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Knowledge Discovery from Satellite Images for Drought Monitoring in Food Insecure Areas

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ABSTRACT

Attributed to climatic change and uncertainty of weather conditions, drought has become a recurrent phenomenon. It is manifested by erratic and uncertain rainfall distribution in rainfall dependent farming areas. The hitherto methods of monitoring drought employed conventional methods that rely on availability of metrological data. The objectives of this research were to: 1) identify the critical factors for efficiently implementing geo-spatial information for drought monitoring, 2) develop a new approach for extracting knowledge from satellite imageries for real time drought monitoring in food insecure areas, and 3) validate and calibrate the new approach for national and regional applications. For this research, satellite data from MSG and NOAA AVHRR were used. The preliminary results confirmed that real time MSG satellite data can be used for monitoring drought in food insecure areas. The output of this research helps decision makers in taking the appropriate actions in time for saving millions of lives in drought affected areas using advanced satellite technology.

Keywords: Data mining; Geospatial Information; Knowledge Discovery; Satellite Images; AgIS

INTRODUCTION

Due to climate change and uncertainty of weather conditions, drought has become a recurrent phenomenon. It is manifested in erratic and uncertain rainfall distribution in rainfall dependent farming areas, especially in arid and semi arid ecosystems

Frequent and severe droughts have become one of the most important natural disasters in sub-Saharan Africa resulting in serious economic, social and environmental crisis. Ethiopia is one of the countries that have been affected by the drought in the sub-Saharan region. As a result, millions of lives have been lost due to recurring droughts in the past several decades. In addition, the cycle of recurrence is shortening while the area of coverage is widening, affecting additional parts of the country that were once unaffected. To respond to the effects of drought, Ethiopia has been conducting drought assessment and monitoring missions.

In Ethiopia, the hitherto efforts of drought assessment and monitoring have been based on conventional methods, which rely on the availability of metrological data. Gathering metrological data is very tedious and time consuming. Consequently, millions of lives may be lost before the actual information is submitted to decision makers. The information produced using conventional approaches is usually highly uncertain for employing rescue missions. Therefore, producing reliable and timely information for decision makers is of utmost importance.

Technologically, there are several drought indices operational in drought assessment and monitoring that are based on rainfall data. These indices are usually not easily accessible and are rarely useful for decision makers (Ji and Peters, 2003). The common approach used to derive the necessary information is the use of a drought monitoring index, such as Palmer Drought Monitoring Index (PDMI), which was widely utilized by the U.S. Department of Agriculture (Jain et al., 2009). Mckee et al. (1993) developed a standard precipitation index (SPI), which can identify emerging drought months for regional and global applications. Mishra and Desai (2005) have adopted SPI for parts of India and developed a drought severity area frequency curve. These drought severity and monitoring indices are based on point data that is measured in different metrological stations located in a wide area, resulting in high uncertainty of their application in real time rescue missions.

Presently, decision makers in developed countries use remote sensing for getting the desired information. Remote sensing data or data from satellite sensors can provide continuous datasets that can be used to detect the onset of a drought, its duration and magnitude (Thiruvengadachari and Gopalkrishana, 1993). Remote sensing is far superior to conventional methods (Jain et al., 2009) for drought monitoring and early warning applications. The challenge in applying remote sensing data in drought monitoring and early warning is that the various indices serving this purpose have to be validated and calibrated to the intended region and ecological conditions (Singh et al., 2003; Jain et al., 2009). So far, there had been no efforts, in Ethiopia, to validate and calibrate remote sensing data in food insecure areas. Thus the available information is unclear, uncertain and not easily accessible by the decision makers (FEWS NET, 2009).

The main objective of this research was: mining knowledge from high temporal resolution satellite products for drought monitoring and early warning system. The specific objectives were: 1) identify the critical factors for efficiently implementing geo-spatial information for drought monitoring, 2) develop a new approach for extracting knowledge from satellite imageries for real time drought monitoring in food insecure areas, and 3) validate and calibrate the new approach for national and regional applications.

The study has the following research questions:

1. Is it possible to model and predict drought as a spatial object in food insecure areas?
2. How would one model drought indicators taking into account uncertainties related to class definitions of drought?
3. What are the appropriate satellite imageries temporal resolutions for modeling drought as a 3 D spatial object?

Advanced technology satellite products with high temporal resolution (every 15 minute data for example from MSG), are cost effective, and can serve to detect the onset of a drought, its duration and magnitude. Such information can help decision makers to take appropriate actions in a timely manner, reduce the impact of drought conditions, and mitigate its adverse effect on the environment.

The remaining parts of this paper are organized as follows. Section two presents the literature review, section three, the detailed methodological approach of the research, section four, GIS data processing and preliminary results, and section five presents the conclusions.

