Use of Hidden Markov Models and Phenology for Multitemporal Satellite Image Classification: Applications to Mountain Vegetation Classification

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***Abstract*— Ground cover classification based on a single satellite image can be challenging. The work reported here concerns the use of multitemporal satellite image data in order to alleviate this problem. We consider the problem of vegetation mapping and model the phenological evolution of the vegetation using a Hidden Markov Model (HMM). The different vegetation classes can be in one of a predefined set of states related to their phenological development. The characteristics of a given class are specified by the state transition probabilities as well as the probability of given satellite observations for that class and state. Classification of a specific pixel is thus reduced to selecting the class that has the highest probability of producing a given series of observations for that pixel. Compared to standard classification techniques such as maximum likelihood (ML) classification, the proposed scheme is flexible in that it derives its properties not only from image specific training data, but also from a model of the temporal behavior of the ground cover. It is shown to produce results that compare favorably to those obtained using ML classification on single satellite images, it also generalizes better than this approach.**

I. Introduction

Obtaining good ground cover classifications based on a single satellite image can be challenging. The work reported here concerns the use of multitemporal satellite image data in order to alleviate this problem. We will consider an application of these methods to mapping of high mountain vegetation in Norway. The traditional mapping method based on manual field work is prohibitively expensive and alternatives are therefore sought. Vegetation classification based on satellite images is an interesting alternative, but the complexity of the vegetation ground cover is high and the use of multitemporal satellite image acquisitions is shown to improve the classification quality. This document is organized as follows: In the next section, we briefly recapitulate previous work related to multitemporal satellite image classification and phenological models. In section IV we discuss the HMM and how it can be used for classification. In section V we show results of the application of our algorithm, conclusions are given in section VI.

II. Previous work

Both vegetation cover change detection and vegetation cover classification based on multitemporal satellite image sequences have for some time been active areas of research. Coppin et. al. provide an excellent review of the different change detection methods in [1], whereas the works reported in [2], [3], [4], [5], [6], [7], [8] and [9] are typical of approaches to classification of such sequences. The study of plant phenology is an old discipline in many countries. Recently, the interest for research in this field has been revived as plant phenology is expected to be a sensitive indicator of local or global climatic changes, see for instance [10]. In order to consider not only local and regional aspects of plant phenology, but to consider it on a national and global scale, plant phenology studies based on remote sensing have attracted much interest, see for instance [11], [12] and [13].

Although many studies of ground cover classification are based on classifying pixels based on their temporal evolution over a growing season, few authors report on using *phenological models* to support the classification process. The development of different models of plant phenology is extensively reported in the literature, see for instance [14]. The use of these models in support of ground cover classification is however rarely reported in the literature. One exception to this is the work reported in [15]. Viovy and his collaborators suggest using a Hidden Markov Model (HMM) of plant phenology and then point out that this model could potentially have value as a tool for classification. The use of HMMs and similar constructs in the study of plant phenology has been exploited by many authors, see for instance [16]. Viovy's suggestion of using HMMs in direct support of vegetation classification seems to be discussed more rarely in the scientific literature.

III. Phenological models

The expected phenological behavior of a standardized Norwegian mountain vegetation ground cover class when observed in the form of its normalized difference vegetation index (NDVI) is illustrated in figure 1. For a vegetation ground cover class with an early development one would expect the curve to be shifted left, similarly a class with a late development should have its corresponding curve shifted right. Different vegetation ground cover types can of course also produce different values of NDVI over the season. The basic idea of the work reported here is that the varying temporal evolutions of different ground cover classes can be used as models in support of the classification process. The problem with this approach is obviously that of defining the models.

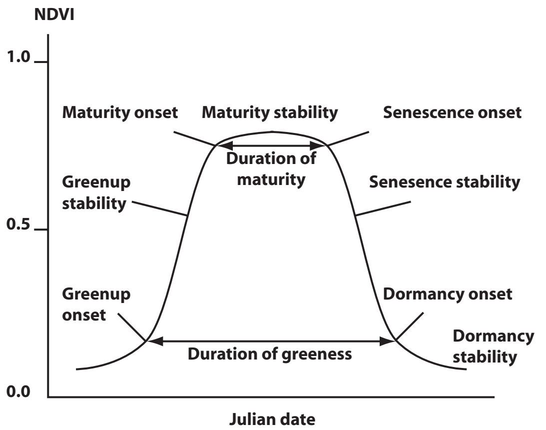

Fig. 1. Standard phenological development of a vegetation ground cover class when observed in the form of NDVI (based on [17].

