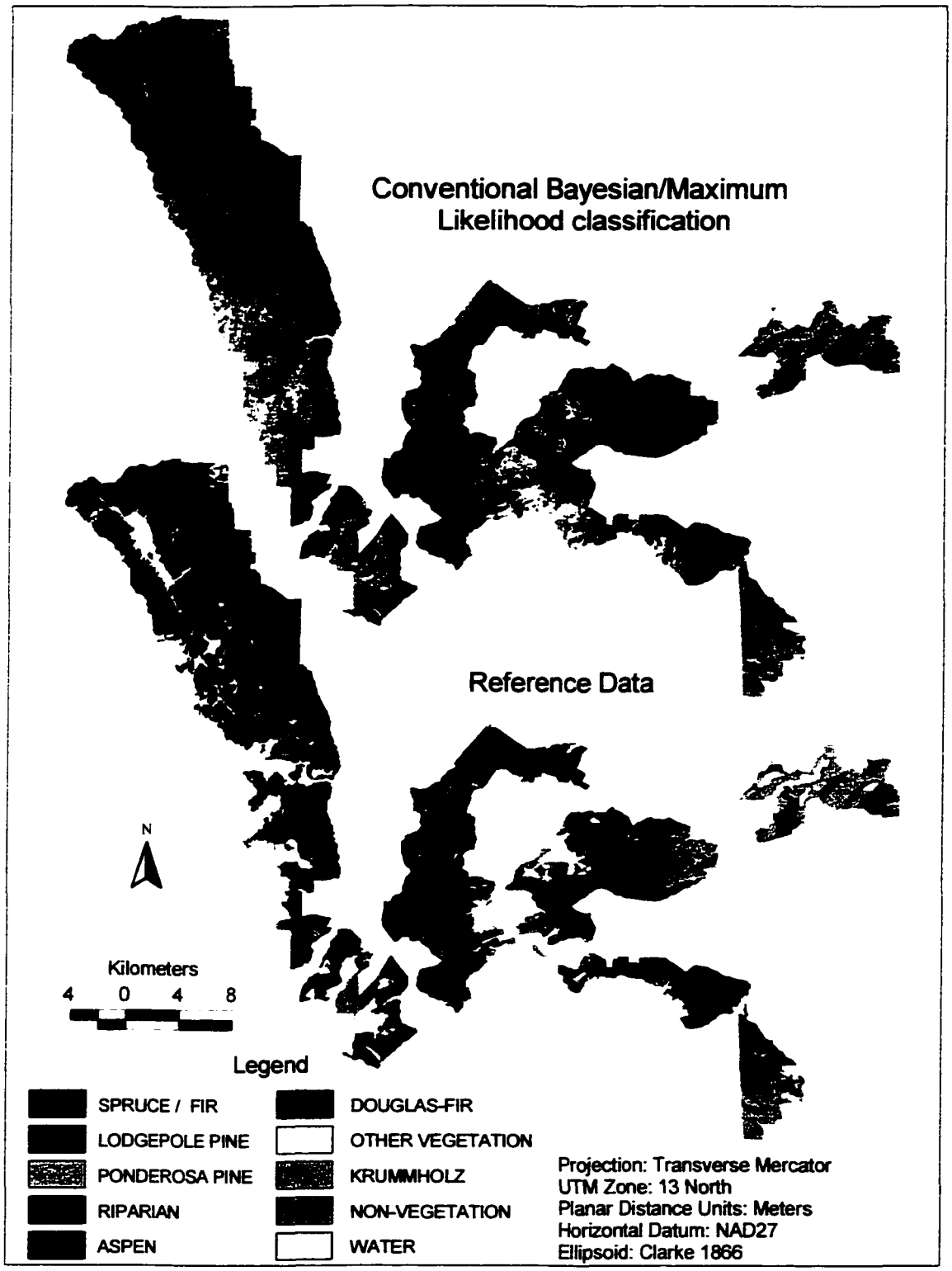


Figure 5.11: "Conventional" Bayesian/Maximum Likelihood classification with probabilities obtained from area proportions of cover types in the Roosevelt National Forest Wilderness areas.

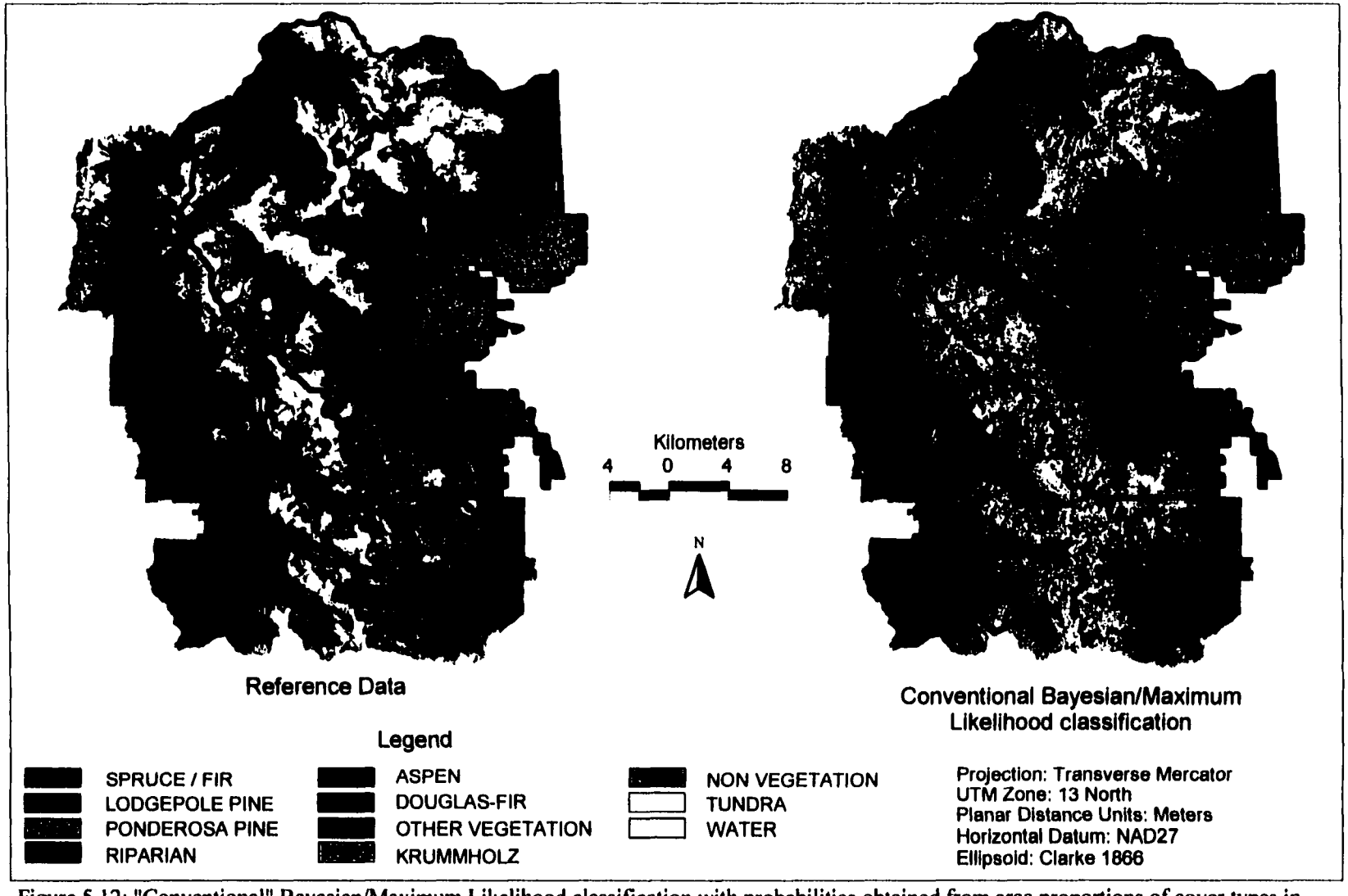


Figure 5.12: "Conventional" Bayesian/Maximum Likelihood classification with probabilities obtained from area proportions of cover types in the Rocky Mountain National Park study area.

prolong the classification time considerably, depending on the interpreter's experience and familiarity with the study area, as well as the availability of information for a particular region (e.g., aerial photos, previous classifications, etc.).

5.4.2 Results of the Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB

The results of the Bayesian / Maximum Likelihood classifications with prior probabilities obtained from MATLAB show a considerable improvement over the results obtained with the supervised Maximum Likelihood classifications. In the Roosevelt National Forest Wilderness areas the overall accuracy increased almost eight percent (from 48.44 to 56.18 percent) and the overall Kappa increased to 0.41 (see Table A.3 in Appendix 1). In the Rocky Mountain National Park study areas, the overall accuracy increment was even better, reaching almost eleven percent (from 46.77 to 57.34 percent) and the overall Kappa increased to 0.48 (see Table A.13 in Appendix 1). The user's and producer's accuracies for all cover types improved considerably in both study areas. However, with the exception of Aspen in the Roosevelt National Forest, and Douglas Fir in the Rocky Mountain National Park study area, a pattern of confusion similar to the one observed in the supervised Maximum Likelihood classification (i.e., the same cover types have the lowest user's and producer's accuracies) is present here too. As displayed by the Kappa coefficients for the individual cover types in the Roosevelt National Forest Wilderness areas (see Table 5.4 and Figure 5.4), there is a particular improvement in the classification of the Aspen, Ponderosa pine, Other-vegetation and Riparian categories. Similarly, the Kappa coefficients for the individual cover types in the Rocky Mountain

National Park study area, presented in Table 5.8 and Figure 5.8, show considerable improvement for the Tundra and Non-vegetation cover types.

As an additional experiment, probability maps were developed using not only GIS data but also the Landsat TM bands themselves. These, in turn, were input to the Bayesian / Maximum Likelihood classifier. The addition of spectral information to the MATLAB neural network modeling process to generate prior probabilities resulted in a very slight improvement in the overall accuracies. In the Roosevelt National Forest Wilderness areas the overall accuracy improved to 58.28 percent and the overall Kappa to 0.4435 (see Table A4 in Appendix 1). An analysis of the producer's and user's accuracies, and individual Kappa values for this study area, in Tables 5.2, 5.3 and 5.4, and Figures 5.2, 5.3 and 5.4 respectively, show that the Spruce/Fir, Lodgepole pine, Water and Krummholz categories are particularly benefited by the inclusion of spectral information in the neural network modeling process. In the Rocky Mountain National Park study area the overall accuracy improved to 58.35 percent and the overall Kappa to 0.5017 (see Table A14 in Appendix 1). In a similar way the producer's and user's accuracies, and the individual Kappa values in Tables 5.6, 5.7, and 5.8 and Figures 5.6, 5.7, and 5.8, respectively, demonstrate an improvement in the Spruce / Fir, Krummholz and Water categories.

In regard to the true geographic representation, there is some improvement evident if compared to the maps obtained by the Maximum Likelihood classification, particularly from the models that included spectral information. This is more apparent in the higher elevations, where Krummholz, Tundra, and Non-Vegetation are depicted better in relation to the reference data. However, to a lesser extent there is still more

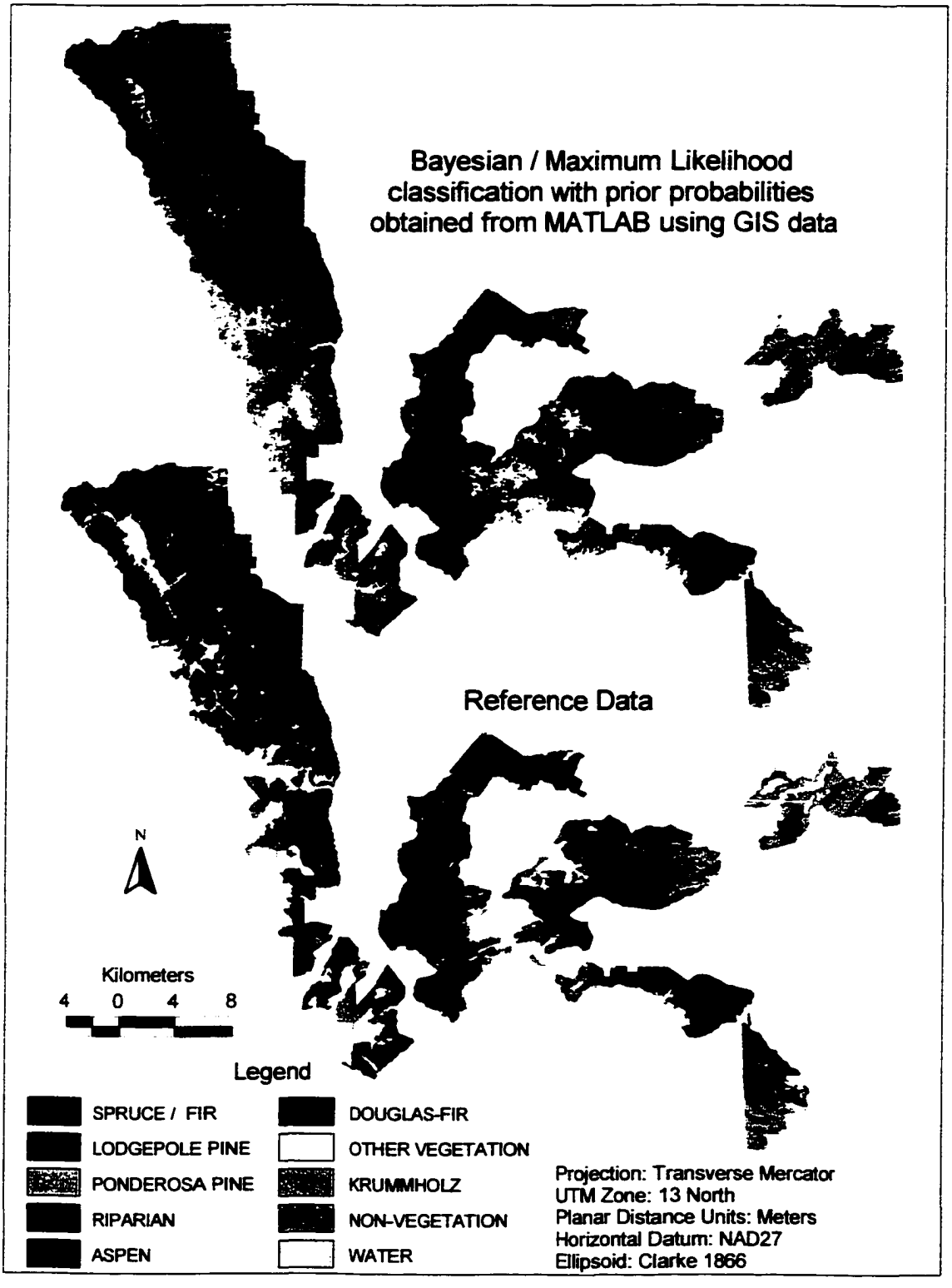


Figure 5.13: Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using only GIS data in the Roosevelt National Forest Wilderness areas.

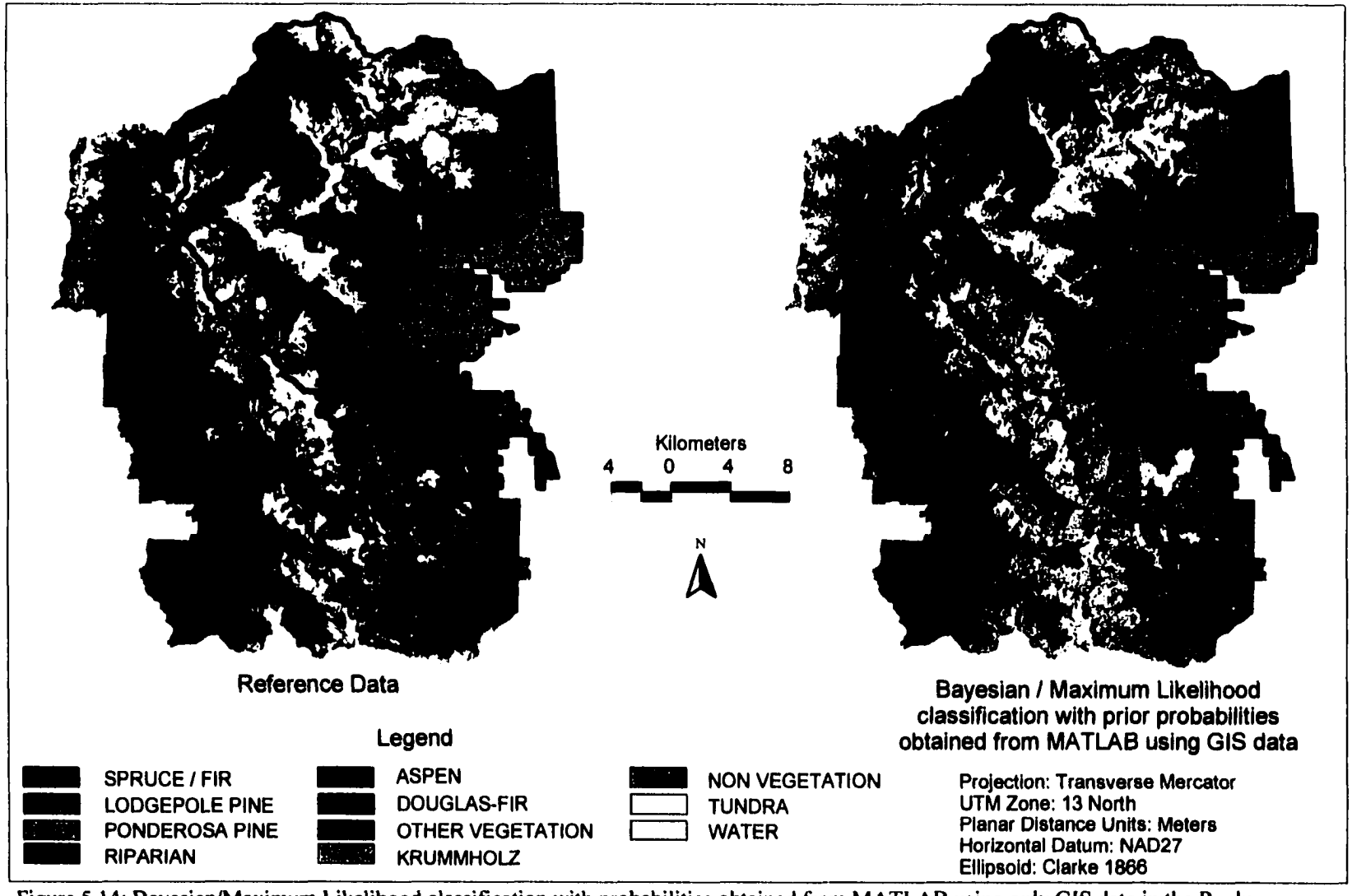


Figure 5.14: Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using only GIS data in the Rocky Mountain National Park study area.

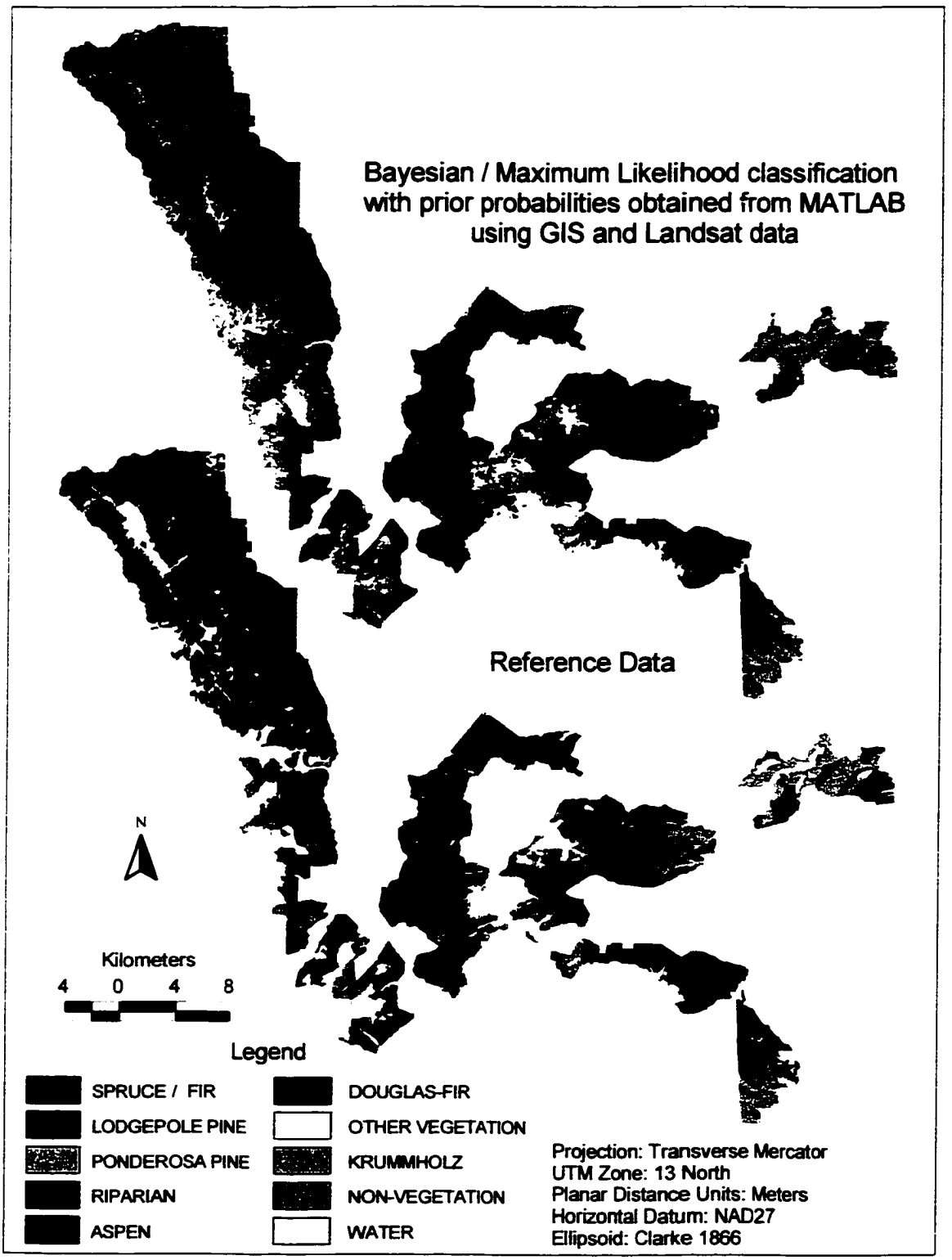


Figure 5.15: Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using GIS and Landsat TM data in the Roosevelt National Forest Wilderness areas.