LITERATURE REVIEW

Drought monitoring

Drought is defined as an extended period of abnormally dry weather that causes water shortage and damage to vegetation (Rulinda, et al., 2009). Drought is also defined as prolonged abnormally dry period when there is not enough water for users' normal needs, resulting in extensive damage to crops and loss of yields (Wilhite, 2005). These definitions of drought are conceptual definitions and are the basis for the operational definition, which focuses on identifying the beginning, end, spatial extent and severity of the drought in a given region and is based on scientific reasoning. The analysis is done using hydro-metrological information and is beneficial in developing drought policies, early warning monitoring systems, mitigation strategies and preparedness plans (Smakhtin and Hughes, 2004). There are three types of drought: metrological, agricultural and hydrological (Obasi, 1994). The focus of this research is on agricultural drought analysis and early warning system.

Monitoring agricultural (vegetative) drought usually requires a large amount of temporal data, and remote sensing technologies. The major source of such data is the normalized difference vegetation index (NDVI) (Rulinda, et al., 2009). NDVI is commonly calculated by using image data from polar orbiting satellites, which carry sensors detecting radiation in red and infrared wavelengths (Fensholt et al., 2006). NDVI is used in this case by comparing the deviation of the long time period data with the time period (window) of interest (i.e., the deviation of the current NDVI from past average values). The formulas for calculating NDVI and deviations of NDVI (Dev_NDVI) are presented in the method section of this paper.

In the analysis of droughts, the onset, duration and severity of a drought are often difficult to determine and the characteristics may vary significantly from one region to another (Rulinda, et al., 2009). In rainfall dependent agriculture production area, seasonal rainfall variability is inevitably reflected in both highly variable production levels and in the risk-averse livelihoods of local farmers (Cooper et al., 2008). Africa has a long history of rainfall fluctuations of varying lengths and intensities (Nicholson, 1994). Recent studies showed different behavior of rainfall trends in Africa, at different spatial and temporal scales. Recent study also demonstrated a decrease in rainfall in East Africa between 2003 and 2008 (Swenson and Wahr, 2009) where drought and famine situations were periodically reported (FEWS NET, 2009). Drought has particularly negative impact on agricultural production in the Eastern African region, as most of its agriculture is dependent on rainfall (Thorton et al., 2009) rather than irrigation.

The conventional approach to drought monitoring and early warning systems using ground based data collection is tedious, time consuming and difficult (Prasad et al., 2007). In recent years, remote sensing data has been used for monitoring agro-climatic conditions, the state of the agricultural fields, vegetation cover and to estimate crop yield in various countries. In particular, the advanced Very High Resolution Radiometer (AVHRR) NDVI data has been used in vegetation monitoring, crop yield assessment and forecasting (Hayes et al., 1982; Benedetti and Rossini, 1993; Quarmby et al., 1993; Unganai and Kogan, 1998; Kogan et al., 2003). The National Oceanic and Atmospheric Administration (NOAA) AVHRR series satellite data provides a long term record of NDVI data that can be used in the prediction of crop yield (Prasad et al., 2007), which is part of drought monitoring, in that crop yield is very important for deciding food assurance of a given region.

Presently, NDVI is used as a primary source of data in remote sensing based drought monitoring. Rulinda, et al. (2009) indicated that other parameters, which can best explain drought, such as soil moisture, rain fall and surface temperature were not included in past analyses. The authors further added that the development of drought monitoring and early warning systems need a priori knowledge of the characteristics of the study areas' vegetation and the time of the day for the acquisition of the satellite imageries. However, past research has not addressed these factors (Rulinda et al., 2009).

To summarize the review, the following research agenda was identified for this study:

1. The accuracy of drought monitoring using NDVI is highly dependent on the vegetation type of a given area. If the vegetation type is not known, misleading information (e.g. false drought warning) may be obtained (Rulinda, et al., 2009). Therefore, a priori knowledge of the vegetation type of the area under monitoring has to be examined, the NDVI values calibrated and the model validated.
2. Past drought monitoring and early warning systems were using only NDVI as data input and other parameters such as soil moisture, rain fall and surface temperature, which can be obtained from satellites and have direct relation to drought were not included (Rulinda, et al., 2009).
3. The time of the day when the satellite imageries were acquired has a great influence on the accuracy of the information, and thus needs further research (Rulinda et al., 2009).
4. In the past, the yield estimation using conventional methods of drought monitoring and early warning systems were found to be very far from reality. These discrepancies resulted in repeated complains and have been seriously affecting the quality of drought-response decisions (FEWS NET, 2009).

Data mining and satellite technologies

Data mining is a technique that uses a variety of data analysis tools to discover patterns and relationships of physical variables. This technique has shown promise in multiple disciplines bringing together techniques from machine learning, pattern recognition, statistics, databases, and visualization to address the issue of information extraction from large databases (Cabena et al., 1998; Groth, 1998). Studies in ecological research have also introduced data mining techniques and found that these techniques are a powerful tool in addressing complex ecological problems handling both numeric and categorical data (De'ath and Fabricius, 2000). Although drought effects on vegetation often result from complex atmospheric and biophysical phenomena, data mining could provide mechanisms for understanding drought characteristics in space and time (Tadesse et al., 2004; Harms et al., 2002). These studies illustrate the potential of data mining for drought analysis and prediction.