There is a large literature detailing phenological observations on different plant species from many countries. Typical of these observations is that they pertain to a single species (not vegetation ground cover classes) and they describe very specific discrete events (such as budburst or flowering) not seasonal evolutions. In Norway, such observations are reported in the monumental works by Lauscher and Printz, see for instance [18]. The translation of this type of data into models of relevance for the phenology of vegetation ground cover classes is quite difficult. Two options therefore remain: The phenological models can be derived automatically from the satellite data or the models can be defined manually based on general botanical knowledge in combination with the satellite data.

Both approaches have been explored in this project. The first approach, that of deriving the phenological models automatically from satellite data does not produce satisfactory results. The main problem is that the temporal resolution of high-resolution data like LANDSAT is too low to enable models to be derived directly from the data whereas medium resolution data like those generated by MODIS and NOAA do not have a sufficient spatial resolution given the high granularity of the vegetation cover in the study area. We have therefore derived the phenological models manually based on general botanical knowledge in combination with the satellite data.

IV. Methods

The vegetation ground cover is observable through radiometric observations from satellite. However, due to seasonal variations, atmospheric disturbances etc., the radiometric observations are only linked to the vegetation ground cover in a statistical sense. This translates directly into a HMM where the unknown states are related to the phenological phases and the observables are the radiometric satellite observations (see [15]). The number of hidden states, the initial state probabilities, the state transition probabilities and the probability densities of the observables are model input. A specific set of transition probabilities is established for fixed length subperiods of the observation period, the overall model is therefore nonstationary. The input image sequence is classified by considering the temporal evolution of each pixel as observables generated by this underlying HMM. Each pixel is assigned to the class that best explains the sequence of observables.

A. Markov chain based classification

In the following paragraphs we will describe the HMM formalism and link it to our problem. Our presentation is based on [19] and [15].

1) Basic HMM formalism: In a HMM we observe a system assumed to evolve through a series of different states. Transitions from one state to another happen with certain probabilities. While in a given state the system will produce observables with a certain probability density. We will denote the set of discrete states Q of the internal system by:

$$Q = \{\Phi_1, \Phi_2, \ldots, \Phi_\nu\} \tag{1}$$

where ν is the number of states. Furthermore, the time series of observations, $\bar{X}$ will be denoted by:

$$\bar{X}^T = \{X^1, \ldots, X^T\} \tag{2}$$

where T is the number of elements of the sequence. The unknown state of the process at time t will be denoted E^t, thus $E^t = \Phi_i$ indicates that the process is in state Φ_i at time t. The states are not directly observable, but are related to observation X^t at times t, $(t = 1, 2, \ldots, T)$ by a probability distribution of measurements:

$$p(X^t \mid E^t = \Phi_i), i = 1, 2, \ldots, \nu \tag{3}$$

For a given time period, the model is also described by an array of transition probabilities between each pair of states $p(E^t = \Phi_i \mid E^{t-1} = \Phi_j), i, j = 1, 2, \ldots, \nu$. The probabilities of transition between the different states are obviously strongly dependent upon season, thus the process is not stationary and the matrices of probabilities of transition are time dependent. The final parameters of the model are the initial conditions defined by the probability of being in a given state at the initial time $p(E^1 = \Phi_i), i = 1, 2, \ldots, \nu$.

2) The HMM formalism and classification: The notion of a *class* from the classification literature becomes the notion of a *model* in the HMM formalism. Traditionally, classification of the vegetation cover observed in a temporal sequence of satellite images is the problem of assigning each pixel in the scene to a *class* based on this pixels spectral properties (or derived properties). In the HMM case, our aim is to assign each pixel to the model that best explains the observed temporal evolution of the pixel. Solutions to this kind of problem are important in many applications and several algorithms are available. For our problem we have chosen to use a method similar to the one reported in [20].

3) HMM formalism applied to our problem: A satellite scene showing vegetation covered ground will almost certainly show several types of plant societies. Each of these societies will, presumably, evolve in a way characteristic for that society. In the HMM formalism, each society represents a *system* with possibly unique hidden states and state transition probabilities. The initial probabilities of being in a given state at $t = 1$ are also unique to each society. If we want to model for instance three different types of plant societies, we will need three HMM, one for each society.

For our problem we will assume that the set of states is common to all the systems describing the various plant societies, they are:

$$Q = \{\Phi_1, \Phi_2, \ldots, \Phi_\nu\} = \{\text{snow,dormancy,greenup,maturity,senescence}\} \quad (4)$$

thus $\nu = 5$. This choice of states is motivated by the typical phenological evolution of a plant society described in figure 1, with the addition of a snow state to accommodate the possibility of the ground being snow covered. The transitions between each pair of these states are described by arrays of transition probabilities. We will assume that conditions are stable over time intervals of 7 days.