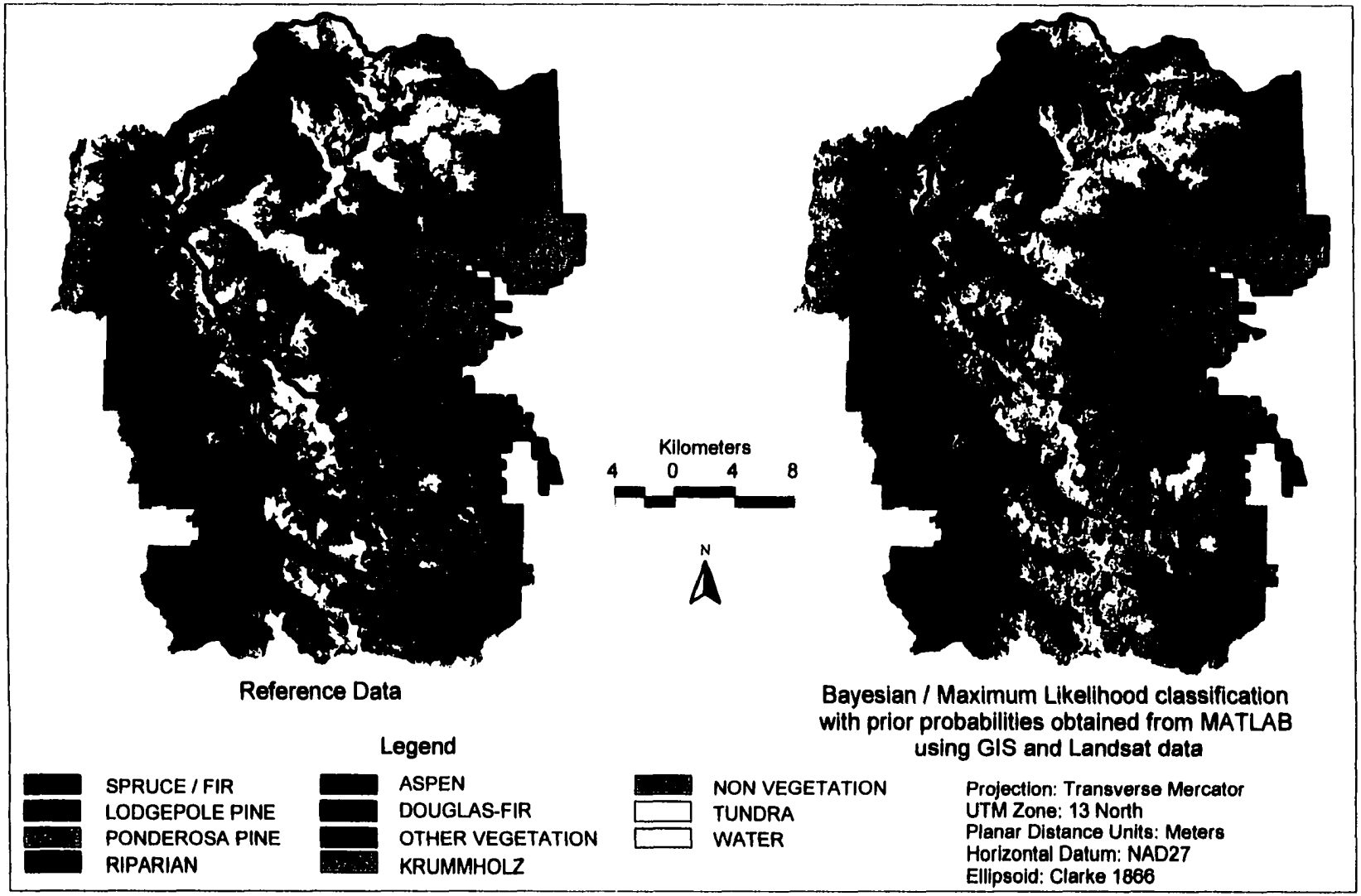


Figure 5.16: Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using GIS and Landsat TM data in the Rocky Mountain National Park study area.

variability present in these maps as compared to the reference data. Figures 5.13 and 5.15, show the classification maps produced with the Bayesian / Maximum Likelihood with probabilities obtained from MATLAB without and with spectral information, respectively. The equivalent maps for the Rocky Mountain National Park study area are presented in Figures 5.14 and 5.16.

When compared to the results of the conventional Bayesian classifier described in the previous section, this new Bayesian classification shows that the inclusion of spatial information in the prior probabilities proves to be considerably more effective. This may indicate that the Bayesian / Maximum Likelihood classifier requires the use of not only accurate prior probabilities, but also of geographically explicit prior probabilities. Nevertheless, there is still a considerable amount of randomness present in all the informational categories included in the classification, indicating that with the current sampling scheme, the combined neural network / Bayesian classification technique is not completely successful in the discrimination of these cover types.

The main disadvantage of this technique is the considerable amount of time it requires to produce results. For instance, it can take several days, even weeks to prepare and make all the variable datasets congruent before they can be fed into the neural network. Even if the inputs were available in a suitable format, the training process of the neural network took an average time of 5 hours for the models using only GIS data and about 7 to 8 hours for the models using GIS and spectral data. The training times for the Rocky Mountain National Park study area increased about two more hours in each case because a larger sample size was used. After the network is trained, the main production of probabilities for each observation in the entire study area took about an hour.

However, before the probabilities could be entered into the Bayesian / Maximum Likelihood classifier, they had to be transformed from a text format to a raster format compatible with IDRISI. This step took an average of four to five hours, since ten or eleven probability maps, depending on the study area, had to be imported. Once the probability maps were ready, the actual Bayesian / Maximum Likelihood classification took only a few minutes.

5.4.3 Results of the Bayesian/Maximum Likelihood Classification with probabilities obtained from NeuralSIM

The results of the Bayesian / Maximum Likelihood classifications with prior probabilities obtained from NeuralSIM show a considerable improvement over the results obtained with the supervised Maximum Likelihood classifications, and also a slight improvement over the results obtained with same technique using MATLAB. In the Roosevelt National Forest Wilderness areas the overall accuracy increased about eleven percent (from 48.44 to 59.56 percent) and the overall Kappa increased to 0.456 (see Table A.5 in Appendix 1) as compared to the supervised Maximum Likelihood classification. The evaluation of the producer's and user's accuracies, and the individual Kappa values for this study area, in Tables 5.2, 5.3 and 5.4, and Figures 5.2, 5.3, and 5.4, respectively, show that there are some differences in the way certain cover types were classified with NeuralSIM as compared to MATLAB. Ponderosa pine, Other-vegetation, Non-vegetation, Krummholz, and Riparian were classified more accurately, while Douglas-fir, Spruce/Fir, and Water showed lower accuracies in NeuralSIM.

The classification results of the Rocky Mountain National Park study areas, showed an overall accuracy increment of over twelve percent (from 46.77 to 60.71

percent) as compared to the Maximum Likelihood classification, and an overall Kappa increase to 0.52 (see Table A.15 in Appendix 1). The producer's and user's accuracies, and the individual Kappa values in Tables 5.6, 5.7, and 5.8 and Figures 5.6, 5.7, and 5.8, respectively, also show some classification differences between the technique that used a NeuralSIM model versus the equivalent technique with MATLAB. In this case, an improvement was evident in the Water, Tundra, Non-vegetation, and Douglas fir categories, while there was a noticeable decrease in Aspen, Douglas fir and Krummholz categories. Since both techniques used the exact same data sets, these differences can possible be attributed to reasons inherent to the operation of the algorithms within NeuralSIM and MATLAB.

As in the case of MATLAB, the addition of spectral information to the NeuralSIM neural network modeling process to generate prior probabilities resulted in a slight improvement in the overall accuracies. In the Roosevelt National Forest Wilderness areas the overall accuracy improved to 60.16 percent and the overall Kappa to 0.4642 (see Table A.6 in Appendix 1). The producer's and user's accuracies, and individual Kappa values for this study area, in Tables 5.2, 5.3 and 5.4, and Figures 5.2, 5.3 and 5.4, respectively, show increments in classification of Spruce/Fir, Aspen, Douglas Fir, and Water, while Ponderosa pine, Tundra, Krummholz, and Non-vegetation exhibit a reduction in their accuracies. In the Rocky Mountain National Park study area the overall accuracy improved to 62.28 percent and the overall Kappa to 0.546 (see Table A.16 in Appendix 1). For this study area, the producer's and user's accuracies, and the individual Kappa values in Tables 5.6, 5.7, and 5.8 and Figures 5.6, 5.7, and 5.8, respectively, show

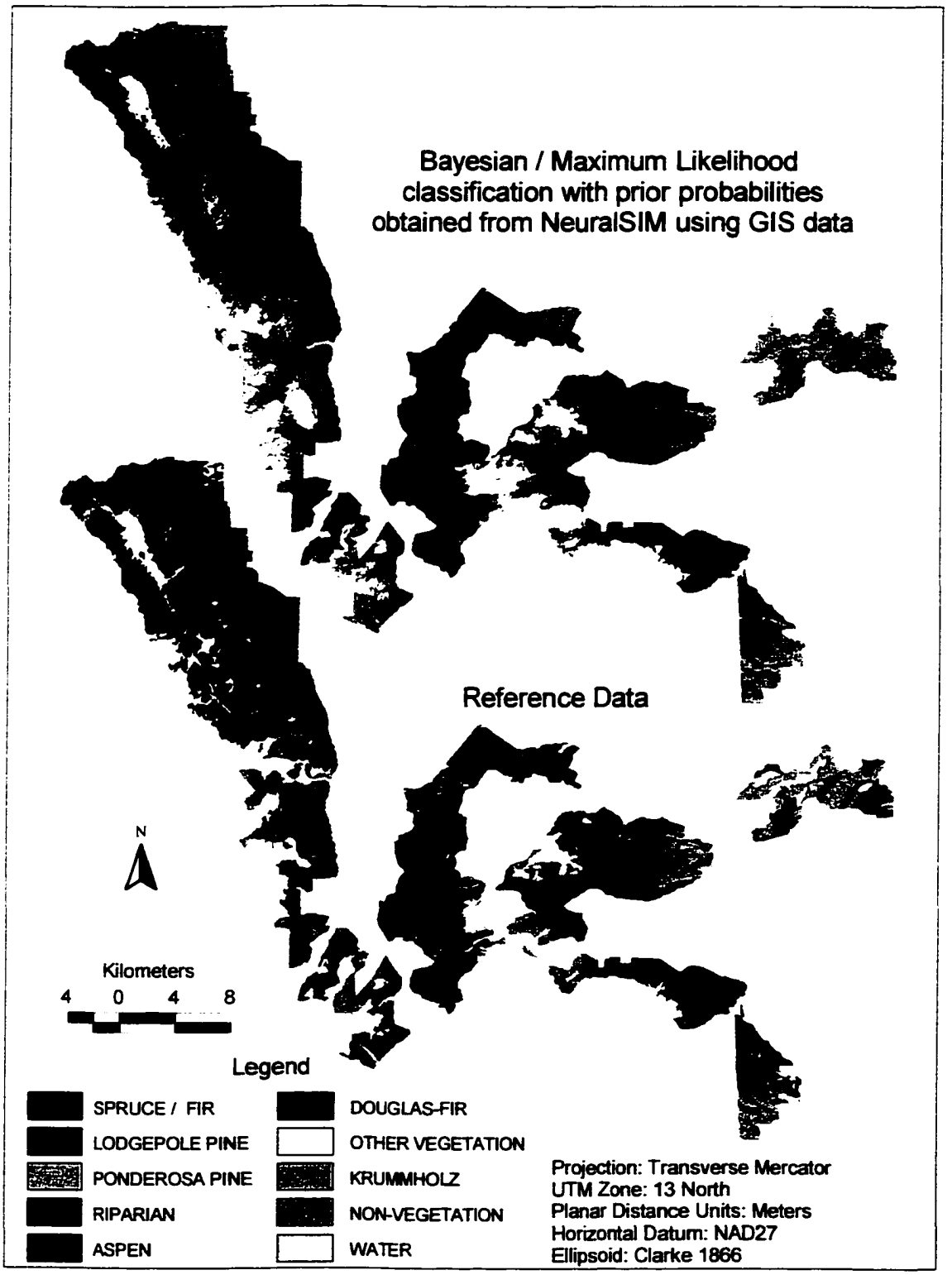


Figure 5.17: Bayesian/Maximum Likelihood Classification with probabilities obtained from NeuralSIM using only GIS data in the Roosevelt National Forest Wilderness areas.

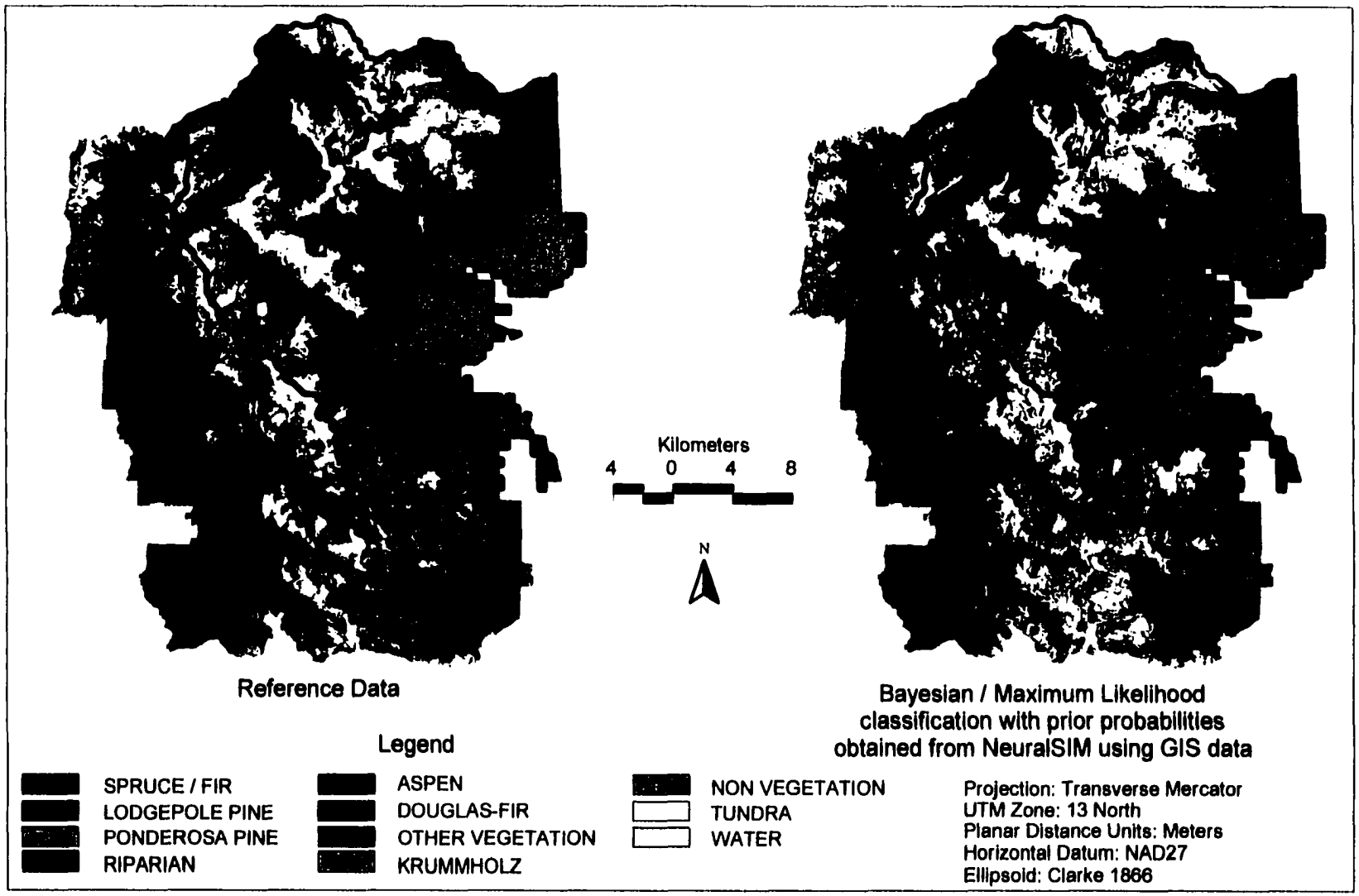


Figure 5.18: Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using only GIS data in the Rocky Mountain National Park study area.

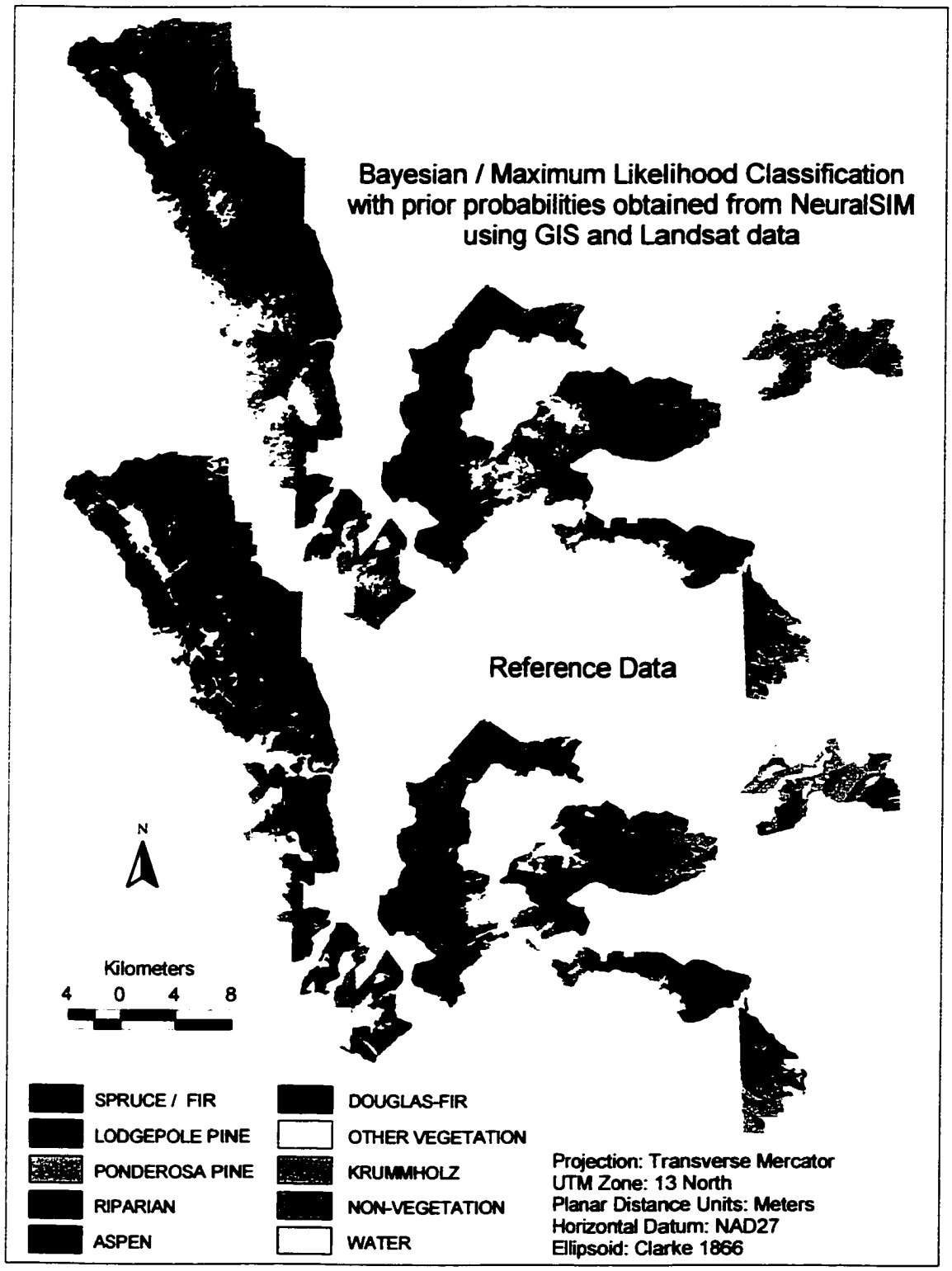


Figure 5.19: Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS and Landsat TM data in the Roosevelt National Forest Wilderness areas.

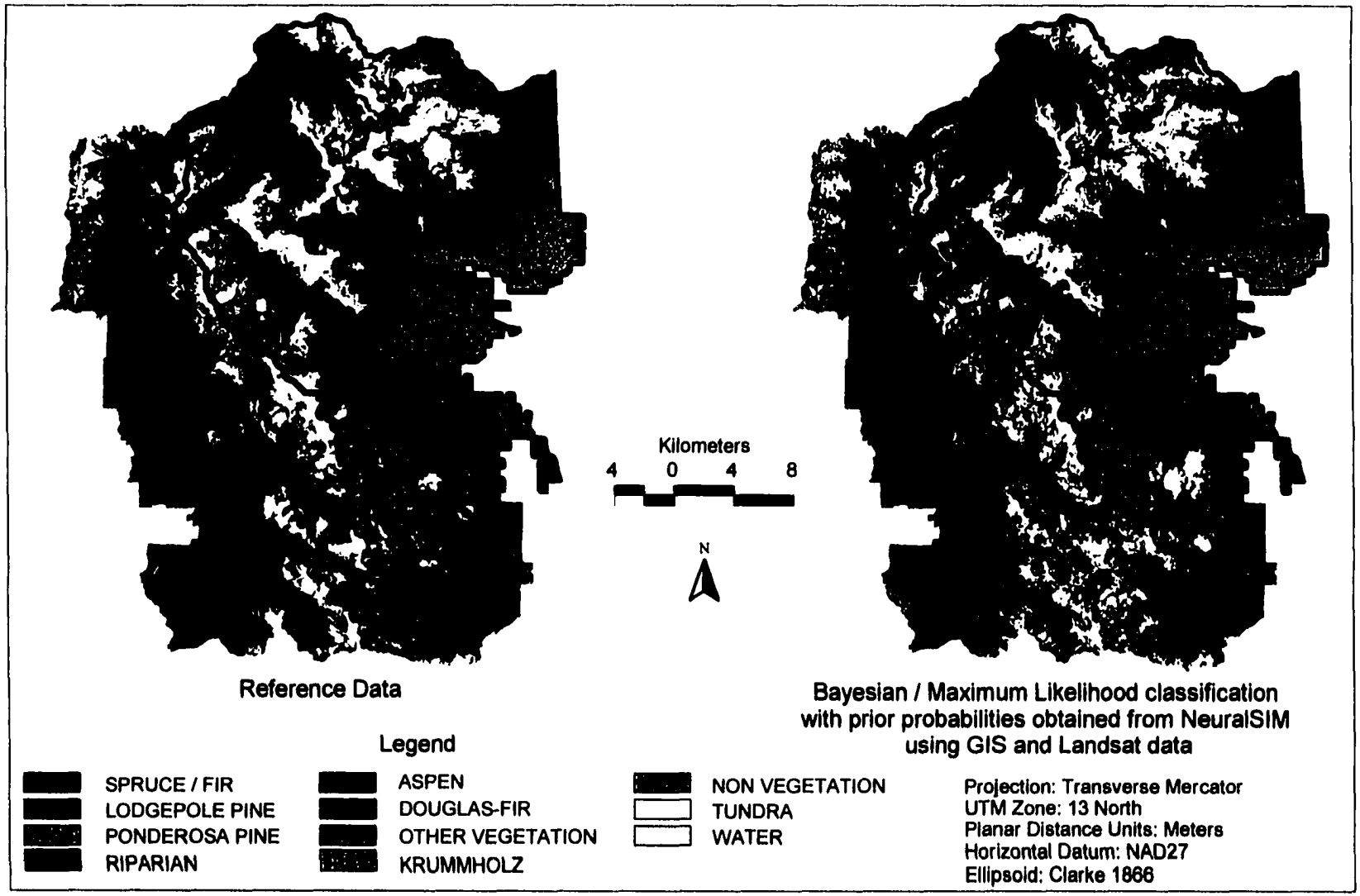


Figure 5.20: Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS and Landsat TM data in the Rocky Mountain National Park study area.

an improvement in all categories, except for Tundra and Other-vegetation, which display a decrease with the addition of spectral information.

