AUTOMATED DETECTION OF FOREST COVER CHANGES

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ABSTRACT

Massive degradation in forest cover over recent decades caused by natural and human activities has made ability to detect changes in forest cover of critical importance. This paper provides a brief overview of our research on identifying changes in forest cover.

Index Terms— Algorithms, Remote Sensing, Land cover change, Forest change

1. INTRODUCTION

The ability to detect changes in forest cover is of critical importance for both economic and scientific reasons, e.g. using forests for economic carbon sink management and studying natural and anthropogenic impacts on ecosystems. A key ingredient for effective forest management, whether for carbon trading or other purposes, is quantifiable knowledge about changes in forest cover. Rich amounts of data from remotely sensed images are now becoming available for detecting changes in forests or more generally, land cover. However, in spite of the importance of this problem and the considerable advances made over the last few years in high-resolution satellite data acquisition, data mining, and online mapping tools and services, end users still lack practical tools to help them manage and transform this data into actionable knowledge of changes in forest ecosystems that can be used for decision making and policy planning purposes. Providing this actionable knowledge requires innovations in a number of technical areas: (i) identification of changes in global forest cover, (ii) characterization of those changes, and (iii) discovery of relationships between the number, magnitude, and type of these changes with natural and anthropogenic variables. To realize progress in the above areas, a number of computational challenges in spatio-temporal data mining need to be addressed. Specifically, analysis and discovery approaches need to be cognizant of climate and ecosystem data characteristics such as seasonality, inter-region variability, multi-scale nature, spatio-temporal autocorrelation, high dimensionality and massive data size. This paper provides a brief overview of our research on identifying changes in forest cover. For additional details in this and other aspects of the research the reader is referred to [1].

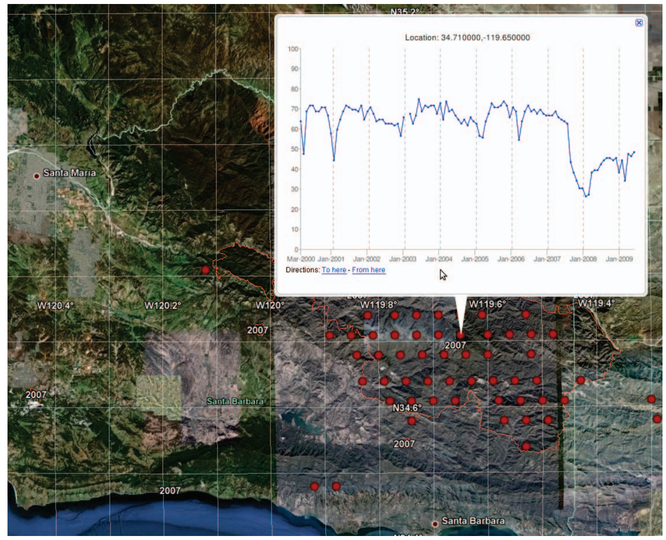
2. TIME SERIES CHANGE DETECTION APPROACHES TO FOREST DISTURBANCE MONITORING

Due to the importance of the land cover change identification problem, it has received extensive attention from the remote sensing community [2, 3, 4]. The previous change detection studies have primarily relied on examining differences between two or more satellite images acquired on different dates [2]. These approaches have a number of limitations; for example, changes that occur outside the image acquisition windows are not mapped, it is difficult to identify when the changes occurred, information about ongoing landscape processes cannot be derived, and they are inherently unsuited for application at global scale.

An alternative approach is to view the data in terms of a vegetation time series at each location on the globe and identify changes in the time series (essentially provide a change score to each location and time that reflects the extent to which it is considered changed). These techniques do not suffer from the above mentioned limitations of the image based approaches. Furthermore, only time series approaches provide information about land cover dynamics that are necessary to quantitatively assess the carbon impact of land cover changes [5]. However, there are a number of specific characteristics associated with Earth Science data that make this a challenging problem. Traditional data mining techniques do not take advantage of the spatial and temporal autocorrelation present in such data. Furthermore, vegetation-related data sets are often of high spatial resolution, which poses computational challenges. Finally, there is the issue of high-dimensionality since long time series are common in Earth Science (and the temporal resolution is increasing).