Extracting relevant information from the huge amounts of available data has been a challenge for decision makers and practitioners in different disciplines (Han and Kamber, 2006). The analysis and conversion of large amounts of data to meaningful information, calls for a new generation of computational techniques and tools, such as knowledge discovery from database (KDD) and data mining. Satellite remote sensing is one example of data source used for various applications.

Remote sensing is the science and art of obtaining information about an object, area or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area or phenomenon under investigation (ITC, 2004). The process involved in acquiring remote sensing data is presented in Figure 1 and include A= energy source or illumination; B= radiation and atmosphere; C= interaction with the target; D= recording of energy by the sensor (satellite); E= transmission, reception and processing; F= Interpretation and analysis; G= application). The process of aquiring remote sensing data, depending on the platforms used, includes two main categories: airborne remote sensing and space borne remote sensing. Airborne remote sensing is carried out using aircraft equiped with sensors (cameras), with a flight heights of 100m to 40km (ITC, 2004). Space borne remote sensing is carried out using satellites positioned at orbit at about 150km and above (ITC, 2004). This research is mainly concerned with satellite remote sensing.

Satellites are artificial bodies placed in orbit around the planet for observing the earth. Details on satellite products used in this research are presented in Appendix 1. For example, the primary interest of Earth Observing System (EOS) from MODIS satellite program is to study the role of terrestrial vegetation in large global process with the goal of understanding how the earth functions as a system. This requires an understanding of the global distribution of vegetation types as well as their biophysical and structural properties and spatial variation (Huete, 2002). Vegetation indices (VI) are used to extract such information. VIs are spectral transformation of two or more satellite bands designed to enhance the contribution of vegetation properties and allow reliable spatial and temporal inter-comparisons of terrestrial photosynthetic activity (Huete, 2002).

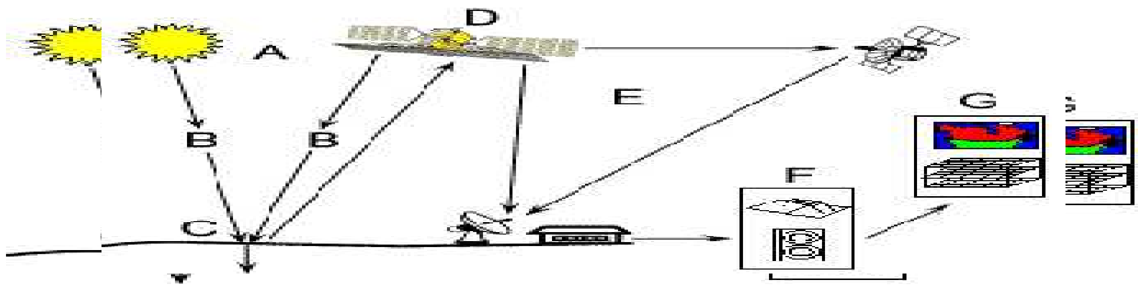

Figure 1: The seven major elements involved in acquiring remote sensing data (adapted from Canada Center for Remote Sensing, 2007)

MATERIALS AND METHODS

Study area

Five study sites will be selected for this research. These study sites are located in five different drought affected areas of Ethiopia. The specific localities of the sites will be determined after the researchers have gathered preliminary data and information at federal, regional and local levels. These sites will be used to develop the analysis model for the drought years of 2009 and 2010. Currently the first author is conducting preliminary surveys of the selected sites which include an assessment of the socio-economic status of the proposed study sites. Spatial and attribute data from the Central Statistical Authority will be used in the preliminary reconnaissance survey of the localities to be selected.

Methodology

Case study for assessing the critical factors

To identify the determinant factors for efficiently utilizing geospatial information for drought monitoring, exploratory case study methodology is used. Case study is an empirical inquiry that investigates a contemporary phenomenon within its real life context (Yin 2003). A semi-structured interview is used to select a set of potential sites. The units of analysis in this case study are both national and international drought monitoring organizations in Ethiopia and with special emphasis on the use of geospatial information technology. Once the determinant factors are identified, the appropriate information system is designed for drought monitoring and early warning systems. The interview questions are available from the first author.

Data mining for modeling drought

In this study, Cubist1 data mining software is used to generate models from a combination of satellite, climate, and biophysical data. The technique is generally referred to as regression-tree modeling. Cubist analyzes data and generates rule-based linear models that are a collection of rules, each of which is associated with a linear expression for computing a target value (Tadesse et al., 2005). To acheive a more reliable estimate of accuracy, the data is automatically divided into a number of folds used to validate the rules. The data is divided into five blocks of almost equal size and target value distribution. For each block, Cubist constructs a model from the cases in the remaining blocks and tests it on the cases in the hold-out block.