A general improvement of the true geographic representation using this technique is evident if compared to the maps produced by all the techniques described previously. The maps obtained by this technique show lower levels of speckle in particular. A possible explanation for this could be that, in contrast to the probabilities obtained with MATLAB, which seem to be more adequate for a fuzzy classification, the probabilities obtained with NeuralSIM are more definite (i.e., each raster cell or observation has a very high probability of belonging to a particular cover type). Very evident is a better representation of the Tundra, Krummholz and Riparian cover types especially in the Roosevelt National Forest Wilderness areas when only GIS data was used to produce probabilities. Also notable is the better discrimination of water features in the higher elevation of Rocky Mountain National Park, previously confused with shadows. Figure 5.17 shows the classification maps produced with the Bayesian / Maximum Likelihood classifier with probabilities obtained from NeuralSIM using GIS data only. The map produced with probabilities obtained with GIS and Landsat data is presented in Figure 5.19. Equivalent maps for the Rocky Mountain National Park study area are presented in Figures 5.18 and 5.20.

Of all the classification techniques evaluated in this study, this was the one that required the longest time to produce a final outcome. Although the data preparation and transformation times were similar to the ones described for MATLAB in Section 6.3.2, the neural network training with NeuralSIM required a considerably longer amount of time. An average time of 24 hours for the models using only GIS data and about 36 hours

for the models using GIS and spectral data was recorded in the case of the Roosevelt National Forest Wilderness areas. Due to the larger data set, the training process for the Rocky Mountain National Park study required between thirty-six and forty-eight hours depending on which case. However, the production of probabilities for each observation in the study areas was faster in NeuralSIM than in MATLAB, averaging ten to fifteen minutes. As in the case of MATLAB, before the probabilities could be entered to the Bayesian / Maximum Likelihood classifier they had to be transformed from a text format to a raster format compatible with IDRISI. Once the probability maps were prepared, the actual Bayesian / Maximum Likelihood classification took only a few minutes.

5.5 Results of the "conventional" artificial neural network classifications techniques

5.5.1 Results of the "conventional" artificial neural network classification using MATLAB

In the "conventional" neural network classification technique the GIS and Landsat TM data were incorporated directly into the neural network to produce the classification maps of the study areas. The results of this "conventional" artificial neural network classifications using MATLAB show a considerable improvement over the results obtained with the supervised Maximum Likelihood classifications, as well as a better performance compared to the Bayesian / Maximum Likelihood classification with probabilities obtained from MATLAB using only GIS data. In the Roosevelt National Forest Wilderness areas the overall accuracy increased almost eleven percent (from 48.44 to 59.32 percent) and the overall Kappa increased to 0.4638 (see Table A.7 in Appendix 1). The evaluation of the classification statistics shows a considerable increment across almost all cover types. Table and Figure 5.4, indicate distinctly higher levels of accuracy

for Ponderosa pine, Riparian, Aspen, Other-vegetation, and Non-vegetation. Only Douglas fir and Water seem to decrease compared to the results of the supervised Maximum Likelihood classification.

In the Rocky Mountain National Park study areas, the overall accuracy was almost sixteen percent better (from 46.77 to 62.71 percent) and the overall Kappa increased to 0.5447 (see Table A.17 in Appendix 1). In this case, the Kappa values for the individual cover types in Table 5.8 and Figure 5.8 show an increase in the classification of Spruce Fir, Ponderosa pine, Riparian, Non-vegetation, Tundra and Water. However, Aspen, Krummholz and Douglas fir show a marked decrease as compared to the supervised Maximum Likelihood classification. As described above, there are some similarities between the results of both areas, but there are also some discrepancies that can possibly be attributed to differences in the spatial distribution of the cover types in relation to the distribution of the sample, as well as to the high level of randomness still present, as evidenced by the Kappa values and the qualitative evaluation of scattered individual pixels in the classification maps.

A comparison between a purely spectral, statistical technique (i.e., supervised Maximum Likelihood classification) and a non-spectral, non-statistical technique (i.e., the "conventional" neural network classification with MATLAB using only GIS data) was performed to gain insight into the behavior of these two different approaches. In Roosevelt National Forest Wilderness areas the neural network model performed better, with an overall accuracy of 52.11 percent and an overall Kappa of 0.3869 (see Table A.8 in Appendix 1). The neural network model performed considerably better in almost every cover type classified, however the Kappa values for the individual cover types show that

the supervised Maximum Likelihood classification performed better in the classification of Spruce/Fir, Lodgepole pine, Douglas fir and Water. A major difference between these techniques was the way the cover types were confused with each other. For instance, in the supervised Maximum Likelihood classification the errors of omission of Spruce/Fir were caused mainly by Lodgepole pine (i.e., 62 percent of the omission error), followed by Aspen (i.e., 15 percent of the omission error) and Krummholz (i.e., 10 percent of the omission error), in that order. On the other hand, in the neural network classification the omission error was more spread out, and caused mainly by Lodgepole pine (i.e., 38 percent of the omission error, followed by Krummholz (i.e., 24 percent of the omission error) and Other-Vegetation (i.e. 20 percent of the omission error). Such differences exist across almost all the cover types classified, but were more evident in the case of Spruce/Fir, Lodgepole pine, Other-vegetation, Krummholz and Water. On the other hand, the errors of commission are much more spread out in the supervised Maximum Likelihood classification.

In Rocky Mountain National Park study area, the overall classification attained with the neural network model using only GIS data was 59.43 percent, around twelve percent more than with the supervised Maximum Likelihood classification. The overall Kappa reached a value of 0.5021 (see Table A.18 in Appendix 1). As in the case of the previous study area, the "conventional" neural network classification also performed considerably better than the Bayesian/Maximum Likelihood classifier. Although, the classification accuracies for Spruce / Fir, Non-vegetation, Tundra and Water were considerably better, as evidenced by the classification statistics, the most noticeable differences between these two classifications were the poorer accuracies of Aspen,

Krummholz and Douglas fir in the neural network classification. This is also evident in the "conventional" neural network classification with MATLAB using GIS and Landsat TM data, where the inclusion of spectral information, although providing slightly better accuracies, is not able to compensate for poor performance in the modeling of the distribution of these cover types.

As presented in Figure 5.21, the classification map of the "conventional" neural network classification with MATLAB in Roosevelt National Forest Wilderness areas provided a much smoother appearance than the supervised Maximum Likelihood classification. When compared to the reference data, the geographic representation can be considered more 'truthful' in the neural network classification map; however, many incongruences are very evident, like the overestimation of Aspen and Krummholz, or the confusion between Other-vegetation, Lodgepole pine and Spruce/Fir. These problems are even more pronounced in the "conventional" neural network classification using only GIS data displayed in Figure 5.23. This particular classification map provides a good example of the major discrepancies contributing to the error that can be attributed to deficiencies in the sampling strategy in this study area. For instance, if we observe the lower part of the Neota wilderness area, there is a notable difference in the representation of Other-vegetation and Spruce / Fir, if compared to same area in the reference data. Another good example is provided by the entire Cache la Poudre Wilderness area, were the model fails to characterize almost every category present in the reference data. It appears that, given the complexity of this particular wilderness area, the information provided by the training data was not comprehensive enough to allow an accurate modeling of the cover types distributions.

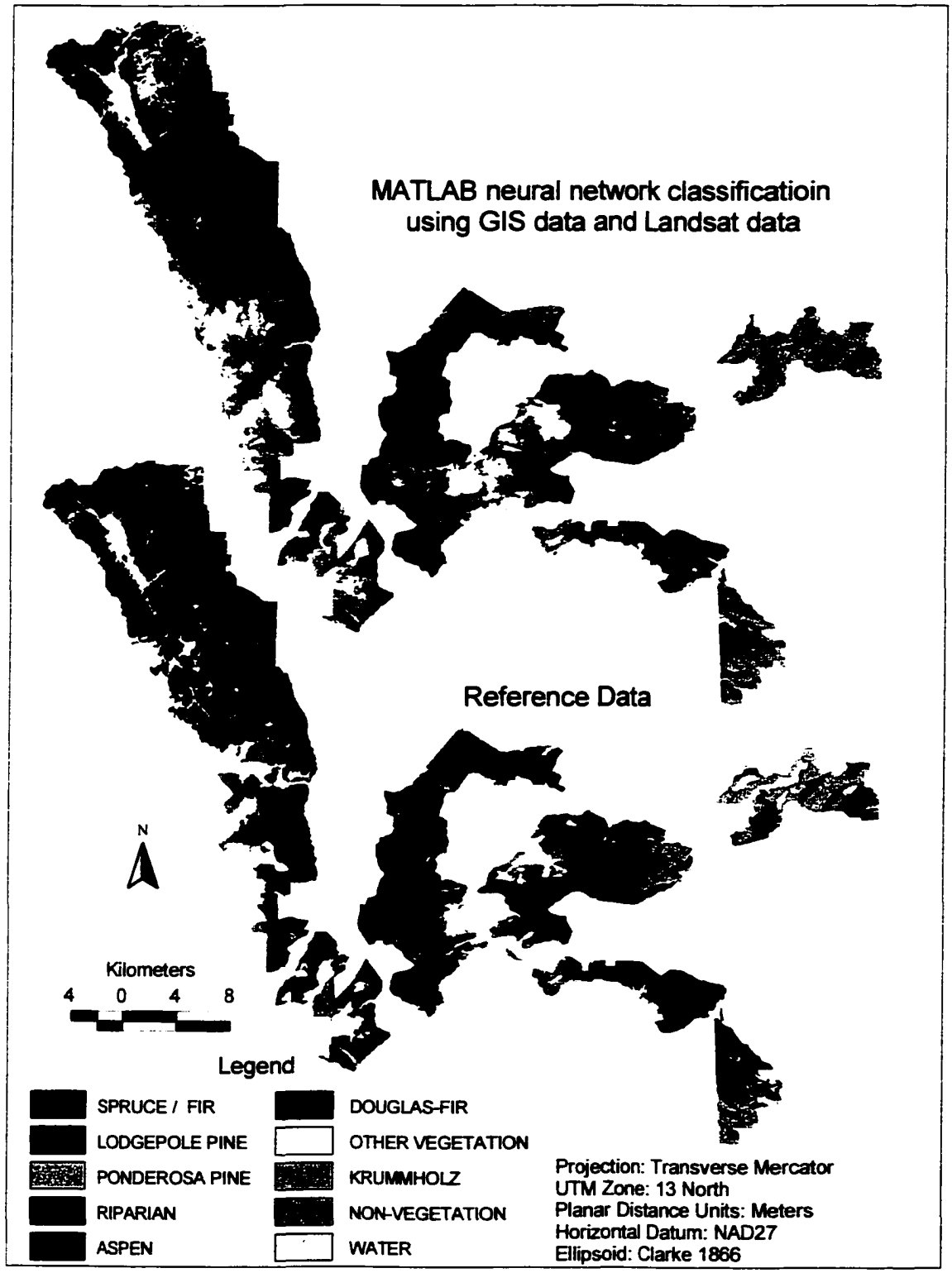


Figure 5.21: "Conventional" neural network classification with MATLAB using GIS and Landsat TM data in the Roosevelt National Forest Wilderness areas.

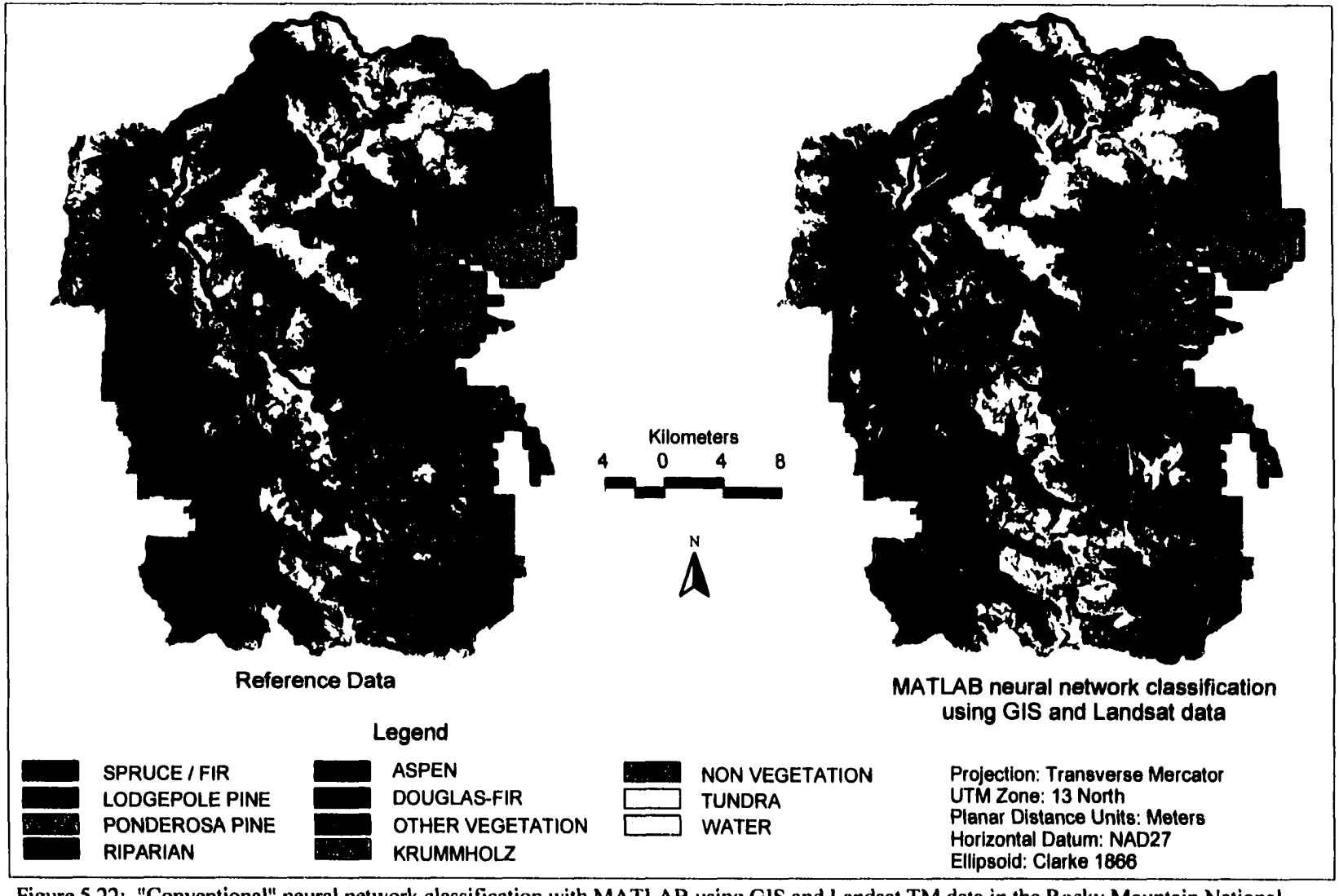


Figure 5.22: "Conventional" neural network classification with MATLAB using GIS and Landsat TM data in the Rocky Mountain National Park study area.

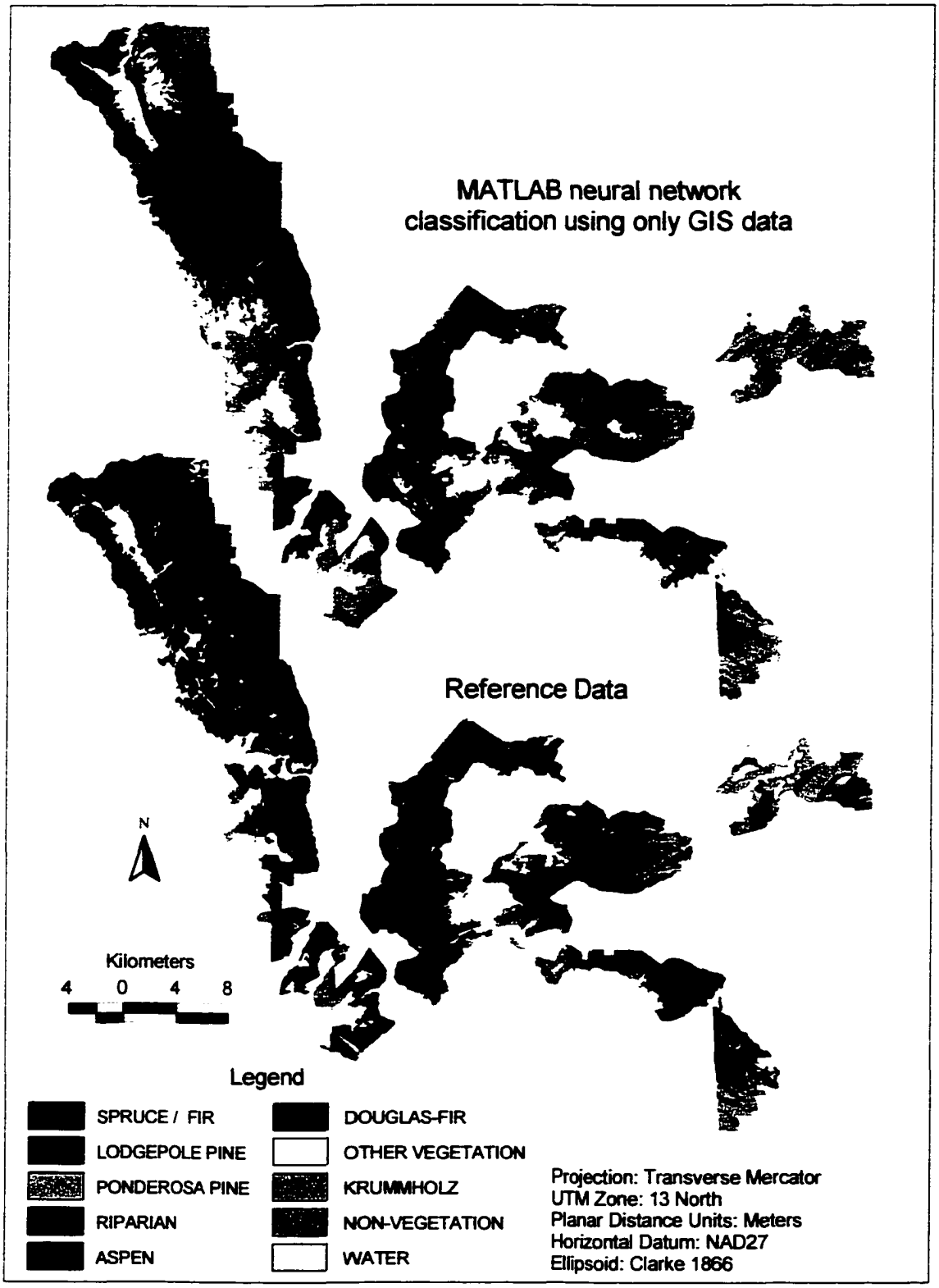


Figure 5.23: "Conventional" neural network classification with MATLAB using only GIS data in the Roosevelt National Forest Wilderness areas.