Whereas the states are common to all systems, the transition probabilities between states are not, on the contrary, the properties of the transition matrices along with the probability densities of observables are exactly what distinguishes the different systems from each other. As we have already mentioned, we derive the properties of these matrices from general botanical knowledge about the typical phenological evolution of the type of plant societies under study. Figure 2 shows curves describing the probability of a certain plant society being in different states as a function of the time of year. Assuming that the system *must* be in one of the given states at a given time, the sum of probabilities at a given instance must be equal to one.

Fig. 2. The probability of a given plant society being in a given state as a function of Julian date.

If curves like these can be established for a given society, the transition matrices can be derived by the following formula:

$$p(E^t = \Phi_i) = \sum_{j=1}^{\nu} p(E^t = \Phi_i \mid E^{t-1} = \Phi_j) p(E^{t-1} = \Phi_j), \quad i = 1, 2, \ldots, \nu \text{ and } t = 2, 3, \ldots, T \quad (5)$$

As we see, equation (5) describes a set of linear relations between the probabilities of a certain system state vector at time t and the probability of another state vector at time $t-1$. Solving this set of linear equations makes it possible to find the elements of the transition matrix. The initial probabilities at $t = 0$ are easily determined given Norwegian climatic conditions, we will simply assume that all systems are in the snowcovered or dormancy state in the first time interval, thus the system is initialized as being in the snowcovered or dormancy states with certain probabilities.

V. Results and Discussion

To test the HMM based classification approach we applied it to a sequence of 7 LANDSAT images (scenes 198-17 and 199-17) covering one summer season (from early June to the middle of October) of southern Norway (the construction of this sequence is the subject of the article by Huseby et. al. [21]). The images we used contained six spectral layers each, these were the standard LANDSAT spectra with the exception of the IR spectra. Georeferenced and radiometrically corrected versions of these images were used as input to the subsequent processing. A color composite from the image acquired on the 24th of July is shown in figure 3.

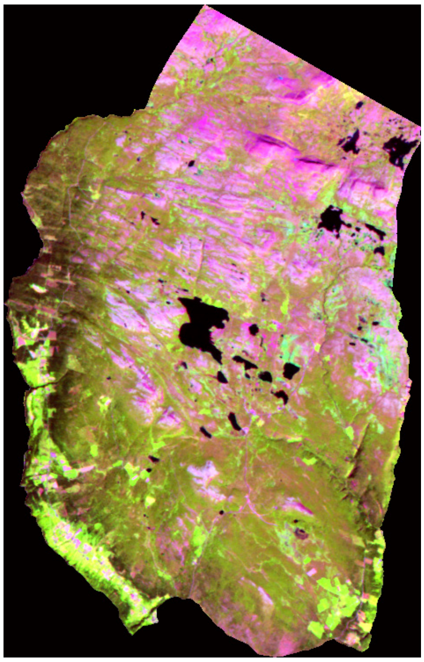

Fig. 3. Color composite of the Vena scene based on channels RGB=543.

We also accumulated a stack of all seven images (in chronological order). From these images we chose two test areas, we will refer to these as *Vena* and *Fron*. The two scenes are separated by roughly 10km. Both test areas span a wide range of altitudes (roughly 1000 m). The vegetation ranges from typical Norwegian inland valley vegetation to high mountain vegetation. From both test areas we dispose of detailed digital vegetation maps made by the Norwegian Institute of Land Inventory, (NIJOS), the vegetation map from the Vena test area is shown in figure 4.

We sought to classify the vegetation cover in both scenes into the classes *coniferous* (mainly spruce and pine), *leaf*

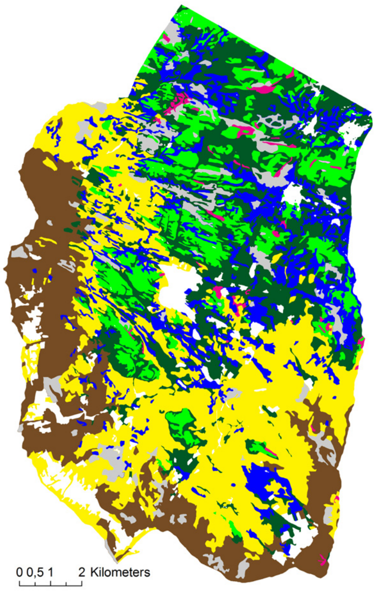

Fig. 4. The NIJOS vegetation map from the Vena test area. The color coding is as follows: coniferous is brown, leaf is yellow, rich heather is light green, poor heather is blue, marsh is dark green and rockland is magenta. White areas are either outside the Vena region or areas not interesting for classification (water e.g.). Gray areas are the areas used for training.