The analysis uses data from a satellite source, climate based drought indices, and biophysical variables. For the climate data, drought indicators are calculated for weather station locations (in the five study sites). These locations became the model generation locations. The satellite data and many of the biophysical, variables are extracted using geographic information systems (GIS) techniques for the same weather station locations. The Standardized Precipitation Index (SPI) and the Palmer Drought Severity Index (PDSI) are used to define and quantify precipitation deficits (McKee et al., 1994; Palmer, 1965). The SPI and PDSI are calculated in such a way that the values correspond to the temporal resolution of the satellite data. Satellite-derived measures of vegetation stress, the Percent Average Seasonal Greenness (PASG) are calculated based on smoothed temporal NDVI curve characteristics.

ILWIS 3.6 software is used in the analysis of the remote sensing imagery. The real time data, which is downloaded from AtlanticBird satellite, is used to produce the drought monitoring and early warning systems. During the analysis, cloud contaminated pixels are removed from each individual image by examining the reflectance and temperatures. After completing the preprocessing of the satellite images, the NDVI values of the images are calculated. NDVI is calculated using Equation 1:

$$NDVI = \frac{\rho_{nir-}\rho_{red}}{\rho_{nir} + \rho_{red}} \quad (1)$$

where ρ_{red} (0.4–0.7 mm) and ρ_{nir} (0.75–1.1 mm) are reflectance in red and near infrared bands of the satellite imageries.

NDVI is the most commonly used vegetation index and has been shown to be related to vegetation vigor, percentage green cover and biomass (Myneni and Asrar, 1994; Anyamba and Tucker, 2003; Tucker and Stenseth, 2005). It is a non-linear function that varies between -1 and +1, and is undefined when both ρ_{red} and ρ_{nir} are zero. NDVI values for vegetated land areas generally range from approximately 0.1 to 0.7, with values greater than 0.5 indicating dense vegetation. Values lower than 0.1 indicate near zero vegetation, such as in barren area, rock, sand or snow (Tucker, 1979).

The daily NDVI values are aggregated into decadal basis. In a year, there are 36 decades (one decade is equal to 10 days). The decadal NDVI values are compared with the long-term mean NDVI value of the same decade from NOAA AVHRR satellite data. The difference of these two data elements is called deviation of drought severity index, or the deviation of the NDVI (Dev_NDVI) (Tucker, 1979). Dev_NDVI is calculated using Equation 2. When Dev_NDVI is negative, it indicates below normal vegetation condition and, therefore might suggest a drought situation, if this condition remains for a prolonged period (Tucker, 1979). We use Dev_NDVI for spatially locating the occurrence of drought. This information can be used by decision makers in setting drought related actions and policies

$$Dev\_NDVI = NDVI\_i - NDVI\_Mean\_i \quad (2)$$

where $NDVI\_i$ and $NDVI\_Mean\_i$ are the actual 10 day composite NDVI, and the long term mean for the same decade NDVI values respectively. The overall conceptual framework of the information produced from the various parameters mentioned above is integrated and the knowledge is delivered to the decision maker in a user friendly format. This can help decision makers in setting an action plan that is likely to save drought victims in food insecure areas. The conceptual framework is depicted in Figure 2.

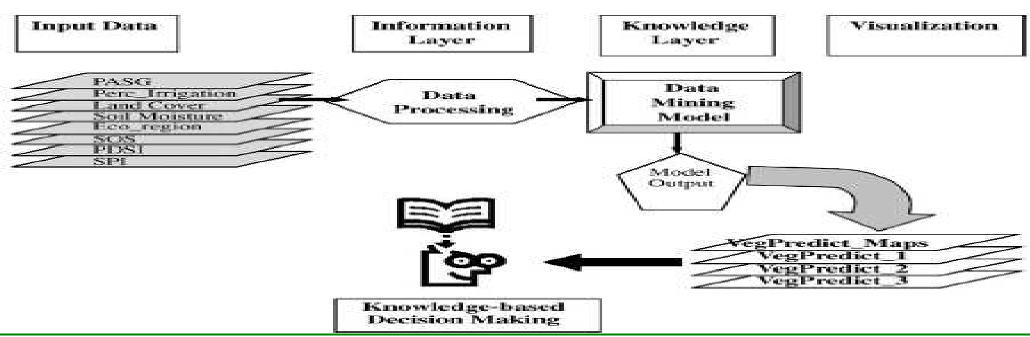

Figure 2: Conceptual framework demonstrating the process used to produce information for decision making (Tadesse et al., 2005).

The overall method for this research is presented in Figure 3 which illustrates the major steps in Knowledge discovery from satellite images for real time drought monitoring and early warning systems. The bbreviation for the independent variables, NDVI = normalized difference vegetation index; SM = soil moisture; ST = surface temperature; and RF = rainfall.

MATERIALS

For this research, satellite data from Meteosat Second Generation (MSG), National Oceanic and Atmospheric Administration (NOAA) AVHRR and Moderate Resolution Imaging Spectroradiometer (MODIS) are used (Appendix 1).