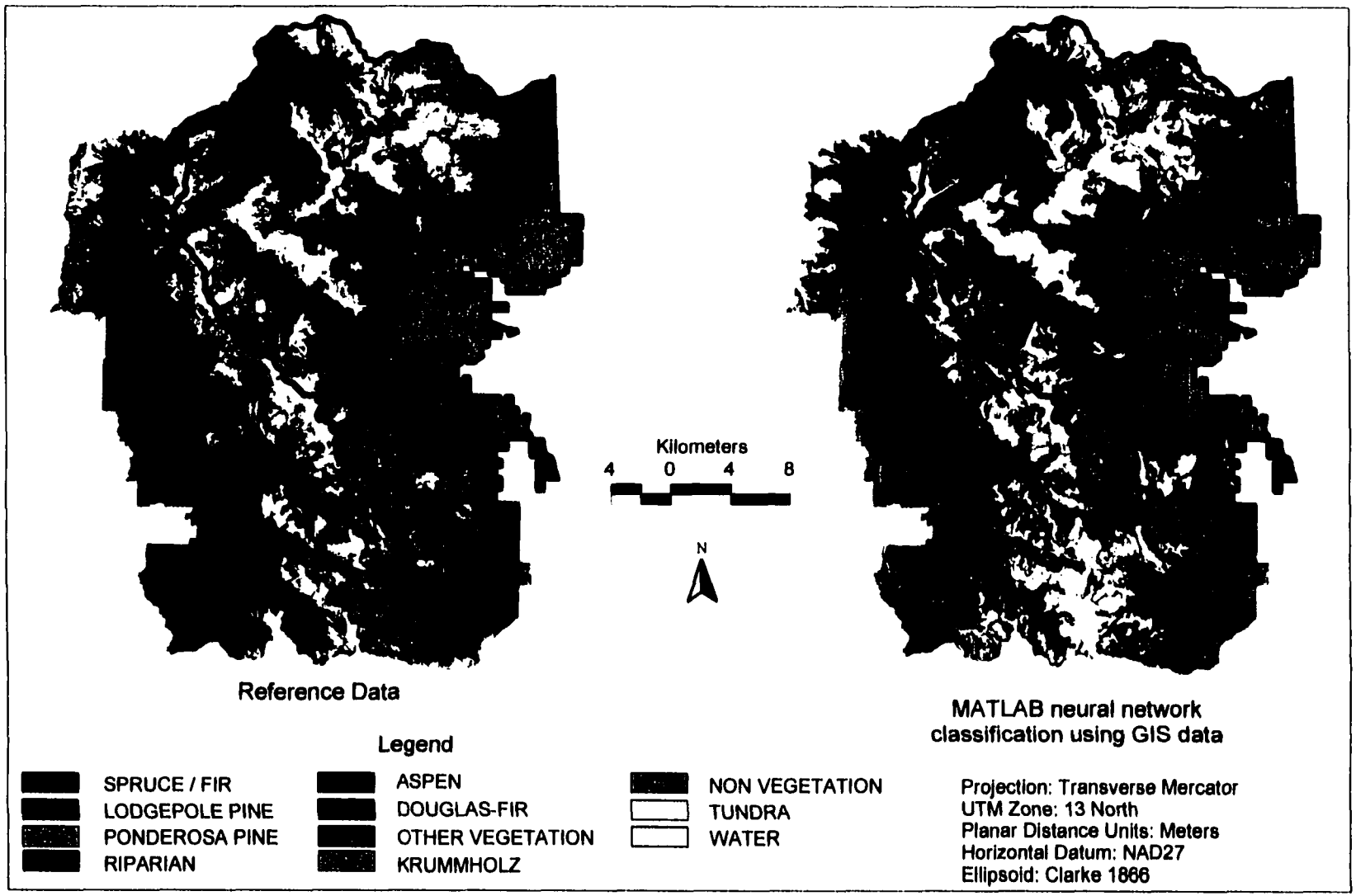


Figure 5.24: "Conventional" neural network classification with MATLAB using only GIS data in the Rocky Mountain National Park study area.

The corresponding classification map for the Rocky Mountain National Park study area, presented in Figure 5.22, demonstrate much better results than the ones obtained in the previous study area, confirming the superior quality of the reference data in this study area. Furthermore, the difference between the neural network classification and the supervised Maximum Likelihood classification is remarkable, demonstrating a better capability to depict the distribution of the cover types presented in the reference data. The "conventional" neural network model using only GIS data, presented in Figure 5.24, also obtained considerably better results, indicating that the sampling scheme applied in this study area was less of a problem.

The time required to apply this techniques, with regards to the data preparation and transformation times, was similar to the ones described for the Bayesian / Maximum Likelihood classification with probabilities obtained from MATLAB in Section 5.4.2. Nevertheless, in this case, using the output posterior probabilities previously standardized to sum to one, each observation in the corresponding study areas was assigned membership to the cover type exhibiting the highest probability value. These values were then transformed from a text format to a GIS raster format to create the classification maps. Consequently, there was no need for the further step of data preparation required by the Bayesian classifiers, making the "conventional" neural network classification a little simpler and faster to apply.

5.5.2 Results of the "conventional" artificial neural network classification using NeuralSIM

As in the case of the equivalent classification technique using MATLAB, the results of the "conventional" artificial neural network classifications using NeuralSIM

showed a considerable improvement over the results obtained with the supervised Maximum Likelihood classifications, as well as a better performance than the Bayesian/ Maximum Likelihood classification with probabilities obtained from NeuralSIM using only GIS data. In the Roosevelt National Forest Wilderness areas the overall accuracy increased eleven percent (from 48.44 to 59.94 percent) and the overall Kappa increased to 0.4641 (see Table A.9 in Appendix 1). This is almost identical to results obtained with MATLAB. Table 5.4 and Figure 5.4 show particularly higher Kappa values across almost all the cover types. As in the case of MATLAB, Ponderosa pine, Riparian, Aspen, Other-vegetation, and Non-vegetation are the categories with the highest Kappa increments, and only Douglas fir and Water seem to decrease compared to the results of the supervised Maximum Likelihood classification.

In the Rocky Mountain National Park study areas, the overall accuracy was almost fifteen percent better (from 46.77 to 61.41 percent) and the overall Kappa increased to 0.5356 (see Table A.19 in Appendix 1). In a consistent manner, here too the "conventional" neural network classification performed considerably better than the Bayesian / Maximum Likelihood classifier with probabilities obtained from NeuralSIM using only GIS data. The classification results also present a very similar behavior as compared to the equivalent classification technique with MATLAB. With some minor variations, the Kappa values for the individual cover types in Table 5.8 and Figure 5.8 show an increase in the classification of the same cover types of Spruce Fir, Ponderosa pine, Riparian, Non-vegetation, Tundra and Water. However, the NeuralSIM model shows a remarkable improvement in the classification of Water and Ponderosa pine, and

slight improvement in Douglas fir. Again, Aspen and Krummholz show a marked decline as compared to the supervised Maximum Likelihood classification.

The comparison between a purely spectral, statistical technique (i.e., the supervised Maximum Likelihood classification) and the non-spectral, non-statistical technique (i.e., the "conventional" neural network classification with NeuralSIM using only GIS data) showed that in Roosevelt National Forest Wilderness areas the neural network model performed better, with an overall accuracy of 52.85 percent and an overall Kappa of 0.383 (see Table A.10 in Appendix 1). The Kappa values for the individual cover types show that the neural network model performed particularly better in the classification of Ponderosa pine, Other-vegetation, Krummholz, Non-vegetation and Riparian, while the supervised Maximum Likelihood classification performed better in the classification of Spruce/Fir, Lodgepole pine, Douglas Fir, Aspen, and Water. In this case, again, there are major differences in the way the cover types were confused in both techniques. For example, while in the supervised Maximum Likelihood classification Other vegetation had errors of omission caused mainly by Krummholz pine (i.e., 37 percent of the omission error), followed by Riparian (i.e., 19 percent of the omission error), Spruce/Fir (i.e., 15 percent of the omission error), and Aspen (i.e., 9 percent of the omission error), in the neural network classification the commission error was mainly caused by Krummholz (i.e., 32 percent of the commission error), followed by Spruce/Fir (i.e., 27 percent of the omission error), Lodgepole pine (i.e., 12 percent of the omission error), Non-vegetation (i.e., 11 percent of the omission error), and Ponderosa pine (i.e., 10 percent of the omission error). As in the case of MATLAB, such differences exist

across almost all the cover types classified, but were more evident in the case of Spruce/Fir, Lodgepole pine, Other-vegetation, Krummholz and Water.

In Rocky Mountain National Park study area, the overall classification attained with the neural network model using only GIS data was 54.60 percent, almost eight percent more than with the supervised Maximum Likelihood classification. The overall Kappa reached a value of 0.4557 (see Table A.20 in Appendix 1). In this case, as in the previous examples, the "conventional" neural network classification performed considerably better than the Bayesian / Maximum Likelihood classifier. The Kappa values for the individual cover types presented in Table 5.8 and Figure 5.8 show that classification accuracies were better for Water, Tundra and Non-vegetation and Douglas fir. However, all the other cover types had a decline in their accuracies. As in the case of the equivalent technique with MATLAB, Aspen and Krummholz had particularly poor accuracies in the "conventional" neural network classification with NeuralSIM using only GIS data. Again the inclusion of spectral information to the model, although providing slightly better accuracies for these cover types, is not able to eliminate this classification error.

The "conventional" neural network classification with NeuralSIM in Roosevelt National Forest Wilderness also provided a better geographic representation than the supervised Maximum Likelihood classification, when compared to the reference data (see Figure 5.25). The maps obtained with this technique were probably the most homogeneous of all the classification techniques compared, and in this aspect they were the closest to the reference data (i.e., a reduced amount of speckle within the boundaries of a cover type). Nevertheless, they still could not match the smoothness of a five-acre

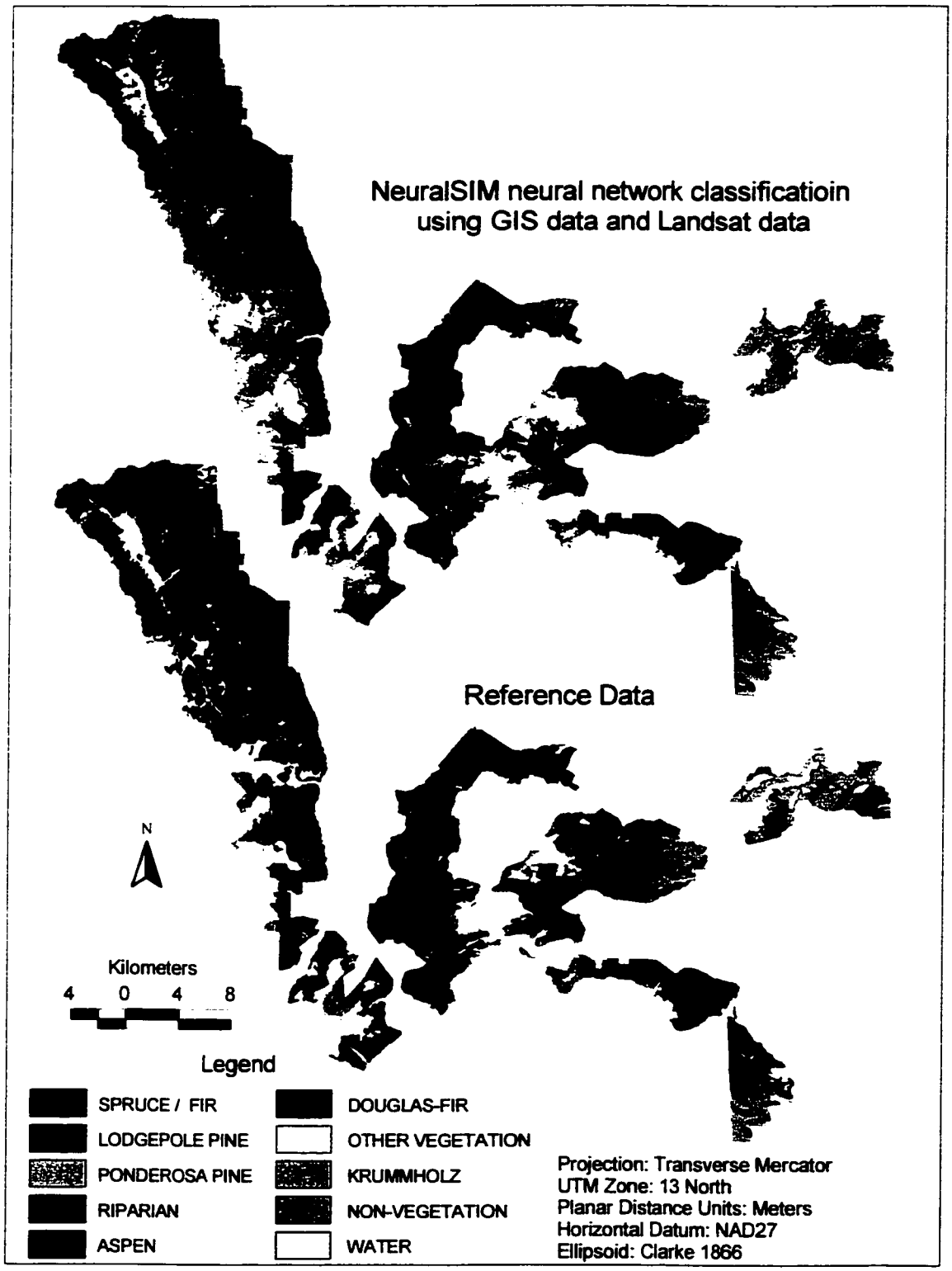


Figure 5.25: "Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data in the Roosevelt National Forest Wilderness areas.

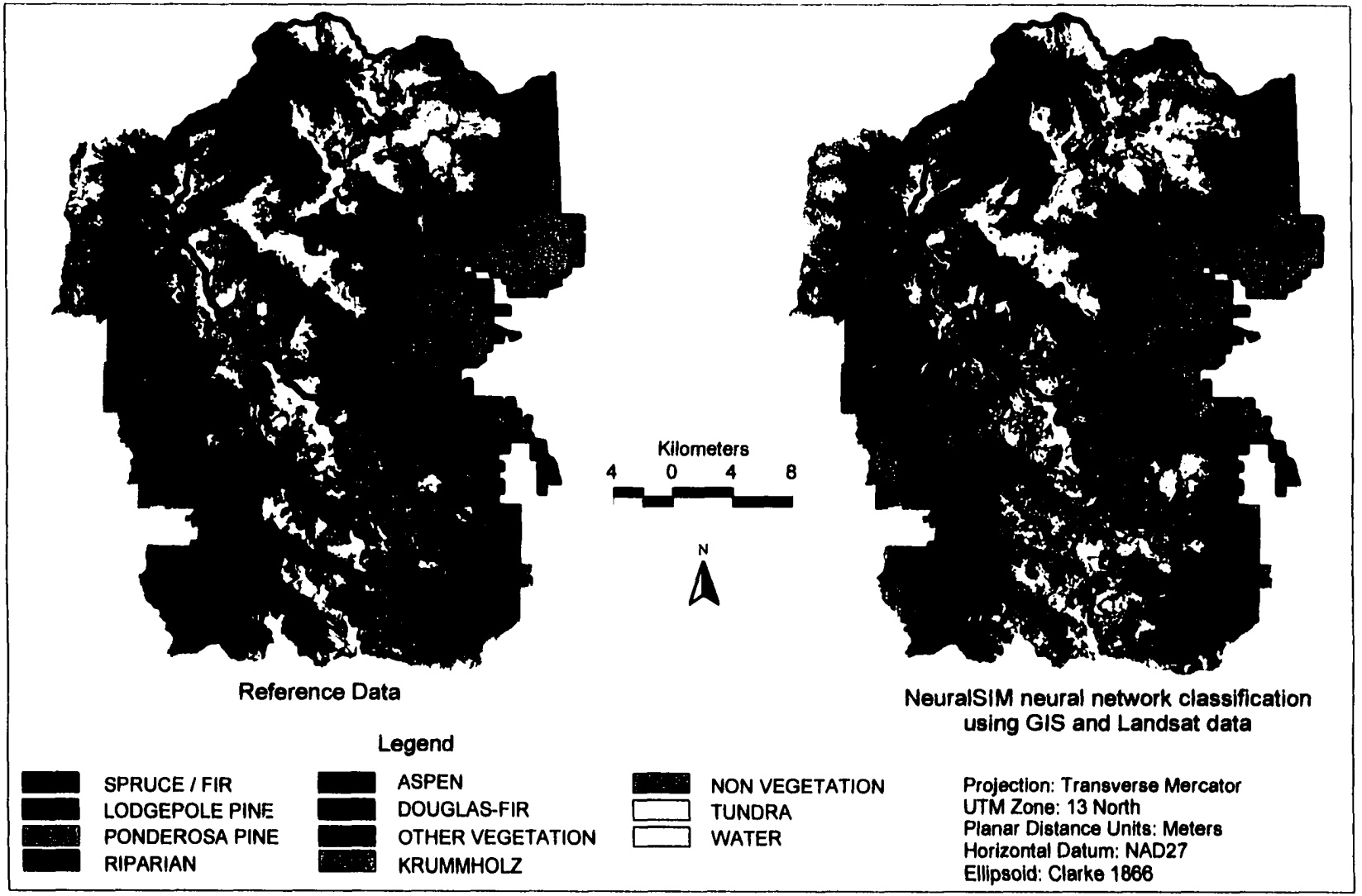


Figure 5.26: "Conventional" neural network classification with NeuralSIM using GIS and Landsat TM data in the Rocky Mountain National Park study area.

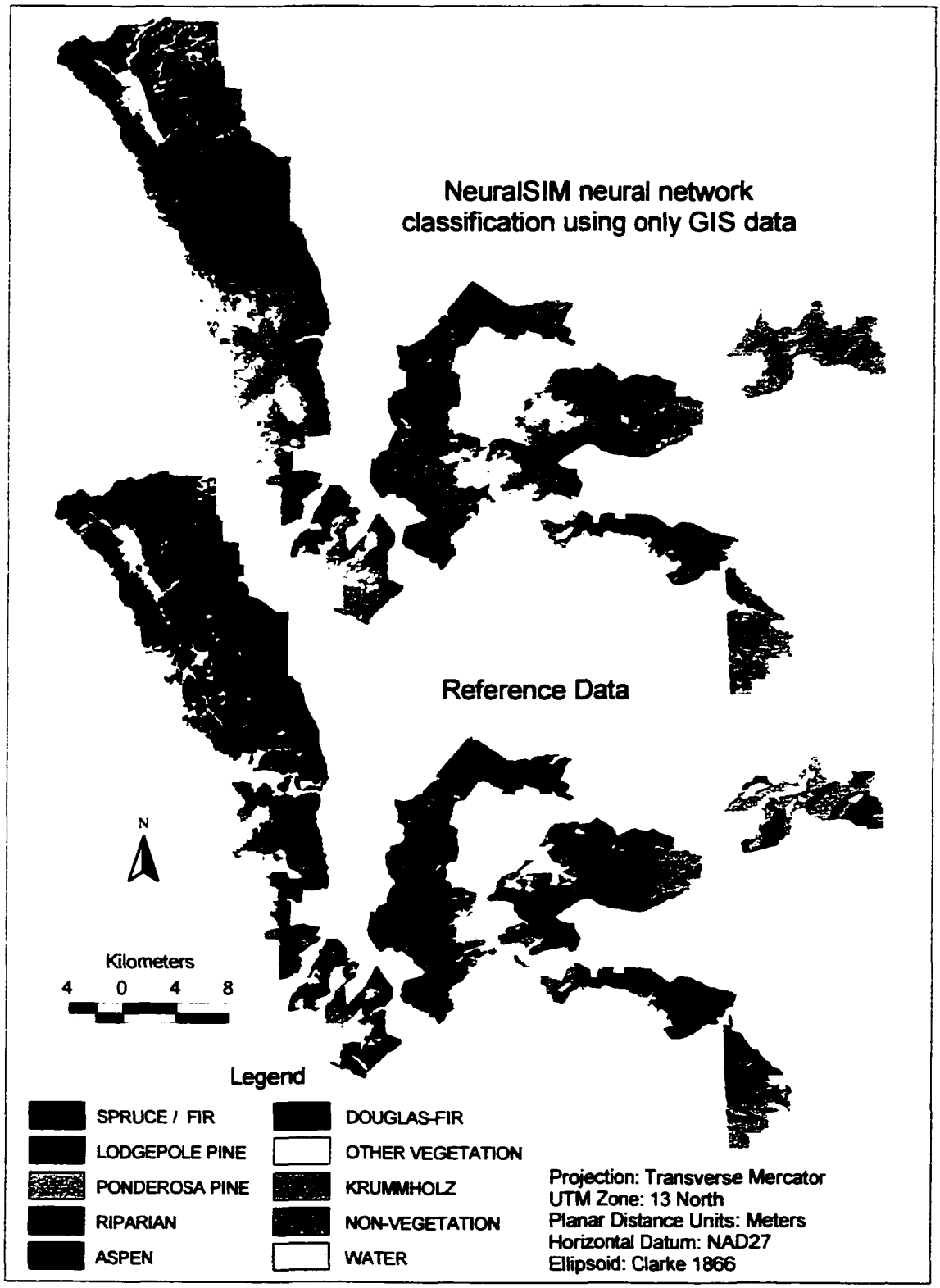


Figure 5.27: "Conventional" neural network classification with NeuralSIM using only GIS data in the Roosevelt National Forest Wilderness areas.

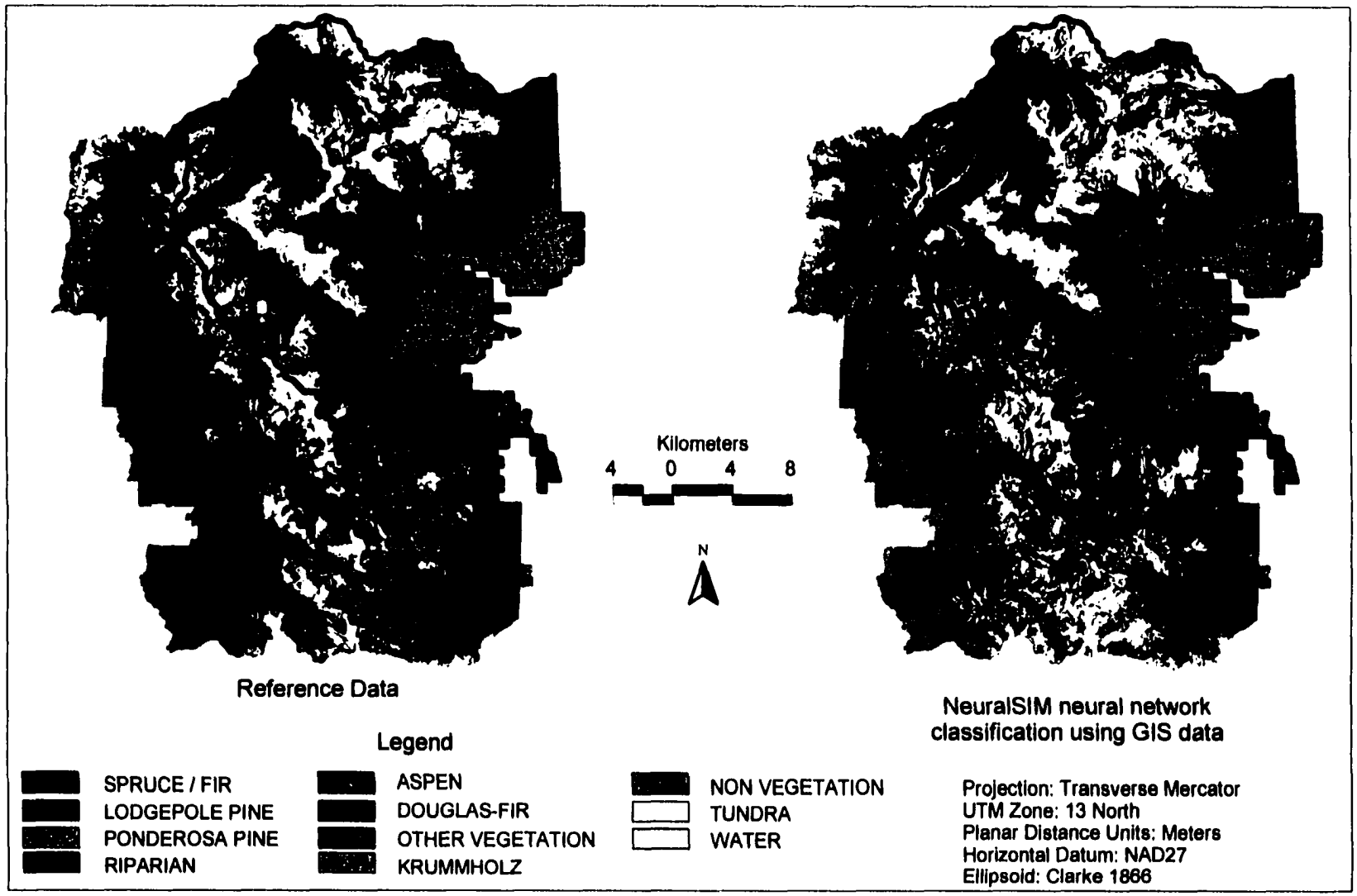


Figure 5.28: "Conventional" neural network classification with NeuralSIM using only GIS data in the Rocky Mountain National Park study area.

minimum mapping unit. Many of the discrepancies described for the previous classifications are still present here. For instance, the presence of Aspen and Riparian vegetation along the streams, not present in the reference data is very evident. This would indicate a possible major problem with the reference data (i.e., the homogenization of cover type maps for management purposes is not suitable for the evaluation of the classification techniques). Another error still present in this classification is the confusion between the Other-vegetation, Krummholz, Lodgepole pine and Spruce/Fir categories.