Though time series change detection has been studied in a wide variety of domains like statistics [6], signal processing [7] and control theory [8] and a number of techniques have been proposed, these techniques are not suitable for the land cover change detection problem primarily because they are not scalable or are unable to take advantage of the inherent structure present in earth science data. For example, the major mode of behavior in the vegetation signal is seasonality, i.e., the natural seasonal growing cycle is a dominant characteristic of a time series and this intrinsic seasonality should not itself be called a change. There exists an inherent natural variability and noise in the earth science data because of the local weather and other atmospheric conditions, that creates additional challenges for the change detection algorithm.

We have developed several approaches for detecting different types of changes in vegetation index time series. These approaches take as input the vegetation index time series and the annual season length for a location and give as output the change score corresponding to that location. The locations under study can be ranked according to their change score given by the algorithm. The higher ranked locations are those that are most likely to have changed. Additional details about some of these approaches are available in [1, 9].



Source: Google Earth imagery.

Fig. 1. Events detected by yearly delta algorithm corresponding to Zaca Fire in Santa Barbara County in California. Also shown is a typical FPAR time series.

3. ILLUSTRATIVE EXAMPLES OF LARGE SCALE VEGETATION DISTURBANCES ACROSS THE GLOBE

In this section we provide illustrative applications of time series based change detection algorithms applied to global vegetation index data to detect a variety of changes in the global ecosystem.

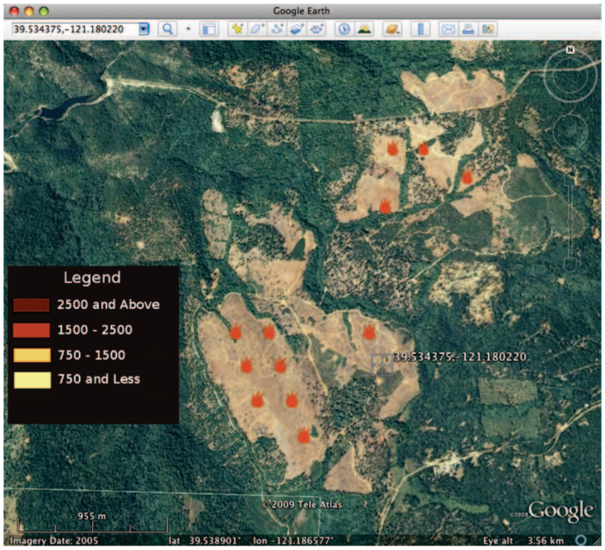
3.1. Forest Fires

Forest fires burn millions of hectares of the world's forests every year resulting in large-scale economic damage, substantial loss of human and animal life and large amounts of carbon being released into the atmosphere [10]. Forest fires can be human induced or due to natural causes such as lightning. In Indonesia, a large number of forest fires are triggered by people clearing land for agriculture, unintentionally causing large fires in adjacent forests. In Canada, the number of natural fires is roughly equal to the number of human induced fires, though natural fires account for 80% of the total 2.5M hectares of land area burned [11].

Time series change detection algorithms can be used for detecting the occurrence of fires and indicate the quantitative loss of vegetation that occurred. There has been some work in time series-based fire detection, but this work has had limited success. For example, the change detection algorithm used to generate the Burned Area Product (a well known MODIS data set) performs poorly in parts of North America such as California [12] and is unable to quantify the amount of vegetation loss due to a fire. Forest fires often occur on a large scale and ground truth in the form of fire polygons is available in several regions of the world including California and Greece. In the last decade, primary disturbances to the forests in these areas have been due to these large-scale fires. Below, we show that fire events detected by our algorithm are in agreement with independent ground truth. Our algorithm is also able to detect the date of occurrence of these events and the quantitative vegetation loss. Figure 1 shows a typical time series for a burnt forest pixel in the Zaca fire in 2007. The vegetation index is high until 2007, when a fire occurs, causing all pixels shown to have an abrupt drop in the vegetation index following 2007.

3.2. Deforestation

Deforestation by land-use conversions from forests to agricultural plantations are bound by many complex socio-economic factors, including macro-economic pressures as land values and commodity prices rise [13]. Deforestation continues at an alarming rate of approximately 13 million hectares per year [10] and produces such immediate consequences as biodiversity loss, loss of hydrological capacity, and increased net emissions of greenhouse gases [14]. Brazil, for instance, lost nearly 150,000 square kilometers of forest from 2000 to 2006, accounting for almost 50% of all the humid tropical forest clearing, nearly four times that of the next highest country [14]. Below, we present illustrative examples of deforestation events detected by our algorithm in California, Brazil and Siberia.