GIS DATA PROCESSING AND PRELIMINARY RESULTS

As mentioned above, NDVI is one of the best drought assessment parameters. In this section, we present the status of drought conditions in parts of Eastern African and Southern Asian countries in 2009 using the NDVI parameter. This analysis was conducted with the aim of testing the applicability of MSG data for spatio-temporal drought monitoring. The preliminary results were obtained by using October 2009 MSG data and the long term average NDVI NOAA AVHRR data. The raw MSG data was obtained from the Ethiopian Metrological Agency in Addis Ababa. The long term records of decadal NDVI data from NOAA, was downloaded from http://earlywarning.cr.usgs.gov/adds/datathemephp and covered the first decade of October from 1982 to 2009. Using these two datasets, the deviation of NDVI was calculated.

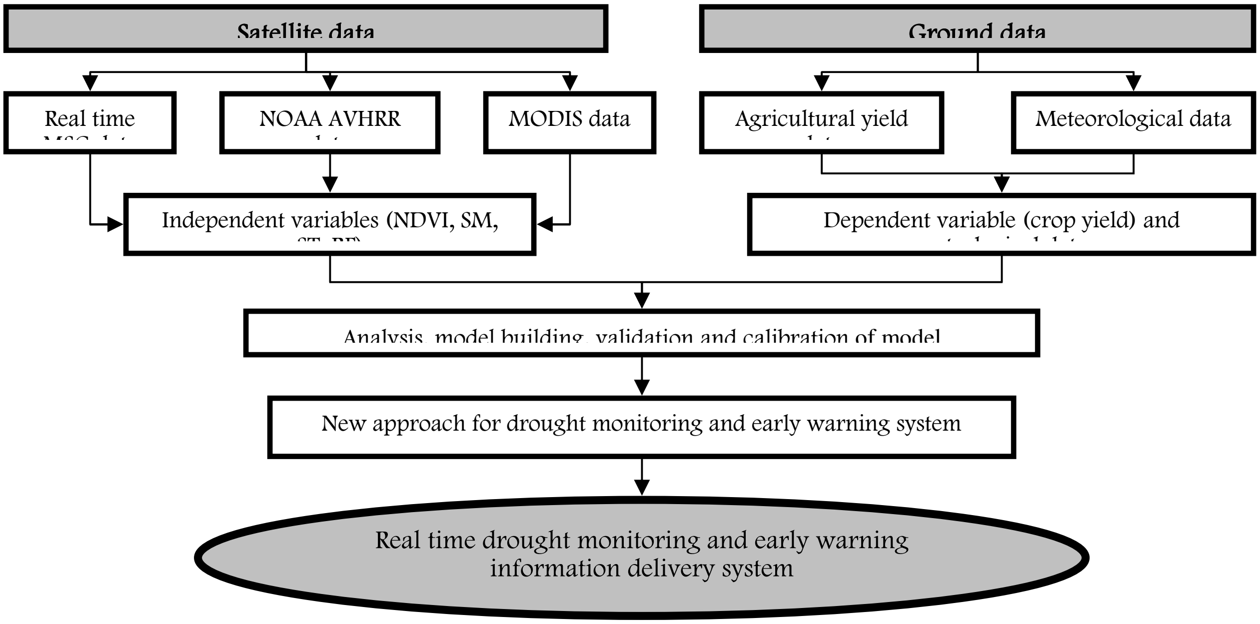

Figure 3: The major steps in Knowledge discovery from satellite images.

The actual drought condition was obtained by comparing the NDVI for the first decade of October 2009 with the long term mean NDVI using NOAA satellite data. The data was analyzed using ILWIS 3.6 software. The 10 days images of MSG (1-10 October 2009) were imported to ILWIS raster image format (Figure 4), using the "Multiple times in one file" option. This means that we have all the 10 bands stacked (maplist) together and ready for the NDVI calculation. After importing the three bands image data to ILWIS 3.6 raster format, a script was written for calculating the deviation of NDVI (Dev_NDVI). The sample script is presented in Appendix 2.

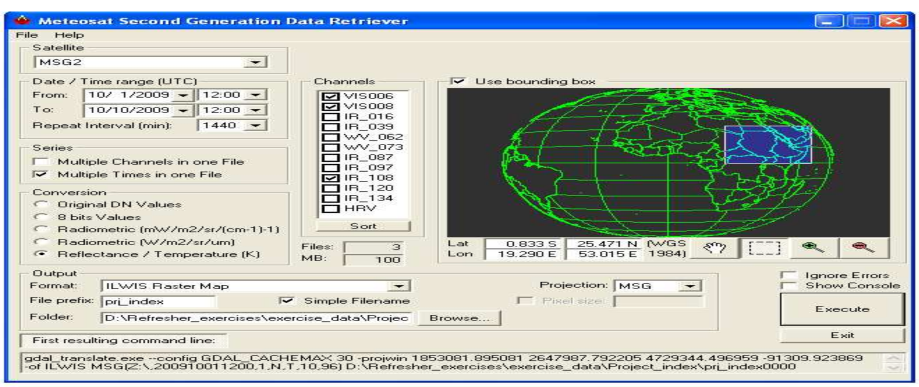

Figure 4: MSG data retriever of ILWIS 3.6 for importing the raw data to raster image.