Again, classification problems related to the sampling design in this study area (i.e. a failure to provide comprehensive training information to the modeling process in certain portions of the study area) can be confirmed in the classification map of the "conventional" neural network classification using only GIS data displayed in Figure 5.27 (i.e., the discrepancies between Other-vegetation, and Spruce / Fir, in lower part of the Neota wilderness area, and the overall very poor classification of the entire Cache la Poudre Wilderness area).

In a consistent manner the corresponding classification map for the Rocky Mountain National Park study area, presented in Figure 5.26, also demonstrates considerably better results than the ones obtained in the previous study area. The comparison of this classification with the supervised Maximum Likelihood classification shows a remarkable overall improvement in relation to the true geographic representation, as compared to the reference data. Noteworthy is the resemblance of the Water category in both maps, indicating that this model was very successful in discriminating water from shadows in the higher elevations. There is also a better representation of the less numerous cover types, like Other-vegetation and Aspen,

although there are still considerable discrepancies between Spruce/Fir and Lodgepole pine, as well as between Non-vegetation and Tundra. This is also very evident in the "conventional" neural network model with NeuralSIM using only GIS data, presented in Figure 5.28, which also displays a better geographic representation than the supervised Maximum Likelihood classification.

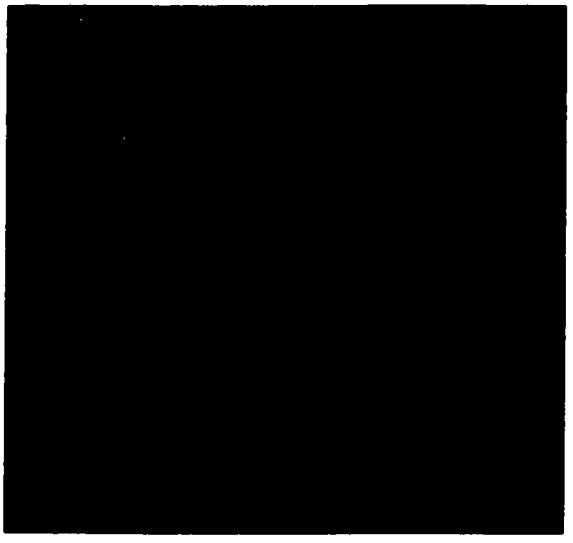
The time required to apply this technique was similar to the ones described for the Bayesian / Maximum Likelihood classification with probabilities obtained from NeuralSIM in Section 5.4.3, without the additional data preparation required by the Bayesian classifier. In a different way than MATLAB, the output of NeuralSIM (in the classification mode) is the classification itself. In other words, the results come out of the model with the original values assigned to the cover types instead of being in the form of probabilities. Therefore, the output of the NeuralSIM classification only requires it to be transformed from a text format to a GIS raster format to create the classification maps, and there is no need to standardize and then assign the cover type membership to the output posterior probabilities with the highest value. In spite of this, the classification with MATLAB is considerably faster due to the considerably longer amount of time required to train the network required by NeuralSIM.

5.6 General discussion

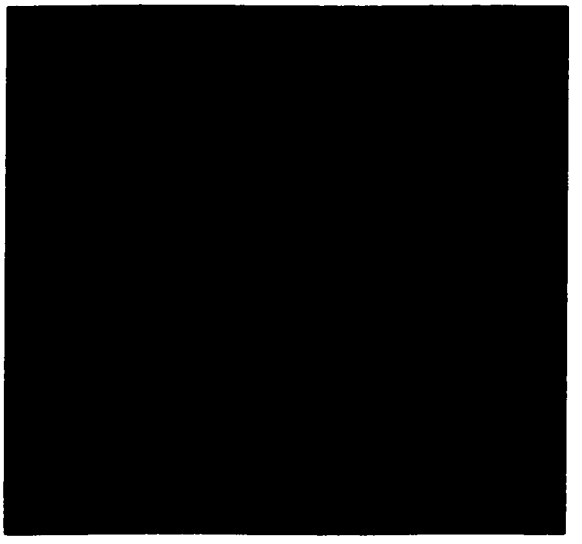
Although the classification techniques developed in this study achieved a higher level of accuracy than the supervised Maximum Likelihood classifier, the overall accuracies achieved by all the classification techniques are relatively low. A variety of factors may have influenced the nature of this outcome. The first one, and perhaps the easiest to amend in future work, involves the large dimensions of the minimum mapping

units of the reference data sets used in this study. All the cover types in the Roosevelt National Forest Wilderness areas and the forest cover types in the Rocky Mountain National Park study area had a minimum mapping unit of five Acres; non-forest cover types in the Rocky Mountain National Park study area had a minimum mapping unit of one acre, which is still fairly large if we consider that a. Landsat TM pixel is approximately equivalent to an area five times smaller (i.e., 0.222 acres). Using a minimum mapping unit tends to homogenize the resulting cover type map, but is a standard procedure performed by photo-interpreters when developing forest type maps for forest management purposes. In addition to common discrepancies caused by the delineation of somewhat arbitrarily defined boundaries (which is characteristic of the production of cover type maps), this homogenization procedure introduces a considerable amount of error when contrasted with the natural spectral variability within cover types present in the Landsat TM image. This error is more pronounced in the case of cover types with very narrow and elongated shapes, such as the Riparian vegetation.

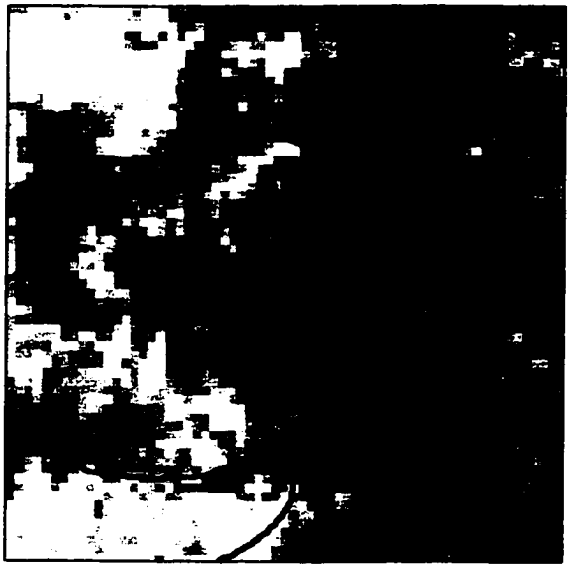
Cover types with relatively small areas and sparse distributions, such as Aspen, are in some cases, also considerably affected by the homogenization of the data. Figure 5.29 shows two examples of the differences between the Landsat TM image and the cover type map of the Roosevelt National Forest Wilderness areas. Differences between the Landsat TM5 4-3-2 composite (A) and the cover type map of the Roosevelt National Forest Wilderness areas (B) are evident; light green areas in the cover type map represent Lodgepole pine, while the dark green areas represent Spruce/Fir. The hydrology coverage is displayed for reference purposes. Noteworthy in this example are the bright red areas



A) Landsat TM 5 (4-3-2 composite) with overlaid hydrology coverage.



B) Roosevelt National Forest Wilderness areas cover type map with overlaid hydrology coverage.



C) Landsat TM 5 (4-3-2 composite) with overlaid hydrology coverage.

D) Roosevelt National Forest Wilderness areas cover type map with overlaid hydrology coverage.

Figure 5.29: Two examples of the difference between the Landsat TM5 image and the cover type maps for selected portions of the Roosevelt National Forest Wilderness area.

distributed along the streams in the Landsat TM image that correspond to riparian vegetation that are not present in the cover type map.Even more dramatic are the differences between the area compared in (C) and (D), where the cover type variability displayed by the Landsat image clearly indicates the presence of at least five different cover types (e.g., Non-vegetation, Riparian vegetation, Krummholz, Spruce / Fir, and Tundra), and the reference map only displays the occurrence of Spruce/Fir (dark green areas) and Tundra (yellow areas).

A further source of error associated with homogenization, was the use of a "hard" classification approach. In the final classification maps of this study, each pixel was allocated to a single class, under the implicit assumption that the satellite image is composed of pure pixels. Unfortunately, boundaries in the natural world are generally not clear-cut and the continuous transition from one cover type to another is reflected in the fact that remotely sensed data often includes many pixels that represent areas containing more than one class. According to Foody (2001) mixed pixels are a major problem in accuracy assessment. For example, the removal of boundary regions in the land cover map of Great Britain enabled the estimated accuracy of the map to increase from forty-six to seventy-one percent (Foody 2001). This would suggest that a similar improvement of the classification accuracy might have been attained in the current study if pixels in the boundary regions had been removed. However, due to the spatial characteristics of some cover types the application of this procedure was not feasible. For instance, a removal of the boundary pixels of narrow strips of Riparian vegetation would imply the elimination all the pixels of that cover type in certain portions of the study area.

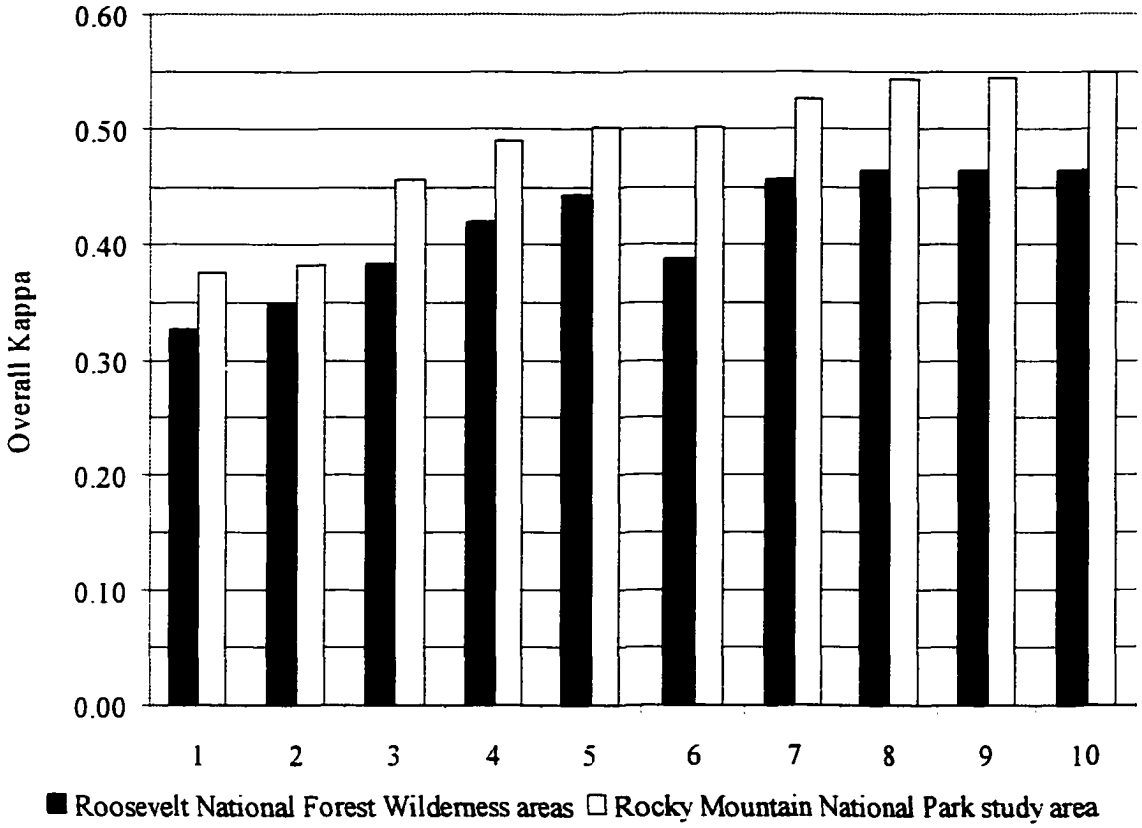
Putting aside the discrepancies caused by the homogenization of the cover type maps, it is important to take into account the fact that there are also errors inherent the quality of the data. This is especially aggravated when using data sets coming from a variety of sources, coordinate and projections systems, and datasets that were created for very different purposes, such as the ones used in this study. As one uses more and more data sets, there is a greater possibility of introducing more errors to the model. Such errors could have been originated in various places along the process, from the collection of raw data and the input of the data into the GIS (e.g. digitizing process), to distortions in the transformation of all data sets to a common projection and coordinate system. For instance, a difference of a few or several pixels, varying with the locations in the study data, can exist between the boundaries of a cover type in the reference data and the same "boundaries" in the satellite imagery. An example of this is presented in a study conducted by Friesen (1994) in the Upper Yumpa watershed, in the Mountains of Northern Colorado, where several problems of using the Forest Service Resource Information System (RIS), such as discrepancies caused by boundary fluctuation and miss-registration, as well as discrepancies in the spectral heterogeneity of the cover type polygons are described in detail.

When compared to the Roosevelt National Forest Wilderness areas, the reference data in the Rocky Mountain National Park study area is of superior quality, as evidenced by the comparative overall Kappa values across all the classification techniques in both study areas, presented in Table 5.9 and Figure 5.30. Overall Kappa values of the classifications in this area are, on average, seven percent better than their counterparts in the Roosevelt National Forest Wilderness areas. The reason for this is probably because

the Rocky Mountain National Park cover type map, developed through detailed interpretation of aerial photos and field checking, has been constantly updated and refined over the last few years by the GIS program of Rocky Mountain National Park.

Classification technique	Kappa		
	Roosevelt National Forest Wilderness areas	Rocky Mountain National Park study area	Difference
Supervised Maximum Likelihood Classification	0.3264	0.3752	0.0488
"Conventional" Bayesian/Maximum Likelihood Classification with probabilities obtained from area proportions of cover types	0.3486	0.3819	0.0333
Neural Network Classification with NeuralSIM using GIS data	0.3830	0.4557	0.0727
Bayesian/Maximum Likelihood Classification with probabilities obtained from MATLAB using only GIS data	0.4195	0.4897	0.0702
Bayesian/Maximum Likelihood Classification with probabilities obtained from MATLAB using GIS data and Landsat TM data	0.4435	0.5017	0.0582
Neural Network Classification with MATLAB using GIS data	0.3869	0.5021	0.1152
Bayesian/Maximum Likelihood Classification with probabilities obtained from NeuralSIM using only GIS data	0.4560	0.5258	0.0698
Neural Network Classification with NeuralSIM using GIS and Landsat TM data	0.4641	0.5430	0.0789
Neural Network Classification with MATLAB using GIS and Landsat TM data	0.4638	0.5440	0.0802
Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data	0.4642	0.5500	0.0858
Average	0.4156	0.4869	0.0713

Table 5.9: Comparison of the overall Kappa for all the classification techniques in both study areas



Legend

Nr.	Classification technique
1	Supervised Maximum Likelihood Classification
2	"Conventional" Bayesian/Maximum Likelihood Classification with probabilities obtained from area proportions of cover types
3	Neural Network Classification with NeuralSIM using GIS data
4	Bayesian/Maximum Likelihood Classification with probabilities obtained from MATLAB using only GIS data
5	Bayesian/Maximum Likelihood Classification with probabilities obtained from MATLAB using GIS data and Landsat TM data
6	Neural Network Classification with MATLAB using GIS data
7	Bayesian/Maximum Likelihood Classification with probabilities obtained from NeuralSIM using only GIS data
8	Neural Network Classification with NeuralSIM using GIS and Landsat TM data
9	Neural Network Classification with MATLAB using GIS and Landsat TM data
10	Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS data and Landsat TM data

Figure 5.30: Comparison of the overall Kappa for all the classification techniques in both study areas

Nevertheless, there are still generalizations present and the results of the classifications performed in this study area are still comparatively low. Furthermore. all errors inherent to the reference data were carried over to the accuracy assessment analysis due to the 100 percent per pixel comparison. Ideally a detailed photo interpretation of a selected sample of aerial photos would have provided a better source for the training and accuracy evaluation data.

The spectral plot in Figure 5.31 was generated using one standard deviation for the training data in the feature space between the red visible channel (band three) and the near infrared channel (band four) of the Landsat TM data. In a similar way, the spectral plot in Figure 5.32 was generated in the feature space between the near infrared channel (band four) and a middle infrared channel (band five), also using one standard deviation. Since three-standard-deviation ellipses would cover the spectral plot almost entirely, only one standard deviation was used to display the highest possible amount of separability between the different cover types.

In general, these band combinations usually display the highest spectral separability among all cover types. As revealed by the spectral plots, there is a considerable amount of overlap among almost all the informational categories present in this study area. This is especially evident in the case of forest cover types and is caused by the fact that many of the informational categories defined for management purposes amalgamate species that are spectrally very similar to species in other informational categories, or in some cases they even contain the same species.

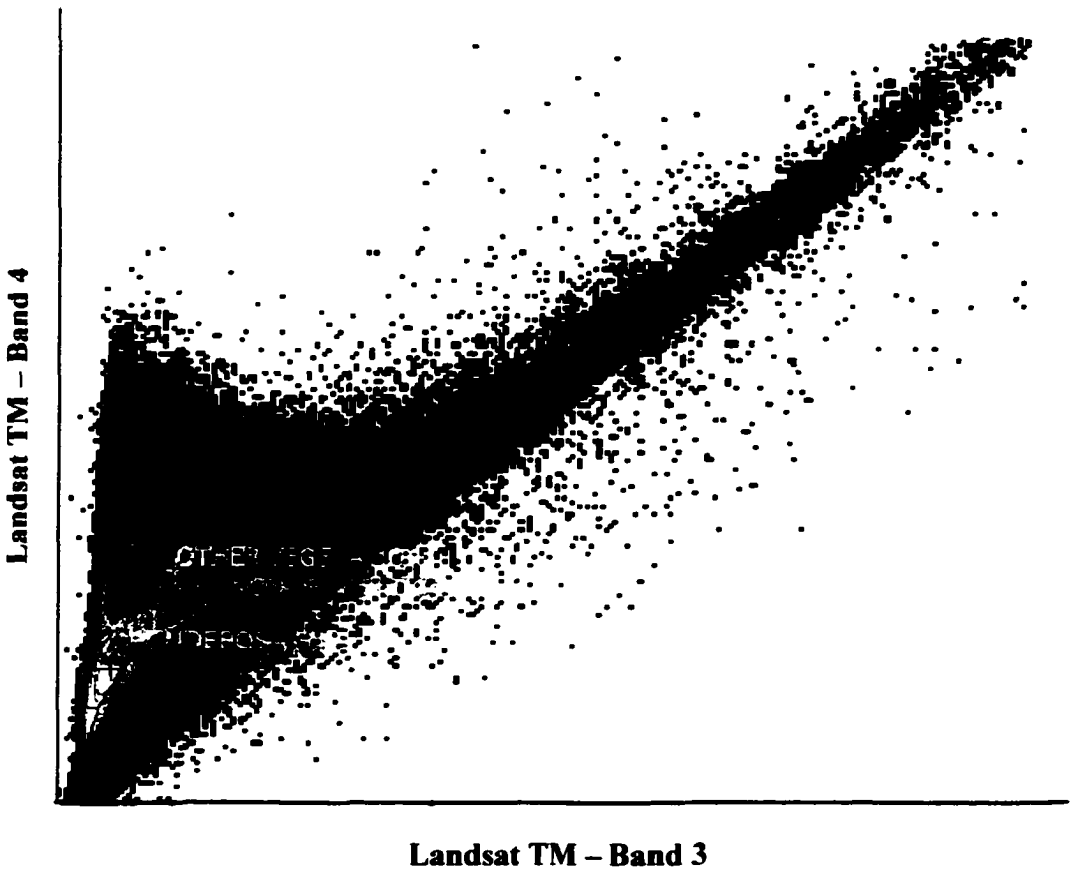


Figure 5.31: Spectral plot of the cover types of the Roosevelt National Forest Wilderness areas in feature space between bands 3 and 4.

A clear example of this is the Krummholz category, which can be described as a combination of dwarfed individuals of *Picea engelmannii*, *Abies lasiocarpa*, and *Pinus aristata*; the first two species also define the spruce/fir category. Another good example is the riparian category, whose principal components are cottonwood and willow (*Populus angustifolia*, *Populus deltoides*, *Salix bebbiana*, *Salix amygdaloides*), which are spectrally very similar to aspen (*Populus tremuloides*).