Source: Google Earth imagery.

Fig. 2. Logging in Northern California

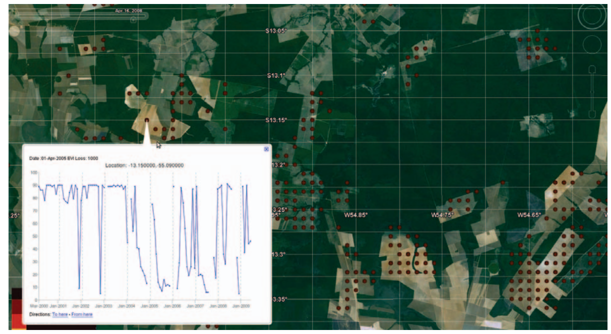
The algorithms found several events in northern California corresponding to logging activities. Logging is different from forest fires as it is unsynchronized, i.e. it does not occur in the entire neighborhood in a short time window. Neighboring locations either are unaffected or get logged at different dates. Also, loss of vegetation tends to be gradual because clearing an area can take several days. Figure 2 shows one of the locations in an area that was logged.

We also detect several locations in Brazil's Amazon basin that were deforested. Most of this activity was found in the Mato Grosso region which is also called the "arc of deforestation." Figure 3 shows the overlay of the locations in Brazil predicted as deforested by our algorithm with the Google Earth imagery. It can be seen that the disturbance events marked with red dots occur where the imagery shows patches of cleared forests. The FPAR time series shows standing forest until year 2004 after which it is converted to pasture or cropland.

We also detect large forested regions in southern Siberia being converted to cropland and pastures. Figure 4 shows the change events with a typical time series. The forested area was green throughout the year, but after conversion it shows a green up-green down cycle which is a characteristic feature of a farm.

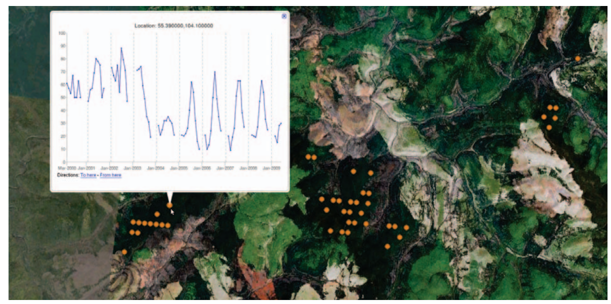
3.3. Natural Disasters

In addition to fires and deforestation, the change detection algorithms also detect events corresponding to natural disasters, such as floods, droughts, earthquakes, and hurricanes, which cause widespread damage to vegetation. We illustrate some of the events detected by our algorithm. The Ob river drains



Source: Google Earth imagery.

Fig. 3. Deforestation events detected by our algorithm in Brazil. Plot shows the FPAR time series corresponding to a deforested location.



Source: Google Earth imagery.

Fig. 4. Conversion of forested areas to cropland/pastures detected in Siberia by the change detection algorithms.

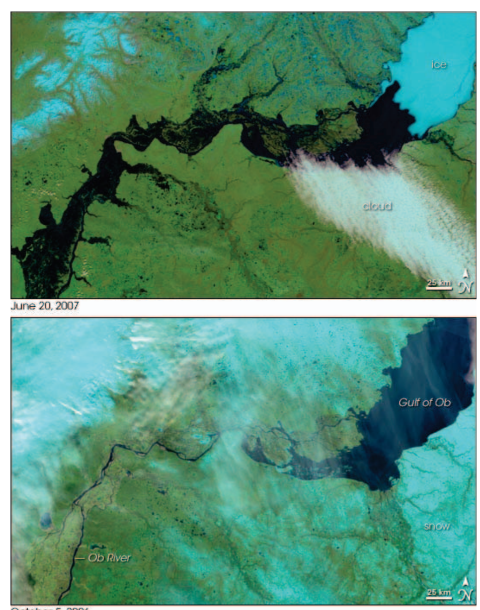


Fig. 5. Images of Ob river and the surrounding area. The image on the top is from a period of flooding and the image at the bottom is the same area when it is not flooded.

into the Kara Sea. During years when the melted water from the southern latitudes fails to drain into the frozen sea in the north, large-scale seasonal flooding occurs (shown in Figure 5) causing devastation of vegetation surrounding the river.

4. REFERENCES

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