Our results show that about 40% of the area observed exhibit negative deviation (Figures 5 and 6). This indicates drought conditions in 2009 in east Africa. These results align with recorded rainfall in 2009 in most parts of Ethiopia. That is, the rainfall amounts recorded were below the overall average (FEWS NET, 2009).

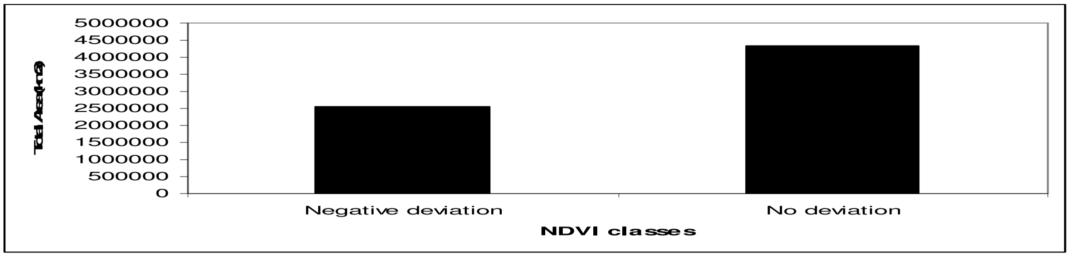

Figure 5: Dev_NDVI comparison of the change in vegetation

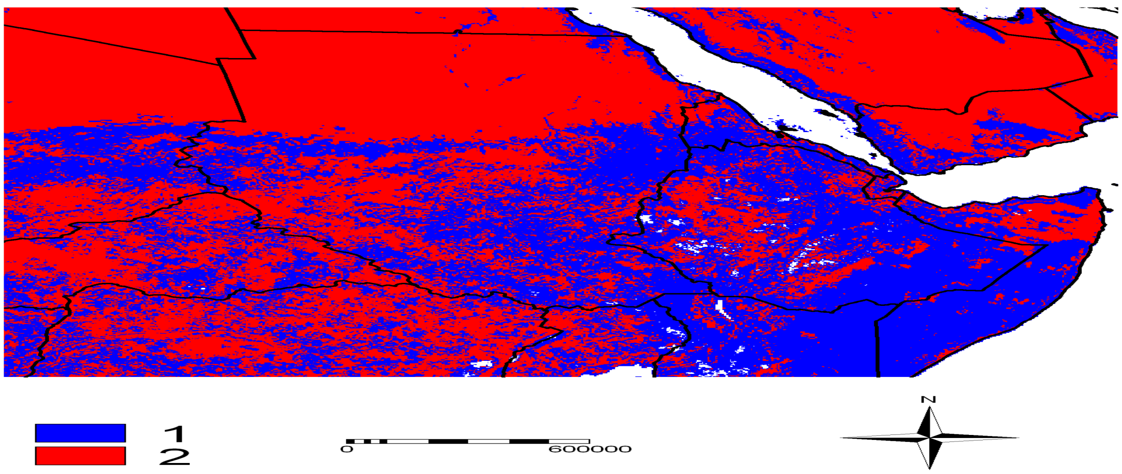

Figure 6: Dev_NDVI spatial distribution.

In figure 6, the red colors are areas where there is no change or positive deviation from the long-term average. The blue colors are areas with negative deviations indicating the prevailing drought. The black colors are country boundaries. The analysis of Vegetation Condition Index (VCI) also shows that there had been drought in the study area (Figure 7). In figure 7, the areas in white are areas where there had been no vegetation in the past and/or found to be water bodies. Country boundaries are marked in red. VCI shows (in percentages), the vegetation condition of the actual decade NDVI compared to long term maximum and minimum of the corresponding decade. In principle, about 50% reflects a fair vegetation condition. Our geo-spatial analysis shows that about 37% of the total area was found to have less than 40% VCI, indicating the occurrence of drought. Areas with below normal vegetation cover were located in the central part of Sudan, and Northern and Southeast Ethiopia. Only 18% of the area was found to have optimal and above normal vegetation conditions (Figure 7). These areas are found in the central part of Sudan and Northwest corner of Ethiopia.

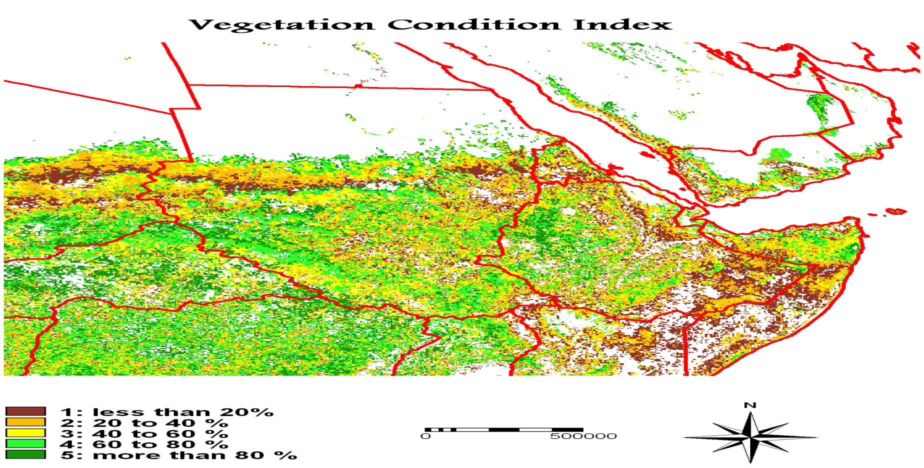

Figure 7: Vegetation Condition Index (VCI) map for monitoring drought.