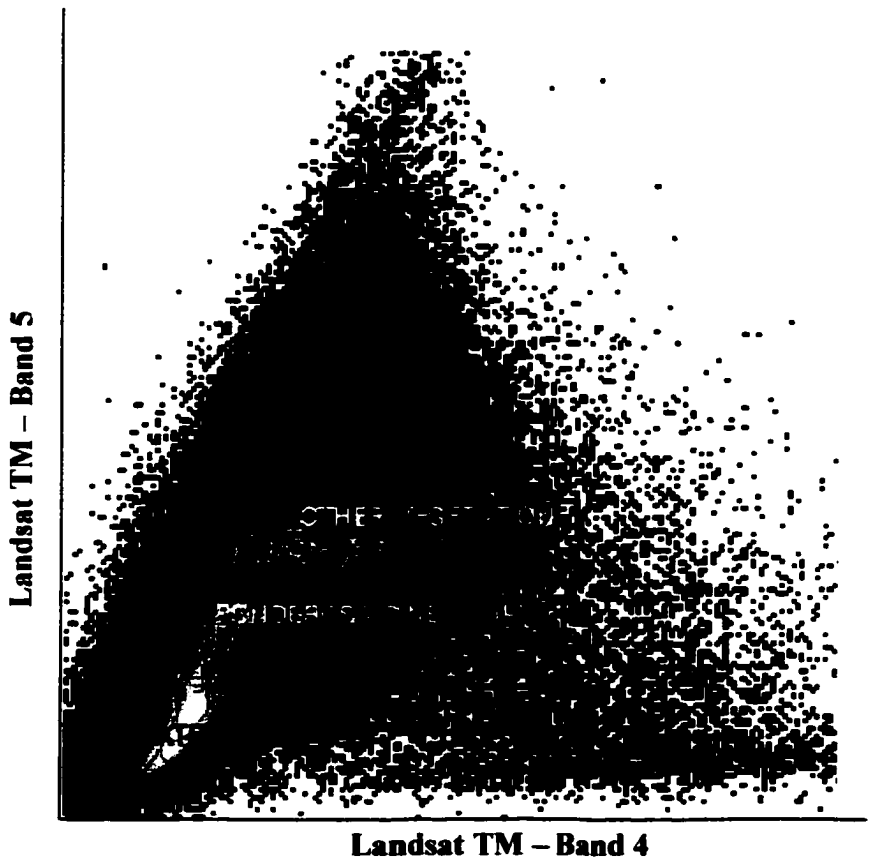


Figure 5.32: Spectral plot of the cover types of the Roosevelt National Forest Wilderness areas in the feature space between bands 4 and 5.

Besides the natural low spectral separability, the high level of spectral overlap between informational categories is augmented by the homogenization of the cover types previously mentioned and becomes even more intricate due to the *topographic effect* discussed in Section 3.2, Classification of remotely sensing data in mountainous terrain. Very similar results were obtained from a spectral analysis of the various cover types conducted for the Rocky Mountain National Park study area.

In contrast to a satellite image classification, based on the spectral characteristics of the data, the reference maps were a product of photo-interpretation. In addition to the color and tone of the vegetation (equivalent to the spectral reflectance used by the computer), the photo-interpreters made use of their experience and skills available only to the human brain to incorporate other equally important parameters (i.e., shape, size, pattern, shadow, texture, association, site) to the process of identifying the cover types, thus often making the classification of spectrally inseparable features possible. Nevertheless, even the reference maps are considered to be accurate only 85 percent of the time (Thomas 2001, personal communication).

In other to compensate for the lack of human-like skills used in conventional photo-interpretation of cover types, one of the objectives of this study was to develop and optimize a neural network based on geographical, topographical and ecological variables incorporated through a GIS to predict the occurrence of forest cover types in the mountains. Through the neural network modeling, other relevant parameters, different than spectral reflectance, were incorporated into the classification process. The model provided a set of prior probabilities for each cover type, which were then incorporated into the Bayesian/Maximum likelihood classifier. There are several limitations in this scheme that need to be addressed. The model of forest cover type prediction, as in almost any attempt to represent nature's complexity, is far from being perfect. In other words, there is a considerable amount of 'noise' or chaotic relationships between the cover types and the cartographic phenomena in nature that cannot be explained by the independent variables used, especially in areas of complex topography, such as the ones used in this study. For instance, a big proportion of the parameters applied in this model are derived

from the DEM (i.e., elevation, slope, aspect, relative incidence of sun light). If we compare the classification maps with the stratified DEM, in some cases it is very apparent that the model seems to follow elevation too closely. This characteristic, advantageous to cover types with very distinct elevation distributions, can be problematic for cover types with complete or even partial overlapping elevation zones (e.g. Spruce/Fir and Lodgepole pine).

On the other hand, in a similar modeling process, Blackard (1998) obtained an accuracy of 70 percent using a stratified random sample over the entire area. In the particular case of the current study, the highest accuracies obtained by the neural network models using only GIS data was 52 percent for the Roosevelt National Forest Wilderness areas and approximately 60 percent for the Rocky Mountain National Park study area. The difference can be explained by the fact that in the current study, in order to develop a widely applicable classification technique, a systematic sample (described in Section 4.3.1) was used to develop the training data instead of the stratified random sample using 100 percent of the data, which was the methohd used in Blackard's study. Consequently, the sample strategy used in the current study was not effective in capturing enough of the spatial complexity of the area to allow an optimal neural network modeling process. This could indicate that the artificial neural network model used in the current study is very sensitive to the characteristics of the sampling design. Two examples can be used to illustrate this problem. The first one, as mentioned before in Section 5.5.1, can be observed in the entire Cache la Poudre Wilderness area, where the model fails to correctly characterize almost every category present in the reference data. The second example refers to the western slope and southern most portions of Rocky Mountain

National Park. It is necessary to emphasize that, as described before in Section 4.3.1.2, these parts of the park were not used in the accuracy assessment because the absence of aerial photos prevented the selection of sampling data for areas of the park outside the boundaries of Larimer County. In spite of this, the area was classified to evaluate the capabilities of the techniques to extrapolate to an area with dissimilar characteristics (e.g., aspect is the most evident in this case). Although the neural network models were able to extrapolate to a certain extent the classification of cover types to these regions, the classification maps clearly demonstrate a higher incidence of discrepancies in these areas, which suggest a high level of localized site dependency. Furthermore, with fifty-five inputs in the case of the Roosevelt National Forest Wilderness areas and fifty-six in the case of the Rocky Mountain National Park study area, the model is very complex. It is very difficult to capture all the variability present in each one of the independent variables unless a very high sample density is used. When dealing with very large areas, such as the ones classified in this study, a very high sample density would make the operational application of the model impracticable for economical and logistical reasons. Furthermore, the time (i.e. in the case of NeuralSIM), and in some cases the computer capacity required to train the neural network (i.e. when using MATLAB) would make such a classification very hard to accomplish.

Another factor that might explain the differences between the results of the current study and the results obtained by Blackard (1998) is that the model capabilities, originally intended to exclusively predict the occurrence of forest cover types, were expanded in the current study to classify three non-forest cover types. Two of these additional cover types (i.e. Water and Non-vegetation) are not directly influenced by

many of parameters that control the distribution of vegetation used in the model (e.g., distance to the nearest wildfire ignition point). The third one (i.e., Other Vegetation or Tundra), although reasonably predictable by the independent variables used in the modeling process, accounted for a considerable amount of the error in all the classification techniques compared (see error matrices in Appendix 1) probably due to a high level of noise. In other words, this cover type evidenced a considerable amount of overlap with other cover types (e.g. Krummholz,) across several of the predicting parameters used in the model (e.g. spectral characteristics, elevation distribution, etc.).

Another important aspect to be addressed is the error propagation. As presented in the comparative results in Tables 5.1 and 5.4, the Bayesian / Maximum Likelihood classifications with probabilities obtained from the neural network modeling using GIS data only, have a lower performance than the "conventional" neural network classifications, in which the seven Landsat TM bands are incorporated in a single step together with the GIS data. In other words, the error produced by the inferior performance of neural network modeling with GIS data only is being transferred to the Bayesian classifier, which is unable to compensate for this deficiency and, in turn, introduces additional error to the classification process. These results are consistent for the classifications performed in both study areas, and also consistent when utilizing both neural network software packages, MATLAB and NeuralSIM

Finally, it is important to mention that if the sources of error described above were effectively minimized, the application of the neural network modeling techniques using GIS and spectral data, developed in this study, have a great potential to improve the classification of forest and other cover types in mountainous terrain. The use of a more

suitable reference dataset, along with a more effective sampling design based on the direct interpretation of carefully distributed aerial photos could result in a considerable improvement of the overall accuracy. Speculatively, the use of a stratified random sample similar to the one applied by Blackard (1998), along with better reference data and the spectral information provided by the satellite imagery, would have yielded accuracies in the order of 85 to 90 percent in the current study. However, such an approach would have been impossible to apply on an operational basis.

CHAPTER 6. SUMMARY AND CONCLUSIONS

6.1 Summary

The main objective of the study was to develop a widely applicable and efficient classification procedure for mapping forest and other cover types in mountainous terrain, using an integrated GIS / neural network / Bayesian classification approach. The essence of the research is based in the use of ecological and cartographic variables in a neural network modeling process to produce *a priori* probabilities, which in turn were incorporated into a Bayesian / Maximum Likelihood classifier. In addition to this all the classifications involving neural network analysis were developed in parallel using MATLAB and NeuralSIM, to evaluate the performance of the model using these two very different neural network programs.

The model was developed and tested in four wilderness areas of the Roosevelt National Forest. It was also evaluated in a second study area within the boundaries of Rocky Mountain National Park. The performance of the new technique was compared to a standard supervised Maximum Likelihood classification technique, a "conventional" Bayesian / Maximum Likelihood classification, and to a "conventional" neural network classifier.

Although the overall performance of all the classification techniques was relatively low (i.e., 62 percent for the best classification technique), the results indicate a

considerable improvement of the new technique over the standard Maximum Likelihood classification technique (13.94 percent improvement), as well as a better accuracy than the "conventional" Bayesian / Maximum Likelihood classifier (13.08 percent improvement). However, the "conventional" neural network classifiers outperformed all the techniques compared in this study, with an overall accuracy improvement of 15.94 percent as compared to the standard Maximum Likelihood classifier. Results were consistent in both study areas, and also for classifiers developed with either the MATLAB or the NeuralSIM neural network programs.

The relatively low overall accuracies (i.e., 46.77 percent to 62.71 percent) can be attributed mainly to problems related to the inadequacy of the reference data. The generalizations introduced to the reference data by photo interpreters for forestry management purposes (i.e., minimum mapping units of five acres or more) are not appropriate for the development and evaluation of remote sensing classification techniques. Furthermore, all errors inherent to the reference data were carried over to the accuracy assessment analysis due to the 100 percent per pixel comparison. Errors related to inaccuracies of the GIS data layers, as well as the miss-registration of the satellite imagery and GIS data layers, along the boundaries of the cover types classified (i.e., edge pixels) might have also contributed to the low overall accuracies.

On the other hand, the results also indicate the need of further research to develop a more accurate and widely applicable neural network classification technique for mapping forest and other cover types at the species level in areas of complex topography. In particular, there is a need to optimize the neural network modeling process through the identification of better prediction parameters. In addition to this, as reported in a

comparative study by Blackard (1998), neural networks appear to be very sensitive to the sampling design. Therefore, a more effective sampling design needs to be developed in order to cover the variability across all the parameters needed by the neural network, while being, at the same time, economically feasible.

6.2 Conclusions

- The new technique developed in this study, involving a combination of GIS, neural networks and Bayesian / Maximum Likelihood classification, proved to be more accurate (i.e., 62.28 percent) than the supervised Maximum Likelihood classification (i.e., 46.77 percent).

  Although the results obtained in this study had lower than expected accuracy levels, all the techniques involving neural network modeling consistently demonstrated better results than the supervised Maximum Likelihood classifier. This was true for the new Bayesian / Maximum Likelihood classification, as well as for the "conventional" neural network classifications.

- The "conventional" neural network classification techniques did a better job of classifying the data (i.e., 62.71 percent) than the new Bayesian/ Maximum Likelihood classifier developed in the current study (i.e., 60.71 percent)

  The "conventional" neural network classifications used in the current study resulted in better accuracies without the additional step of incorporating the probabilities required by the Bayesian /Maximum Likelihood classifier. Also to be pointed out is the fact that when the satellite imagery is included in the modeling process to generate prior probabilities, and these are subsequently incorporated to the

Bayesian/Maximum likelihood classification, the performance of the Bayesian classifiers increased to the accuracy levels similar to the ones achieved by the "conventional" neural network classification techniques. In other words, no additional benefit to the classification process was obtained from the Bayesian / Maximum Likelihood classifier as compared to the "conventional" neural network classification technique.

- The new Bayesian /Maximum Likelihood classifiers performed considerably better (e.g., 60.71 percent) than the "conventional" Bayesian / Maximum likelihood classifier with probabilities obtained from area proportions of cover types (47.63 percent).

  This result indicates the importance of using spatially explicit probabilities (i.e., probability values for each observation or pixel in the study area) instead of a general probability value for each cover type. Although there was almost no difference between the overall accuracies obtained with the MATLAB and NeuralSIM neural network classifications, the output of both software packages was very different. This was probably due to the different mechanisms of both software packages, as well as to the random initialization of the neural network weights. While the output of MATLAB can be considered more suitable for a *fuzzy* classification, the output of the classification mode of NeuralSIM had the characteristics of a "hard" classification (i.e., where each pixel belongs to a single cover type). This might be an advantage or disadvantage, depending on the objectives and type of the classification one wishes to accomplish. However, the Bayesian classification with probabilities obtained from NeuralSIM obtained better results than the equivalent models with MATLAB, which

could be an indication that Bayesian / Maximum Likelihood classifiers are benefited more from very definitive probabilities (i.e., an extremely high probability in favor a particular class) in contrast to a less clear-cut distinction between classes (i.e., a fuzzy classification). This is, however, a hypothesis, and it can only be proved through further experimentation.

- In general, the most accurate techniques involved the use of GIS, spectral data and neural network modeling.

  The inclusion of spectral data to the neural networks improved the modeling process, indicating that the additional information allowed the network to derive better relationships between input and targets.

- The homogeneity of the reference data (due, in part, to artificially introduced minimum mapping units) resulted in a major source of error.

  In the selection of the training, testing and validation data (described in detail in Section 4.3.4) for Spruce / Fir, for example, a particular number of observations (i.e., individual pixels were randomly selected, based on the information of the reference data. However, as described before in relation to Figure 5.29, due to the homogenization of the forest stands in the reference data sets, in reality some of these randomly selected pixels might have belonged to cover types other than the one indicated by the reference data, such as Tundra, Non-vegetation Riparian or Krummholz. Consequently, the neural networks might have been provided with misleading information right from the beginning. Furthermore, all errors inherent to the reference data were carried over to the accuracy assessment analysis due to the

100 percent, per pixel comparison between the classification maps and the reference data.

- The considerable amount of error present in all the classification techniques compared in this study suggests that the current sampling design used to obtain the training, test, and validation data needs to be improved.

  When compared to the accuracy (i.e., 70.58 percent) obtained by Blackard (1998) based on a random sample using 100 percent of the data, the accuracies obtained in the current study (i.e., 52 percent) with a practical sampling approach, using only 10 percent of the reference data as input, evidence the sampling sensitivity of the neural network analysis. In relation to this, Blackard (1998) reported an accuracy improvement of almost 24 percent when comparing a classification performed with a sample obtained from subjectively chosen contiguous areas (i.e., 47.13 percent) versus a classification performed with a stratified random sample (i.e., 70.58 percent). Therefore, the model requires the development of a different sampling design in order to more effectively cover the variability across all the parameters needed by the neural network. At the same time, such a sampling design must necessarily be practical and economically feasible in order to be widely applicable. To combine these two requirements is not an easy task, and perhaps is the problem that presents the greatest challenge to the development of an effective model.

- The model for prediction of cover type occurrence used in this study needs to be optimized.

  The neural network model used in the current study is very complex, requiring a considerable number of inputs, some of which are not widely available, and whose

level of accuracy and relevance to the model needs to be revised. For instance, the current model relies too heavily on parameters derived from a DEM (i.e., elevation, slope, aspect, and relative incidence of sunlight). The use of these parameters is justified and they are very important parameters but they seemed to override the other parameters used. For instance, as described in Section 5.5.1 the model seems to follow elevation too much (e.g., in some areas it was observed that the boundaries of Lodgepole pine and Spruce/ Fir correspond to elevation contour lines).

- The "conventional" neural network classification technique used in this study still has important limitations that need to be resolved before they can be considered widely applicable.

  As described in Chapter 5, NeuralSIM requires considerably longer training times than MATLAB. On the other hand, MATLAB has some limitations when working with very large datasets, primarily related to computer random access memory capacity. Consequently, another important drawback of the techniques involving neural network modeling processes is the time they require to produce final results, as compared to a Maximum Likelihood classifier. However, this not only refers to the neural network training time, which is continuously reduced by the constant improvement of computer capacity, but to the lengthy series of procedures required to prepare the inputs to the model. This makes the neural network classifiers used in this study very unmanageable from a practical perspective, in the sense that it is very hard to go back and retrain the model with an improved training data set, or perform any type of classification refinement, as is commonly the case when using a Maximum Likelihood classifier (e.g., a refinement of the spectral signatures of the training data).

Moreover, whether one is using NeuralSIM or MATLAB, a number of different software packages (i.e. ARCVIEW, ARC/INFO, ERDAS IMAGINE, TEXTEDITOR) and several small custom-made programs were necessary to conduct a classification involving neural network modeling. The development of an effective and complete neural network module within image processing or geomatics software would facilitate the manipulation and integration of GIS, satellite or any other type of data (e.g. text data from a statistical analysis). It would also simplify the selection of training data, making the entire procedure more efficient and easier to apply. This would also smooth the progress of hybrid techniques (e.g. like the combined GIS neural network and Bayesian classifier developed in this study) and open possibilities of experimentation with new hybrid techniques (e.g. a combination of an unsupervised -ISODATA and neural network classifier).

6.3 Recommendations for further research

There are still many issues that require careful consideration and problems that need to be solved in order to obtain a significant improvement in terms of overcoming the effects of topography and improving the overall accuracy of the classification of cover types in mountainous terrain. Several insights have been gained that might contribute to future research on the development of new, widely applicable techniques aimed at improving the classification at the species level of cover types in complex topographic conditions. The following recommendations include some of the practical and theoretical aspects that need to be taken into consideration in order to facilitate further research attempts:

- **Consider using a more manageable study area size.**

  The development of neural network models demand a considerable amount of "fine-tuning" in order to determine the best network architecture and learning parameters. Since they required a considerable amount of time to be trained, this can be a very lengthy process, especially when working very large datasets. In the current study, large areas were used in order two developed a technique under realistic conditions. The availability of a complete dataset in the Roosevelt National Forest Wilderness provided a good starting point to develop the new techniques, while the Rocky Mountain National Park dataset provided the possibility to validate the model in a different area. However, for research purposes, the use of a smaller, more manageable, and carefully selected study area (e.g. a subset within Rocky Mountain National Park) would provide faster returns and therefore allow more experimentation cycles. This is also true for the refinement of the training data. Shorter training times would give the researcher the flexibility to go back, and add or modify the training data more quickly if the performance of the model is not satisfactory, as well as the possibility to experiment with different sampling strategies to optimize the classification results.

- **Improve the sampling strategy:**

  The selection of a good (i.e. truly representative) set of training statistics is a key element for the success of any classification. To accomplish this, a sampling design needs to be developed which provides effective coverage of the statistical variability across all the parameters needed by the neural network model. Since neural networks learn by example, the manual delineation of training polygons from carefully selected

aerial photos (i.e., statistically representative areas) in a supervised fashion might be more effective than the random sampling of individual pixels, as was the method used in this study. As compared to sparsely distributed randomly defined observations, multi-pixel training polygons can provide the neural network models with additional information concerning the spatial relationship between adjacent pixels (i.e. texture patterns). Some cover types have very distinctive texture patterns (e.g. pasture or grass is usually smooth as compared to a mature stand of deciduous trees). Thus, texture differences might be very beneficial in the separation of spectrally similar cover types. As in the case of the spectral texture, there are other spatial relationships between adjacent observations that could have been ignored by a sparse random sampling procedure (e.g. spatial auto-correlation). The manual selection of training polygons would also help to eliminate some of the cover type confusion that occurred in the selection of training data in this study, caused by the discrepancies of the reference data and the satellite imagery described in Section 5.6. However, a strictly supervised selection of training polygons has a very high risk of being biased by the interpreter. In addition to this, the selection would be based only on the information provided by the aerial photos, without considering the characteristics of any of the other multiple inputs to the model (e.g. soils, elevation, etc.). In this case too, a compromise must be attained between statistically sound and economically feasible experimental designs.

- **Explore alternative hybrid techniques**

  A different approach for the selection of better training data could be provided by the combination of unsupervised classification techniques (e.g., ISODATA clustering

procedure) and the neural networks modeling procedure. Image segmentation or clustering techniques usually cover the entire spectral variability of satellite imagery and this capability could be extended to cluster other types of information as well (e.g., some types of GIS datasets where the data is represented as a continuum of values). In addition to this, unsupervised methods of training statistics development come along with effective classification refinement techniques (e.g. cluster busting) that could result in overall improvement of information extraction. Another possibility would be to develop an automated process, in which the ISODATA and neural network algorithms are linked iteratively in a loop until a desired classification error level is reached. All these experiments would be easier to perform with the availability of competent neural network modules within image processing software.

- **Use more suitable reference data:**

  Closely related to the previous recommendation, is the use of accurate reference data. The results of this study demonstrate that careful consideration is needed in the selection of the reference data. Available cover type maps are usually produced for purposes that are different than the evaluation of classification accuracy, and large minimum mapping units (e.g. two to five acres to even forty acres), although suitable for management practices, can introduce a considerable amount of error to the modeling process. Instead of existing cover type maps with defined boundaries and minimum mapping units, the use of color infrared aerial photos, tied to a limited amount of field checking, would provide a better source to select the training, test and validation data required by the neural network, as well as a more accurate basis for the accuracy assessment. The carefully selected field observations should be geo-

referenced through differential GPS measurements. In addition to this, and with regard to the first recommendation for further research, another ideal property of the study area would be that it should be located in an area of good accessibility to facilitate field reconnaissance.

- **Optimize the neural network modeling process.**

  To make the classification techniques involving neural networks more efficient, a reduction of the network's training time is imperative. A detailed analysis of the relevance of each independent variable to the model must be conducted to eliminate redundancy and simplify the model. However, the development of effective methods of model optimization could well be the topic of a research project by itself. On the other hand, according to Arora and Foody (1997), and Benediksson and Sveinsson (1997), neural network models seem to be particularly benefited from variables that contribute very distinct types of information. Consequently, a thorough selection of a limited number, but better quality inputs, could represent a major contribution in the development of more accurate and efficient neural network classification techniques. In this sense, the use of new, currently available sources of information should be explored; for example, the application of satellite hyper-spectral imagery. Neural network classifications of cover types in mountainous terrain would probably be benefited by the subtle spectral differences between cover types species detected by a few carefully selected narrow spectral bands. In a similar way, future experiments with conventional neural network classifications should contemplate the possibility of using LIDAR data. Differences in such things as stand density, height, canopy and

ground surface characteristics, currently provided by LIDAR scanners might also contribute valuable information to the modeling process.