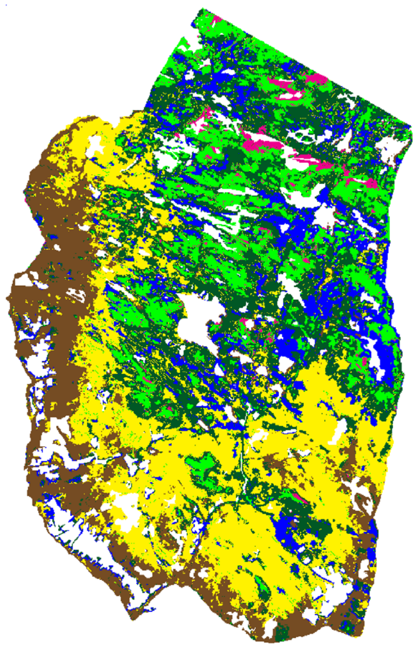

Fig. 5. Result of classifying the chronological stack of all images for the Vena scene using the HMM classification algorithm. The color coding is as given in figure 4.

(mainly mountain birch), *rich heather*, *poor heather*, *marsh* and *rockland*. Using the digital vegetation maps we selected regions representative of each class in the Vena scene. These training regions were then used to establish the necessary class statistics both for each separate image and the stack of all seven images.

A priori probabilities for each class were established (see figure 2) and transition matrices for probabilities of transition between states were established according to equation (5). Classifying the Vena scene using the seven images as input to the HMM method we get an overall classification accuracy of 63.1%. The result is shown in figure 5. Using the HMM approach on the Fron scene, still with training data from the Vena scene, the overall classification accuracy was 62.4%, thus a very slight decrease in relation to the results obtained on the Vena scene.

For comparison both scenes were also classified using the ML approach. Classifying one single image, we obtain the best results using as input the image acquired on the 24th of July. For this image the overall classification accuracy was 58.2% when compared with the digital vegetation maps. The result of an ML classification of the chronological stack of all seven images is shown in figure 6. Using the stack as input the overall classification accuracy was 63.4%, thus using the full stack clearly improves the results. This result is marginally better than the results obtained using the HMM. This is not surprising for several reasons. First of all the ML algorithm was both trained and applied to the Vena region (although the training regions were not included in the regions on which the algorithm was tested). Secondly, the ML approach takes as input the entire covariance matrix for all the bands in the stack of images. Thus all correlations, even between bands stemming from acquisitions on different dates, were known to the ML algorithm. This is obviously not the case for the HMM approach.

In order to test the general validity of the training data acquired in the Vena scene we used the same training data to classify the Fron scene using the ML approach. The overall classification accuracy falls to 56.3% showing that the ML approach is highly sensitive to the validity of the training data. In this case the HMM approach clearly outperforms the ML approach, indicating that the HMM based classification method generalizes better than the ML method. A summary of the classification results is given in table I

	HMM	ML single	ML stack
Vena	63.1%	58.2%	63.4%
Fron	62.4%	-	56.3%

TABLE I

SUMMARY OF CLASSIFICATION RESULTS.

VI. CONCLUSION

We observe the vegetation ground cover of mountainous regions in a multitemporal sequence of LANDSAT images. In order to classify the sequences, we have developed a new methodology for vegetation ground cover classification incorporating knowledge of phenology into the classification process. The phenological knowledge is represented in the form of a HMM. The classification quality obtained using

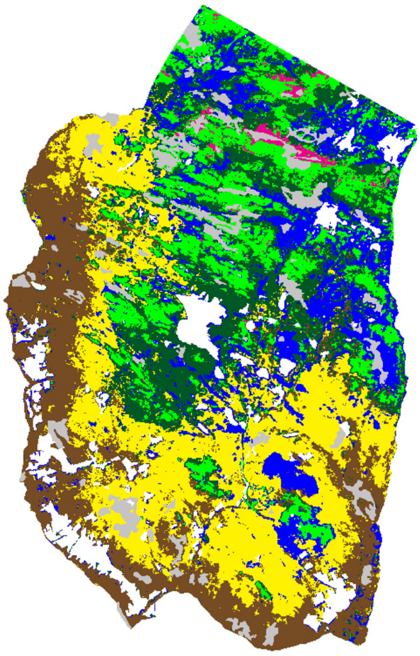

Fig. 6. Result of classifying the chronological stack of all images for the Vena scene using a standard ML classification algorithm. The color coding is as given in figure 4.

the HMM approach compares well to that obtained using traditional supervised ML methods. The suggested method is flexible and easily adaptable to other applications.

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