CONCLUSSIONS

The findings of this research are based on an ongoing PhD research project. The preliminary results produced promising scientific outputs for implementing satellite data for drought monitoring using data mining techniques. The answer to the research question; is it possible to model drought as spatial object is: yes. At present, the above research is in its early stages and there is some convincing evidence that it is possible to model and predict drought conditions using real time MSG data. The research questions; how to model drought indicators taking into account uncertainties related to class definitions of drought, and what are the appropriate satellite imageries temporal resolutions for modeling drought as a 3 D spatial object, are still pending and will be addressed in future research.

The preliminary results confirm that real time spatio-temporal MSG data can be used for drought monitoring and early warning systems in food insecure areas. In 2009, there had been drought in most parts of Ethiopia and Sudan. Our analysis confirms this fact. The drought was due to rainfall shortage during the crop growing season (July to September).

Water and food shortage are a major concern and our results can be helpful in using advanced satellite technology for effective drought monitoring and early warning systems in various regions. Combined with proper policies, these systems can help avert femine and starvation in food insecure regions. In the past, satellite technologies have mostly been used in areas of meteorological applications. In this research, the main emphasis is in mining knowledge for drought hazard assessment and saving millions of lives that are being affected by recurring droughts. The output of this research helps decision makers to take the appropriate actions, in time for saving millions of lives in drought affected areas using advanced satellite technology.

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APPENDIX 1: DATA PROPOSED TO BE USED IN THIS RESEARCH

MSG data

MSG stationed over Africa provides a continuous eye in the sky. Its recordings provide relevant (dynamic) environmental variables that can be used to assess the actual conditions of the area's natural resources. Details about this satellite are obtained from Maathuis et al. (2006). The advanced Spinning Enhanced Visible and Infrared Imager (SEVIRI) radiometer onboard the MSG series of geostationary satellites enables the Earth to be scanned in 12 spectral channels from visible to thermal infrared at 15 minute intervals. The specifications of SEVIRI have been chosen carefully to match operational requirements. Each of the 12 channels has one or more specific applications, either when used alone or in conjunction with data from other channels. Meteosat-8 data can be directly received via the EUMETSAT Multicast Distribution System (EUMETCast) or obtained from the archive at EUMETSAT (http://archive.eumetsat.int/).

From its geostationary position Meteosat-8 continuously scans the Earth surface and transmits the data to the EUMETSAT Primary Ground Station in Darmstadt (Germany). The received data is pre-processed and rectified into a so called Level 1.5 data-format; furthermore the data is compressed and split into small data packages. These packages are sent to the uplink station in Usingen (Germany) and are subsequently transmitted to the HotBird-6 satellite (combined with some other services) for European reception. Figure 2-1 shows how EUMETCast fits within the overall EUMETSAT Ground Segment architecture.

The dissemination service for Africa is a C-band based transmission also covering selective regions outside the EUMETSAT Member States and Cooperating States. For Africa the EUTELSAT AtlanticBird-3 satellite carries the C-Band dissemination service for MSG. The format of the C-band dissemination is the same as for HotBird-6 dissemination. The data is re-transmitted to AtlanticBird-3 via the Fucino ground station in Italy (Figure 2-1). C-Band covers the frequencies 3.70 GHz to 4.2 GHz. The EUMETSAT Council decided to use EUTELSAT's AtlanticBird-3 satellite for the C-Band dissemination of MSG data to Africa as this frequency is less susceptible to intensive rainfall as it causes attenuation of the Ku-band signal which might result in reception failure. This satellite is stationed at 5° West and is one of EUTELSAT's 'Atlantic Gate' series of satellites. The C-band beam used covers the whole of Europe and Africa.

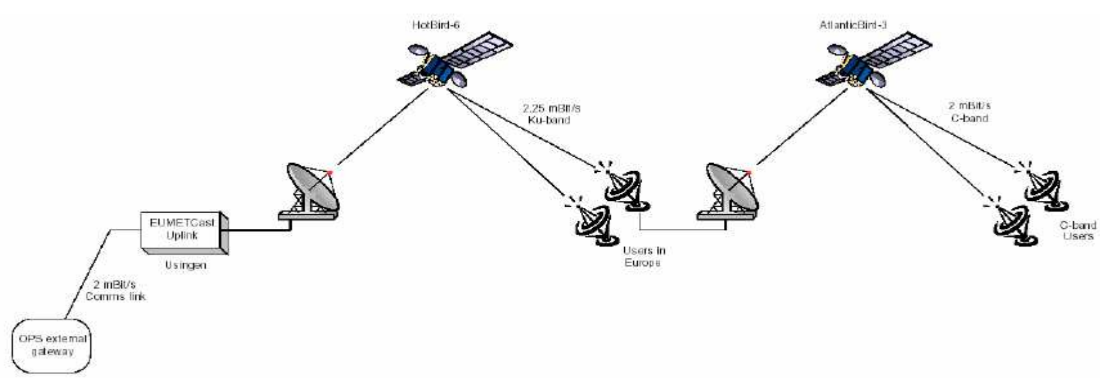


Figure 2-1: EUMETCast system overview for Ku and C-Band reception (Maathuis et al., 2006).