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APPENDIX 1: ERROR MATRICES

ERROR MATRIX

Reference Data

Supervised Maximum Likelihood classification

Category	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	WATER	Total	Errors of Comission	User's Accuracy
SPRUCE / FIR	128587	67821	10	1626	659	189	16311	7698	437	226	223564	42.48%	57.52%
LODGEPOLE PINE	52270	163875	3776	173	2705	3592	3822	1362	127	163	231865	29.32%	70.68%
PONDEROSA PINE	255	2525	11068	1370	109	1551	7527	57	14	20	24496	54.82%	45.18%
RIPARIAN	5243	5596	1629	959	705	987	20075	1863	25	60	37142	97.42%	2.58%
ASPEN	12893	18956	478	417	4994	594	9577	1577	22	20	49528	89.92%	10.08%
DOUGLAS-FIR	1065	18292	18418	517	231	9967	883	7	1	95	49476	79.85%	20.15%
OTHER VEGETATION	1868	439	99	156	11	7	17102	1971	722	32	22407	23.68%	76.32%
KRUMMHOLZ	8718	3850	123	242	82	35	38224	7382	1232	23	59911	87.68%	12.32%
NON-VEGETATION	572	50	6	19	0	1	6516	1034	1052	23	9273	88.66%	11.34%
WATER	1452	2344	161	7	3	448	904	226	471	1407	7423	81.05%	18.95%
Total	212923	283748	35768	5486	9499	17371	120941	23177	4103	2069	715085	**67.49%**	**32.51%**
Errors of Omission	39.61%	42.25%	69.06%	82.52%	47.43%	42.62%	85.86%	68.15%	74.36%	32.00%	**58.39%**	**51.56%**	
Producer's accuracy	60.39%	57.75%	30.94%	17.48%	52.57%	57.38%	14.14%	31.85%	25.64%	68.00%	**41.61%**		
Kappa Index of Agreement (KIA)	0.4238	0.3748	0.2849	0.1296	0.4904	0.5421	0.1136	0.2562	0.2466	0.6767			
Overall Accuracy												**48.44%**	
Overall Kappa												**0.3264**	

Table A.1: Error matrix of the supervised Maximum Likelihood classification in the Roosevelt National Forest Wilderness areas.

ERROR MATRIX

Reference Data

"Conventional" Bayesian/Maximum Likelihood classification with probabilities obtained from area proportions of cover types

Category	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	WATER	Total	Errors of Comission	User's Accuracy
SPRUCE / FIR	133713	72348	15	1692	827	277	18201	8257	463	252	236045	43.35%	56.65%
LODGEPOLE PINE	53722	173167	5336	213	3208	4778	4491	1464	123	182	246684	29.80%	70.20%
PONDEROSA PINE	232	2511	11020	1321	114	1474	7328	40	9	23	24072	54.22%	45.78%
RIPARIAN	4063	4785	1691	916	646	1022	15183	1162	13	57	29538	96.90%	3.10%
ASPEN	7915	11680	347	337	4421	388	8996	1403	20	9	35516	87.55%	12.45%
DOUGLAS-FIR	546	12889	16914	503	176	9015	856	4	0	90	40993	78.01%	21.99%
OTHER VEGETATION	2823	797	170	276	22	10	23930	2782	965	42	31817	24.79%	75.21%
KRUMMHOLZ	8350	3756	104	206	82	32	35511	6952	1113	22	56128	87.61%	12.39%
NON-VEGETATION	488	27	7	21	0	1	5616	911	946	21	8038	88.23%	11.77%
WATER	1071	1788	164	1	3	374	829	202	451	1371	6254	78.08%	21.92%
Total	212923	283748	35768	5486	9499	17371	120941	23177	4103	2069	715085	**66.85%**	**33.15%**
Errors of Omission	37.20%	38.97%	69.19%	83.30%	53.46%	48.10%	80.21%	70.00%	76.94%	33.74%	**59.11%**	**48.89%**	
Producer's accuracy	62.80%	61.03%	30.81%	16.70%	46.54%	51.90%	19.79%	30.00%	23.06%	66.26%	**40.89%**		
Kappa Index of Agreement (KIA)	0.4447	0.405	0.284	0.1311	0.4375	0.4897	0.1605	0.2403	0.2218	0.6597			
Overall Accuracy												**51.11%**	
Overall Kappa												**0.3486**	

Table A.2: Error matrix of "conventional" Bayesian/Maximum Likelihood classification with probabilities obtained from area proportions of cover types in the Roosevelt National Forest Wilderness areas.

ERROR MATRIX

Reference Data

Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using only GIS data

Category	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	WATER	Total	Errors of Comission	User's Accuracy
SPRUCE / FIR	141355	66590	1	1616	50	0	17869	7316	543	140	235480	39.97%	60.03%
LODGEPOLE PINE	45206	169644	3897	152	2182	3013	3121	1210	72	142	228639	25.80%	74.20%
PONDEROSA PINE	171	4646	16052	1402	175	2074	7356	20	9	30	31935	49.74%	50.26%
RIPARIAN	2142	3423	886	1277	354	869	8093	948	7	80	18079	92.94%	7.06%
ASPEN	9696	26209	764	202	6493	1128	6628	789	18	152	52079	87.53%	12.47%
DOUGLAS-FIR	349	7901	13994	336	148	10076	616	2	0	65	33487	69.91%	30.09%
OTHER VEGETATION	5347	1416	103	377	54	18	45673	3433	1024	46	57491	20.56%	79.44%
KRUMMHOLZ	7658	2836	44	119	42	16	25900	8486	771	17	45889	81.51%	18.49%
NON-VEGETATION	281	137	10	5	0	1	5081	820	1342	25	7702	82.58%	17.42%
WATER	718	946	17	0	1	176	604	153	317	1372	4304	68.12%	31.88%
Total	212923	283748	35768	5486	9499	17371	120941	23177	4103	2069	715085	**61.87%**	**38.13%**
Errors of Omission	33.61%	40.21%	55.12%	76.72%	31.65%	42.00%	62.24%	63.39%	67.29%	33.69%	**50.59%**	**43.82%**	
Producer's accuracy	66.39%	59.79%	44.88%	23.28%	68.35%	58.00%	37.76%	36.61%	32.71%	66.31%	**49.41%**		
Kappa Index of Agreement (KIA)	0.4988	0.4089	0.423	0.2129	0.6587	0.5594	0.3232	0.3227	0.3198	0.6611			
Overall Accuracy												**56.18%**	
Overall Kappa												**0.4195**	

Table A.3: Error matrix of the Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using only GIS data in the Roosevelt National Forest Wilderness areas.

ERROR MATRIX

Reference Data

Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using GIS data and Landsat TM data

Category	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	WATER	Total	Errors of Comission	User's Accuracy
SPRUCE / FIR	147169	63680	4	1579	74	17	16989	7099	501	186	237298	37.98%	62.02%
LODGEPOLE PINE	41205	180728	4901	167	2484	3467	3201	826	80	139	237198	23.81%	76.19%
PONDEROSA PINE	129	3729	15490	1369	143	2233	7377	14	14	9	30507	49.22%	50.78%
RIPARIAN	2011	3257	874	1239	361	926	7796	924	7	79	17474	92.91%	7.09%
ASPEN	7778	20030	514	212	6265	1197	6315	1102	42	76	43531	85.61%	14.39%
DOUGLAS-FIR	290	6907	13793	378	91	9432	624	3	0	76	31594	70.15%	29.85%
OTHER VEGETATION	5543	1989	104	406	37	6	44611	3339	1056	32	57123	21.90%	78.10%
KRUMMHOLZ	7788	2303	51	128	38	23	28234	9069	787	19	48440	81.28%	18.72%
NON-VEGETATION	392	187	6	8	5	1	5166	696	1351	29	7841	82.77%	17.23%
WATER	618	938	31	0	1	69	628	105	265	1424	4079	65.09%	34.91%
Total	212923	283748	35768	5486	9499	17371	120941	23177	4103	2069	715085	**61.07%**	**38.93%**
Errors of Omission	30.88%	36.31%	56.69%	77.42%	34.05%	45.70%	63.11%	60.87%	67.07%	31.17%	**50.33%**	**41.72%**	
Producer's accuracy	69.12%	63.69%	43.31%	22.58%	65.95%	54.30%	36.89%	39.13%	32.93%	68.83%	**49.67%**		
Kappa Index of Agreement (KIA)	0.5378	0.4567	0.4078	0.2065	0.6375	0.5218	0.3141	0.3471	0.3218	0.6865			
Overall Accuracy												**58.28%**	
Overall Kappa												**0.4435**	

Table A.4: Error matrix of the Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using GIS and Landsat TM data in the Roosevelt National Forest Wilderness areas.

ERROR MATRIX

Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using only GIS data

Category	SPRUCE / FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	WATER	Total	Errors of Comission	User's Accuracy
Reference Data													
SPRUCE / FIR	129354	67431	17	1070	133	173	14354	5497	427	211	218667	40.84%	59.16%
LODGEPOLE PINE	57331	177670	4121	299	3455	2684	3696	95	91	85	249527	28.80%	71.20%
PONDEROSA PINE	102	6162	21630	1389	103	4417	6705	0	10	45	40563	46.68%	53.32%
RIPARIAN	611	1330	853	1719	85	908	1399	516	4	105	7530	77.17%	22.83%
ASPEN	5171	23452	1082	174	5543	916	2024	122	10	238	38732	85.69%	14.31%
DOUGLAS-FIR	49	2291	7932	182	36	8208	325	0	0	12	19035	56.88%	43.12%
OTHER VEGETATION	7754	2409	133	425	125	63	69079	6528	1039	50	87605	21.15%	78.85%
KRUMMHOLZ	11867	2191	0	221	8	0	18864	9798	884	33	43866	77.66%	22.34%
NON-VEGETATION	440	589	0	7	11	0	4355	612	1638	38	7690	78.70%	21.30%
WATER	244	223	0	0	0	2	140	9	0	1252	1870	33.05%	66.95%
Total	212923	283748	35768	5486	9499	17371	120941	23177	4103	2069	715085	**54.66%**	**45.34%**
Errors of Omission	39.25%	37.38%	39.53%	68.67%	41.65%	52.75%	42.88%	57.73%	60.08%	39.49%	**47.94%**	**40.44%**	
Producer's accuracy	60.75%	62.62%	60.47%	31.33%	58.35%	47.25%	57.12%	42.27%	39.92%	60.51%	**52.06%**		
Kappa Index of Agreement (KIA)	0.4346	0.4258	0.581	0.306	0.5597	0.4581	0.5113	0.385	0.3927	0.6041			
Overall Accuracy												**59.56%**	
Overall Kappa												**0.456**	

Table A.5: Error matrix of the Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using only GIS data in the Roosevelt National Forest Wilderness areas.

ERROR MATRIX

Reference Data

Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS and Landsat TM data

Category	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	WATER	Total	Errors of Comission	User's Accuracy
SPRUCE / FIR	146683	78600	18	1411	159	460	13652	6547	432	359	248321	40.93%	59.07%
LODGEPOLE PINE	42924	169697	4838	142	2883	3295	3401	331	62	5	227578	25.43%	74.57%
PONDEROSA PINE	51	6479	18726	1335	273	2893	6961	11	18	18	36765	49.07%	50.93%
RIPARIAN	1115	1583	1188	1596	73	1227	1105	116	3	116	8122	80.35%	19.65%
ASPEN	4458	18124	432	99	5939	338	1942	264	6	80	31682	81.25%	18.75%
DOUGLAS-FIR	62	2800	10355	221	59	9086	437	0	0	15	23035	60.56%	39.44%
OTHER VEGETATION	9131	4016	206	499	102	57	66299	5834	1166	29	87339	24.09%	75.91%
KRUMMHOLZ	7427	1396	0	175	2	0	22146	9150	784	26	41106	77.74%	22.26%
NON-VEGETATION	310	363	0	3	4	0	4859	919	1599	24	8081	80.21%	19.79%
WATER	762	690	5	5	5	15	139	5	33	1397	3056	54.29%	45.71%
Total	212923	283748	35768	5486	9499	17371	120941	23177	4103	2069	715085	**57.39%**	**42.61%**
Errors of Omission	31.11%	40.19%	47.65%	70.91%	37.48%	47.69%	45.18%	60.52%	61.03%	32.48%	**47.42%**	**39.84%**	
Producer's accuracy	68.89%	59.81%	52.35%	29.09%	62.52%	52.31%	54.82%	39.48%	38.97%	67.52%	**52.58%**		
Kappa Index of Agreement (KIA)	0.5234	0.4104	0.4977	0.2828	0.6078	0.5072	0.4853	0.3579	0.3827	0.6738			
Overall Accuracy												**60.16%**	
Overall Kappa												**0.4642**	

Table A.6: Error matrix of the Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS and Landsat TM data in the Roosevelt National Forest Wilderness areas.

ERROR MATRIX

Neural network classification with MATLAB using GIS and Landsat TM data

Reference Data

Category	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	WATER	Total	Errors of Comission	User's Accuracy
SPRUCE / FIR	142165	66170	0	916	158	21	12969	3287	330	215	226231	37.16%	62.84%
LODGEPOLE PINE	33011	162377	4278	198	2682	3131	3518	12	54	101	209362	22.44%	77.56%
PONDEROSA PINE	49	5881	19626	1249	162	3600	5151	0	24	1	35743	45.09%	54.91%
RIPARIAN	1185	1613	1130	1511	93	1419	961	471	2	146	8531	82.29%	17.71%
ASPEN	8067	27973	1059	199	6140	1202	1961	143	66	134	46944	86.92%	13.08%
DOUGLAS-FIR	2	1820	9567	355	12	7995	1478	0	0	23	21252	62.38%	37.62%
OTHER VEGETATION	12921	13444	108	660	252	0	68636	6084	1258	32	103395	33.62%	66.38%
KRUMMHOLZ	13335	2914	0	250	0	1	21223	12665	652	26	51066	75.20%	24.80%
NON-VEGETATION	1030	1215	0	0	0	2	4872	473	1717	20	9329	81.60%	18.40%
WATER	1158	341	0	148	0	0	172	42	0	1371	3232	57.58%	42.42%
Total	212923	283748	35768	5486	9499	17371	120941	23177	4103	2069	715085	**58.43%**	**41.57%**
Errors of Omission	33.23%	42.77%	45.13%	72.46%	35.36%	53.98%	43.25%	45.36%	58.15%	33.74%	**46.34%**	**40.68%**	
Producer's accuracy	66.77%	57.23%	54.87%	27.54%	64.64%	46.02%	56.75%	54.64%	41.85%	66.26%	**53.66%**		
Kappa Index of Agreement (KIA)	0.5139	0.3952	0.525	0.2667	0.6215	0.4437	0.4944	0.5116	0.4108	0.6611			
Overall Accuracy												**59.32%**	
Overall Kappa												**0.4638**	

Table A.7: Error Matrix of the "conventional" neural network classification with MATLAB using GIS and Landsat TM data in the Roosevelt National Forest Wilderness areas.

ERROR MATRIX

Reference Data

Neural network classification with MATLAB using only GIS data

Category	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	WATER	Total	Errors of Comission	User's Accuracy
SPRUCE / FIR	119549	65133	0	1158	39	3	14197	2661	498	183	203421	41.23%	58.77%
LODGEPOLE PINE	35815	131912	2943	175	2527	2554	2994	61	53	92	179126	26.36%	73.64%
PONDEROSA PINE	77	7899	21171	1357	234	4524	5683	35	18	16	41014	48.38%	51.62%
RIPARIAN	1105	1364	692	1727	104	741	765	435	0	161	7094	75.66%	24.34%
ASPEN	10336	43942	2034	92	6309	1523	2624	126	55	251	67292	90.62%	9.38%
DOUGLAS-FIR	187	2399	8927	270	29	8010	995	2	0	6	20825	61.54%	38.46%
OTHER VEGETATION	19112	14813	1	528	20	5	69644	7754	1094	58	113029	38.38%	61.62%
KRUMMHOLZ	22409	12949	0	164	237	0	18501	11556	690	219	66725	82.68%	17.32%
NON-VEGETATION	3165	2714	0	5	0	11	5043	526	1693	32	13189	87.16%	12.84%
WATER	1168	623	0	10	0	0	495	21	2	1051	3370	68.81%	31.19%
Total	212923	283748	35768	5486	9499	17371	120941	23177	4103	2069	715085	**62.08%**	**37.92%**
Errors of Omission	43.85%	53.51%	40.81%	68.52%	33.58%	53.89%	42.41%	50.14%	58.74%	49.20%	**49.47%**	**47.89%**	
Producer's accuracy	56.15%	46.49%	59.19%	31.48%	66.42%	46.11%	57.59%	49.86%	41.26%	50.80%	**50.54%**		
Kappa Index of Agreement (KIA)	0.3871	0.286	0.5671	0.3079	0.6293	0.4449	0.4962	0.447	0.4016	0.5056			
Overall Accuracy												**52.11%**	
Overall Kappa												**0.3869**	

Table A.8: Error matrix of the "conventional" neural network classification with MATLAB using only GIS data in the Roosevelt National Forest Wilderness areas.

ERROR MATRIX

Reference Data

Neural network classification with NeuralSIM using GIS and Landsat TM data

Category	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	WATER	Total	Errors of Comission	User's Accuracy
SPRUCE / FIR	136680	72244	163	1248	302	638	12589	3266	431	194	227755	39.99%	60.01%
LODGEPOLE PINE	44211	171515	3630	108	3045	2299	5500	137	44	225	230714	25.66%	74.34%
PONDEROSA PINE	76	6228	21239	1176	125	4798	4506	0	24	13	38185	44.38%	55.62%
RIPARIAN	1201	1376	1095	1662	104	787	733	311	3	132	7404	77.55%	22.45%
ASPEN	4268	19155	606	46	5831	432	1589	139	48	88	32202	81.89%	18.11%
DOUGLAS-FIR	64	2909	8831	236	58	8288	971	0	0	8	21365	61.21%	38.79%
OTHER VEGETATION	12638	6045	178	858	18	74	70271	8407	1267	25	99781	29.57%	70.43%
KRUMMHOLZ	11384	2111	0	133	0	0	17375	10126	612	20	41761	75.75%	24.25%
NON-VEGETATION	755	1281	10	3	15	4	7113	742	1668	19	11610	85.63%	14.37%
WATER	1646	884	16	16	1	51	294	49	6	1345	4308	68.78%	31.22%
Total	212923	283748	35768	5486	9499	17371	120941	23177	4103	2069	715085	**59.04%**	**40.96%**
Errors of Omission	35.81%	39.55%	40.62%	69.70%	38.61%	52.29%	41.90%	56.31%	59.35%	34.99%	**46.91%**	**40.06%**	
Producer's accuracy	64.19%	60.45%	59.38%	30.30%	61.39%	47.71%	58.10%	43.69%	40.65%	65.01%	**53.09%**		
Kappa Index of Agreement (KIA)	0.4746	0.4161	0.5709	0.2957	0.5956	0.461	0.5131	0.402	0.3967	0.648			
Overall Accuracy												**59.94%**	
Overall Kappa												**0.4641**	

Table A.9: Error matrix of the "conventional" neural network classification with NeuralSIM using GIS and Landsat TM data in the Roosevelt National Forest Wilderness areas.

ERROR MATRIX

Reference Data

Neural network classification with NeuralSIM using only GIS data

Category	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	WATER	Total	Errors of Comission	User's Accuracy
SPRUCE / FIR	106641	71332	86	507	459	238	13240	2349	360	209	195421	45.43%	54.57%
LODGEPOLE PINE	51759	151060	3105	292	4328	1796	5810	79	62	86	218377	30.83%	69.17%
PONDEROSA PINE	343	7511	22653	1384	104	5859	5046	0	44	45	42989	47.31%	52.69%
RIPARIAN	1618	1593	988	1769	99	732	1322	642	13	101	8877	80.07%	19.93%
ASPEN	5266	24974	1603	142	4270	741	1534	140	2	251	38923	89.03%	10.97%
DOUGLAS-FIR	80	2139	6782	216	89	7298	667	0	0	2	17273	57.75%	42.25%
OTHER VEGETATION	15295	12992	501	516	109	620	70983	8367	1093	58	110534	35.78%	64.22%
KRUMMHOLZ	23476	6026	0	304	0	0	15848	10348	818	64	56884	81.81%	18.19%
NON-VEGETATION	6584	5333	49	346	40	47	5690	980	1711	37	20817	91.78%	8.22%
WATER	1861	788	1	10	1	40	801	272	0	1216	4990	75.63%	24.37%
Total	212923	283748	35768	5486	9499	17371	120941	23177	4103	2069	715085	**63.54%**	**36.46%**
Errors of Omission	49.92%	46.76%	36.67%	67.75%	55.05%	57.99%	41.31%	55.35%	58.30%	41.23%	**51.03%**	**47.15%**	
Producer's accuracy	50.08%	53.24%	63.33%	32.25%	44.95%	42.01%	58.69%	44.65%	41.70%	58.77%	**48.97%**		
Kappa Index of Agreement (KIA)	0.3131	0.3268	0.6099	0.3139	0.4178	0.4058	0.5114	0.3986	0.3995	0.5848			
Overall Accuracy												**52.85%**	
Overall Kappa												**0.383**	

Table A.10: Error matrix of the "conventional" neural network classification with NeuralSIM using only GIS data in the Roosevelt National Forest Wilderness areas.

ERROR MATRIX

Reference Data

Supervised Maximum Likelihood classification

Category	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	TUNDRA	WATER	Total	Errors of Comission	User's Accuracy
SPRUCE / FIR	119042	28060	258	2893	214	285	418	3538	5964	2991	365	164028	27.43%	72.57%
LODGEPOLE PINE	46006	71103	6506	383	446	4965	584	198	650	210	51	131102	45.77%	54.23%
PONDEROSA PINE	479	5693	21802	130	143	2825	1515	1	828	33	2	33451	34.82%	65.18%
RIPARIAN	5501	494	58	20688	107	16	633	4996	3552	18079	142	54266	61.88%	38.12%
ASPEN	4138	4687	1750	4968	2512	508	912	917	314	286	73	21065	88.08%	11.92%
DOUGLAS-FIR	3809	8428	5215	63	150	4524	227	282	741	112	264	23815	81.00%	19.00%
OTHER VEGETATION	335	798	5350	1524	368	177	6268	533	587	1547	1	17488	64.16%	35.84%
KRUMMHOLZ	10697	3084	898	3362	153	121	350	13367	34579	43524	71	110206	87.87%	12.13%
NON-VEGETATION	286	76	78	409	9	25	17	231	23281	6395	184	30991	24.88%	75.12%
TUNDRA	981	138	98	873	23	23	57	681	18682	16225	58	37839	57.12%	42.88%
WATER	574	186	40	202	3	47	7	148	13978	924	1245	17354	92.83%	7.17%
Total	191848	122747	42053	35495	4128	13516	10988	24892	103156	90326	2456	641605	**60.53%**	**39.47%**
Errors of Omission	37.95%	42.07%	48.16%	41.72%	39.15%	66.53%	42.96%	46.30%	77.43%	82.04%	49.31%	**52.15%**	**53.23%**	
Producer's accuracy	62.05%	57.93%	51.84%	58.28%	60.85%	33.47%	57.04%	53.70%	22.57%	17.96%	50.69%	**47.85%**		
Kappa Index of Agreement (KIA)	0.49	0.47	0.49	0.54	0.6	0.31	0.56	0.44	0.19	0.13	0.49			
Overall Accuracy													**46.77%**	
Overall Kappa													**0.3752**	

Table A.11: Error matrix of the supervised Maximum Likelihood classification in the Rocky Mountain National Park study area.

ERROR MATRIX

Reference Data

"Conventional" Bayesian/Maximum Likelihood classification with probabilities obtained from area proportions of cover types

Category	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	TUNDRA	WATER	Total	Errors of Commission	User's Accuracy
SPRUCE / FIR	123420	30401	328	3163	256	398	474	4083	6200	3466	352	172541	28.47%	71.53%
LODGEPOLE PINE	44715	72980	8181	376	542	6012	619	219	740	219	51	134654	45.80%	54.20%
PONDEROSA PINE	449	5334	21479	132	135	2738	1549	0	843	33	2	32694	34.30%	65.70%
RIPARIAN	5418	481	55	20686	100	23	639	5065	3559	18206	139	54371	61.95%	38.05%
ASPEN	3494	4153	1655	4886	2446	477	880	844	290	259	71	19455	87.43%	12.57%
DOUGLAS-FIR	2293	5458	3992	53	106	3475	182	239	628	102	238	16766	79.27%	20.73%
OTHER VEGETATION	340	776	5251	1513	367	172	6224	529	580	1534	1	17287	64.00%	36.00%
KRUMMHOLZ	9588	2713	866	3079	127	114	334	12714	32297	41417	59	103308	87.69%	12.31%
NON-VEGETATION	291	80	88	410	8	26	18	245	23529	6619	175	31489	25.28%	74.72%
TUNDRA	1041	150	101	974	35	27	61	765	18895	17306	51	39406	56.08%	43.92%
WATER	799	221	57	223	6	54	8	189	15595	1165	1317	19634	93.29%	6.71%
Total	191848	122747	42053	35495	4128	13516	10988	24892	103156	90326	2456	641605	**60.32%**	**39.68%**
Errors of Omission	35.67%	40.54%	48.92%	41.72%	40.75%	74.29%	43.36%	48.92%	77.19%	80.84%	46.38%	**52.68%**	**52.37%**	
Producer's accuracy	64.33%	59.46%	51.08%	58.28%	59.25%	25.71%	56.64%	51.08%	22.81%	19.16%	53.62%	**47.40%**		
Kappa Index of Agreement (KIA)	0.5121	0.4869	0.4845	0.5442	0.5798	0.2372	0.5544	0.4169	0.1883	0.1387	0.5216			
Overall Accuracy													**47.63%**	
Overall Kappa													**0.3819**	

Table A.12: Error matrix of "conventional" Bayesian/Maximum Likelihood classification with probabilities obtained from area proportions of cover types in the Rocky Mountain National Park study area.

ERROR MATRIX

Reference Data

Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using only GIS data

Category	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	TUNDRA	WATER	Total	Errors of Comission	User's Accuracy
SPRUCE / FIR	136357	30381	144	2400	296	102	428	3557	5865	2733	177	182440	25.26%	74.74%
LODGEPOLE PINE	32811	75032	7540	413	547	6215	663	141	1019	124	35	124540	39.75%	60.25%
PONDEROSA PINE	490	4554	23692	240	336	2458	1681	0	976	16	5	34448	31.22%	68.78%
RIPARIAN	5557	699	44	22705	99	54	820	6353	3806	15413	173	55723	59.25%	40.75%
ASPEN	1999	3027	1286	3799	2217	230	622	384	183	100	63	13910	84.06%	15.94%
DOUGLAS-FIR	3130	5598	2479	98	245	4147	125	75	418	89	217	16621	75.05%	24.95%
OTHER VEGETATION	263	695	6103	1396	253	127	6324	276	513	890	2	16842	62.45%	37.55%
KRUMMHOLZ	8792	2319	529	2473	90	102	246	11387	19949	17581	42	63510	82.07%	17.93%
NON-VEGETATION	391	135	133	410	19	52	30	357	37465	5947	179	45118	16.96%	83.04%
TUNDRA	1627	179	65	1387	24	8	46	2256	25096	47018	37	77743	39.52%	60.48%
WATER	431	128	38	174	2	21	3	106	7866	415	1526	10710	85.75%	14.25%
Total	191848	122747	42053	35495	4128	13516	10988	24892	103156	90326	2456	641605	**54.67%**	**45.33%**
Errors of Omission	28.92%	38.87%	43.66%	36.03%	46.29%	69.32%	42.45%	54.25%	63.68%	47.95%	37.87%	**46.30%**	**42.66%**	
Producer's accuracy	71.08%	61.13%	56.34%	63.97%	53.71%	30.68%	57.55%	45.75%	36.32%	52.05%	62.13%	**53.70%**		
Kappa Index of Agreement (KIA)	0.5958	0.5176	0.5386	0.6054	0.5268	0.2884	0.5641	0.3979	0.315	0.4544	0.6149			
Overall Accuracy													**57.34%**	
Overall Kappa													**0.4897**	

Table A.13: Error matrix of the Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using only GIS data in the Rocky Mountain National Park study area.

ERROR MATRIX

Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using GIS and Landsat TM data

Category	Reference Data: SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	TUNDRA	WATER	Total	Errors of Comission	User's Accuracy
SPRUCE / FIR	143427	37372	71	2178	384	255	452	2946	5538	2407	134	195164	26.51%	73.49%
LODGEPOLE PINE	24878	64111	5536	503	393	5047	479	46	730	93	46	101862	37.06%	62.94%
PONDEROSA PINE	353	4915	25506	121	267	2886	1446	3	1076	14	5	36592	30.30%	69.70%
RIPARIAN	5714	762	70	22883	157	49	810	5218	3332	14196	160	53351	57.11%	42.89%
ASPEN	1772	3026	1379	3520	2249	227	775	383	163	116	59	13669	83.55%	16.45%
DOUGLAS-FIR	4008	9071	4513	117	236	4804	202	23	561	35	162	23732	79.76%	20.24%
OTHER VEGETATION	173	556	4216	1498	295	87	6514	195	375	837	0	14746	55.83%	44.17%
KRUMMHOLZ	9823	2558	578	2574	118	91	247	13810	22092	17503	42	69436	80.11%	19.89%
NON-VEGETATION	484	99	72	477	21	27	16	417	41022	6527	199	49361	16.89%	83.11%
TUNDRA	919	183	84	1454	7	25	42	1753	22567	48426	20	75480	35.84%	64.16%
WATER	297	94	28	170	1	18	5	98	5700	172	1629	8212	80.16%	19.84%
Total	191848	122747	42053	35495	4128	13516	10988	24892	103156	90326	2456	641605	53.01%	46.99%
Errors of Omission	25.24%	47.77%	39.35%	35.53%	45.52%	64.46%	40.72%	44.52%	60.23%	46.39%	33.67%	43.95%	41.65%	
Producer's accuracy	74.76%	52.23%	60.65%	64.47%	54.48%	35.54%	59.28%	55.48%	39.77%	53.61%	66.33%	56.05%		
Kappa Index of Agreement (KIA)	0.6373	0.4321	0.5827	0.6125	0.5349	0.3307	0.5833	0.5008	0.3475	0.4743	0.6589			
Overall Accuracy													58.35%	
Overall Kappa													0.5017	

Table A.14: Error matrix of the Bayesian/Maximum Likelihood classification with probabilities obtained from MATLAB using GIS and Landsat TM data in the Rocky Mountain National Park study area.

ERROR MATRIX

Reference Data

Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using only GIS data

Category	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	TUNDRA	WATER	Total	Errors of Comission	User's Accuracy
SPRUCE / FIR	139550	34437	72	2285	459	335	558	2846	5643	2268	94	188547	0.2599	74.01%
LODGEPOLE PINE	28521	66069	6782	306	603	4714	764	152	1132	78	27	109148	0.3947	60.53%
PONDEROSA PINE	648	8211	24163	175	577	1953	2365	0	1345	0	7	39444	0.3874	61.26%
RIPARIAN	6601	1998	80	20933	235	45	892	4992	3064	8853	144	47837	0.5624	43.76%
ASPEN	2158	2960	741	2126	974	76	258	20	68	2	80	9463	0.8971	10.29%
DOUGLAS-FIR	1361	6120	3460	293	789	5656	387	0	250	0	28	18344	0.6917	30.83%
OTHER VEGETATION	154	816	6697	2064	431	711	5663	1	422	17	3	16979	0.6665	33.35%
KRUMMHOLZ	7750	1288	48	2273	23	7	47	8961	8748	9314	38	38497	0.7672	23.28%
NON-VEGETATION	1661	241	10	855	22	13	32	1682	54193	8162	151	67022	0.1914	80.86%
TUNDRA	3070	570	0	3912	14	2	3	6149	27386	61481	13	102600	0.4008	59.92%
WATER	374	37	0	273	1	4	19	89	905	151	1871	3724	0.4976	50.24%
Total	191848	122747	42053	35495	4128	13516	10988	24892	103156	90326	2456	641605	**51.97%**	**49.03%**
Errors of Omission	27.26%	46.17%	42.54%	41.03%	76.41%	58.15%	48.46%	64.00%	47.47%	31.93%	23.82%	**46.11%**	**39.29%**	
Producer's accuracy	72.74%	53.83%	57.46%	58.97%	23.59%	41.85%	51.54%	36.00%	52.53%	68.07%	76.18%	**53.89%**		
Kappa Index of Agreement (KIA)	0.614	0.4436	0.5467	0.5567	0.2245	0.4014	0.5022	0.3191	0.47	0.6199	0.7604			
Overall Accuracy													**60.71%**	
Overall Kappa													**0.5258**	

Table A.15: Error matrix of the Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using only GIS data in the Rocky Mountain National Park study area.

ERROR MATRIX

Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS and Landsat TM data

	Reference Data													
Category	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	TUNDRA	WATER	Total	Errors of Comission	User's Accuracy
SPRUCE / FIR	137961	33610	33	2096	422	235	414	2821	5710	2362	116	185780	25.74%	74.26%
LODGEPOLE PINE	32434	69480	4291	399	491	3621	579	120	1090	131	33	112669	38.33%	61.67%
PONDEROSA PINE	945	6883	31330	360	270	3539	2741	0	1785	0	9	47862	34.54%	65.46%
RIPARIAN	6229	1504	99	22757	247	69	1153	5144	2549	10520	121	50392	54.84%	45.16%
ASPEN	1574	1794	883	2965	1590	156	401	38	77	17	43	9538	83.33%	16.67%
DOUGLAS-FIR	561	6360	2702	201	515	5776	266	0	242	0	5	16628	65.26%	34.74%
OTHER VEGETATION	179	837	2551	1035	460	59	5277	41	147	163	1	10750	50.91%	49.09%
KRUMMHOLZ	9078	1838	125	2490	105	43	130	11758	13691	11609	23	50890	76.90%	23.10%
NON-VEGETATION	1213	210	39	730	17	17	7	948	55354	9051	180	67766	18.32%	81.68%
TUNDRA	1378	190	0	2258	6	0	9	3933	21678	56399	4	85855	34.31%	65.69%
WATER	296	41	0	204	5	1	11	89	833	74	1921	3475	44.72%	55.28%
Total	191848	122747	42053	35495	4128	13516	10988	24892	103156	90326	2456	641605	47.93%	52.07%
Errors of Omission	28.09%	43.40%	25.50%	35.89%	61.48%	57.27%	51.97%	52.76%	46.34%	37.56%	21.78%	42.00%	37.72%	
Producer's accuracy	71.91%	56.60%	74.50%	64.11%	38.52%	42.73%	48.03%	47.24%	53.66%	62.44%	78.22%	58.00%		
Kappa Index of Agreement (KIA)	0.6046	0.4736	0.7245	0.6105	0.3759	0.4121	0.4714	0.4269	0.4819	0.5664	0.781			
Overall Accuracy													62.28%	
Overall Kappa													0.546	

Table A.16: Error matrix of the Bayesian/Maximum Likelihood classification with probabilities obtained from NeuralSIM using GIS and Landsat TM data in the Rocky Mountain National Park study area.

ERROR MATRIX

Reference Data

Neural network classification with MATLAB using GIS and Landsat TM data

Category	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	TUNDRA	WATER	Total	Errors of Comission	User's Accuracy
SPRUCE / FIR	142981	42553	384	2261	740	225	869	3029	6576	2693	162	202473	29.38%	70.62%
LODGEPOLE PINE	19949	62277	5347	490	847	5120	631	152	2126	99	49	97087	35.85%	64.15%
PONDEROSA PINE	122	5868	26873	129	833	2923	1942	0	1582	0	6	40278	33.28%	66.72%
RIPARIAN	5373	1103	283	23269	227	172	900	4632	1518	5805	147	43429	46.42%	53.58%
ASPEN	168	837	122	805	869	78	152	0	2	0	26	3059	71.59%	28.41%
DOUGLAS-FIR	1161	4900	3844	161	381	4376	297	0	257	0	12	15389	71.56%	28.44%
OTHER VEGETATION	14	105	3930	946	68	32	5972	0	207	0	0	11274	47.03%	52.97%
KRUMMHOLZ	5852	1103	935	1111	46	354	69	6355	4236	4305	31	24397	73.95%	26.05%
NON-VEGETATION	12960	2040	60	2452	117	39	96	5123	65494	15328	169	103878	36.95%	63.05%
TUNDRA	3162	1932	268	3700	0	197	60	5565	20618	62028	18	97548	36.41%	63.59%
WATER	106	29	7	171	0	0	0	36	540	68	1836	2793	34.26%	65.74%
Total	191848	122747	42053	35495	4128	13516	10988	24892	103156	90326	2456	641605	**46.97%**	**53.03%**
Errors of Omission	25.47%	49.26%	36.10%	34.44%	78.95%	67.62%	45.65%	74.47%	36.51%	31.33%	25.24%	**45.91%**	**37.29%**	
Producer's accuracy	74.53%	50.74%	63.90%	65.56%	21.05%	32.38%	54.35%	25.53%	63.49%	68.67%	74.76%	**54.09%**		
Kappa Index of Agreement (KIA)	0.6278	0.4195	0.6148	0.6305	0.2067	0.3071	0.5353	0.2259	0.5644	0.6305	0.7465			
Overall Accuracy													**62.71%**	
Overall Kappa													**0.5447**	

Table A.17: Error Matrix of the "conventional" neural network classification with MATLAB using GIS and Landsat TM data in the Rocky Mountain National Park study area.

ERROR MATRIX

Reference Data

Neural network classification with MATLAB using only GIS data

Category	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	TUNDRA	WATER	Total	Errors of Comission	User's Accuracy
SPRUCE / FIR	140872	46360	4982	3620	1138	2982	860	3440	7994	3219	133	215600	34.66%	65.34%
LODGEPOLE PINE	20806	58689	6074	636	847	4830	731	440	1980	385	61	95479	38.53%	61.47%
PONDEROSA PINE	633	5410	21663	580	1281	1410	2935	0	1331	0	14	35257	38.56%	61.44%
RIPARIAN	9040	3873	622	21257	219	430	900	5181	3083	7078	224	51907	59.05%	40.95%
ASPEN	208	1038	464	933	212	138	287	0	30	0	8	3318	93.61%	6.39%
DOUGLAS-FIR	1911	3614	2087	178	316	3626	223	0	61	0	0	12016	69.82%	30.18%
OTHER VEGETATION	228	329	5872	853	72	52	4903	0	95	0	5	12409	60.49%	39.51%
KRUMMHOLZ	3820	400	1	821	1	0	0	4043	3154	3276	40	15556	74.01%	25.99%
NON-VEGETATION	9275	1660	145	2795	13	7	76	5990	65204	17181	204	102550	36.42%	63.58%
TUNDRA	4998	1346	137	3668	29	41	69	5779	19622	59145	44	94878	37.66%	62.34%
WATER	57	28	6	154	0	0	4	19	602	42	1723	2635	34.61%	65.39%
Total	191848	122747	42053	35495	4128	13516	10988	24892	103156	90326	2456	641605	**52.49%**	**47.51%**
Errors of Omission	26.57%	52.19%	48.49%	40.11%	94.86%	73.17%	55.38%	83.76%	36.79%	34.52%	29.85%	**52.34%**	**40.57%**	
Producer's accuracy	73.43%	47.81%	51.51%	59.89%	5.14%	26.83%	44.62%	16.24%	63.21%	65.48%	70.15%	**47.66%**		
Kappa Index of Agreement (KIA)	0.5998	0.3869	0.4869	0.5636	0.0464	0.2543	0.4353	0.1416	0.5621	0.5949	0.7003			
Overall Accuracy													**59.43%**	
Overall Kappa													**0.5021**	

Table A.18: Error matrix of the "conventional" neural network classification with MATLAB using only GIS data in the Rocky Mountain National Park study area.

ERROR MATRIX

Reference Data

Neural Network Classification with NeuralSIM using GIS and Landsat TM data

Category	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	TUNDRA	WATER	Total	Errors of Comission	User's Accuracy
SPRUCE / FIR	131184	33542	27	2203	663	225	345	2243	4309	2073	127	176941	25.86%	74.14%
LODGEPOLE PINE	30918	64249	4070	401	792	3217	670	474	2406	439	28	107664	40.32%	59.68%
PONDEROSA PINE	1078	9546	31696	665	385	4002	3330	0	2118	0	11	52831	40.00%	60.00%
RIPARIAN	9426	3486	224	21409	251	165	1268	4002	2278	7897	117	50523	57.63%	42.37%
ASPEN	2184	1737	525	1752	880	133	192	2	38	17	16	7476	88.23%	11.77%
DOUGLAS-FIR	496	6700	3132	290	526	5672	326	0	208	0	1	17351	67.31%	32.69%
OTHER VEGETATION	802	1461	2364	1198	496	92	4770	3	135	22	3	11346	57.96%	42.04%
KRUMMHOLZ	7735	1164	7	2123	100	10	50	8478	7535	7026	14	34242	75.24%	24.76%
NON-VEGETATION	3756	427	0	1692	15	0	7	3429	64983	13787	115	88211	26.33%	73.67%
TUNDRA	2770	299	0	3096	6	0	14	6069	17662	58633	0	88549	33.78%	66.22%
WATER	1499	136	8	666	14	0	16	192	1484	432	2024	6471	68.72%	31.28%
Total	191848	122747	42053	35495	4128	13516	10988	24892	103156	90326	2456	641605	**52.85%**	**47.15%**
Errors of Omission	31.62%	47.66%	24.63%	39.68%	78.68%	58.03%	56.59%	65.94%	37.01%	35.09%	17.59%	**44.77%**	**38.59%**	
Producer's accuracy	68.38%	52.34%	75.37%	60.32%	21.32%	41.97%	43.41%	34.06%	62.99%	64.91%	82.41%	**55.23%**		
Kappa Index of Agreement (KIA)	0.5634	0.4273	0.7316	0.5692	0.2039	0.4035	0.4239	0.3034	0.571	0.5929	0.8223			
Overall Accuracy													**61.41%**	
Overall Kappa													**0.5356**	

Table A.19: Error matrix of the "conventional" neural network classification with NeuralSIM using GIS and Landsat TM data in the Rocky Mountain National Park study area.

ERROR MATRIX

Neural network Classification with NeuralSIM using only GIS data

Category	SPRUCE FIR	LODGEPOLE PINE	PONDEROSA PINE	RIPARIAN	ASPEN	DOUGLAS-FIR	OTHER VEGETATION	KRUMMHOLZ	NON-VEGETATION	TUNDRA	WATER	Total	Errors of Comission	User's Accuracy
Reference Data														
SPRUCE / FIR	116471	31051	340	3841	482	588	587	3257	6118	2896	60	165691	29.71%	70.29%
LODGEPOLE PINE	28409	59860	7669	543	688	4590	1015	315	2241	288	10	105628	43.33%	56.67%
PONDEROSA PINE	1272	11018	20858	591	1489	2222	2630	0	1127	0	58	41265	49.45%	50.55%
RIPARIAN	12535	6516	352	17012	106	136	716	3298	3189	7179	192	51231	66.79%	33.21%
ASPEN	3370	3246	1078	631	482	83	286	0	157	9	77	9419	94.88%	5.12%
DOUGLAS-FIR	1373	5447	4296	433	487	5234	696	5	364	0	7	18342	71.46%	28.54%
OTHER VEGETATION	632	1259	7460	3256	231	609	4919	0	491	0	13	18870	73.93%	26.07%
KRUMMHOLZ	9788	1650	0	1948	0	54	46	6373	4878	6381	29	31147	79.54%	20.46%
NON-VEGETATION	10080	1455	0	2850	118	0	73	5722	59375	15089	112	94874	37.42%	62.58%
TUNDRA	6936	895	0	3681	28	0	5	5785	23792	57850	20	98992	41.56%	58.44%
WATER	982	350	0	709	17	0	15	137	1424	634	1878	6146	69.44%	30.56%
Total	191848	122747	42053	35495	4128	13516	10988	24892	103156	90326	2456	641605	59.77%	40.23%
Errors of Omission	39.29%	51.23%	50.40%	52.07%	88.32%	61.28%	55.23%	74.40%	42.44%	35.95%	23.53%	52.19%	45.40%	
Producer's accuracy	60.71%	48.77%	49.60%	47.93%	11.68%	38.72%	44.77%	25.60%	57.56%	64.05%	76.47%	47.81%		
Kappa Index of Agreement (KIA)	0.4703	0.3867	0.4613	0.4341	0.1036	0.3692	0.4309	0.2181	0.5019	0.5749	0.7624			
Overall Accuracy													54.60%	
Overall Kappa													0.4557	

Table A.20: Error matrix of the "conventional" neural network classification with MATLAB using only GIS data in the Rocky Mountain National Park study area.