NOAA AVHRR

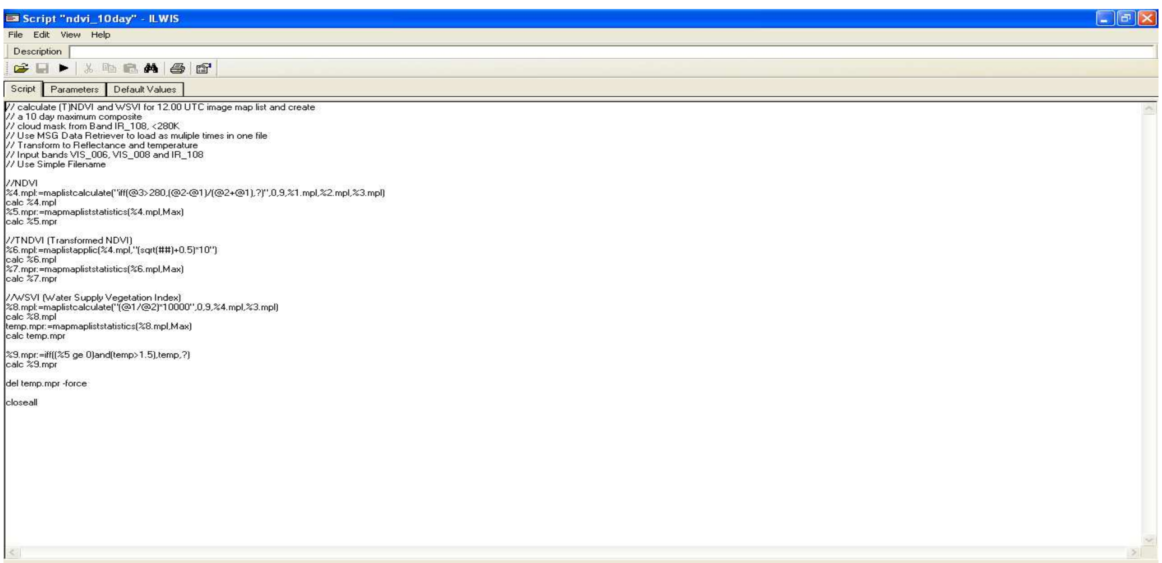
NOAA is owned by the U.S. government. The sensor on board NOAA mission that is relevant for earth observation is the advanced very high resolution radiometer (AVHRR). The platform is 850 km from the earth at $98.7^{0.}$ Cloud cover map based on AVHRR data are used for rainfall estimates, which can be used in crop growing models. Another derived product of AVHRR data is the NDVI, which is used for quantifying quantity of biomass (ton per ha). NDVI data is used in crop growth models and climate change models.

NOAA and NASA have jointly produced long term AVHRR datasets that have been processed in consistent manner for global change research. These datasets cover the period from July 1981 to present. The datasets are 10-day composites of daily data (red, near infra red (NIR), and thermal wavelengths), mapped to a global equal area projection at 0.10 resolution. To minimize the effects of cloud and atmospheric contaminants, the compositing procedure selects the observation for each 0.10 pixel that has the fewest clouds within a 10-day period, as identified by the highest NDVI values (maximum value compositing). There are three 10-day composites per month and the first is for days 1 through 10, the second is for days 11 through 20, and the third is for the remaining days. The composite dataset is similar to the daily data in structure but the process of compositing removes much of the cloud and atmospheric contamination found in the daily dataset (Holben, 1986). The data also contain NDVI, a highly correlated parameter to surface vegetation, derived from the visible and near IR channel reflectance. This pathfinder dataset has gone through many stages of calibration and correction (Smith et al., 1997).

MODIS image

The MODIS sensor is mounted on Terra and Aqua platforms and has 36 spectral bands, seven of them are primarily designed for the study of vegetation and land surface. The MODIS sensor acquires daily images of the globe at a spatial resolution of 250m in red and NIR band, 500m for the blue, green and SWIR/MIR bands, and 1000m for the rest of its bands. The MODIS sensor is supported by a scientific program to produce high quality, calibrated physical parameters of the earth's surface and the atmosphere (Van Laake and Sanchez-Azofeifa, 2004). All MODIS data products can be obtained from the EOS (Earth Observing System) Data Gateway (http://edcimswww.cr.usgs.gov/pub/imswelcom) using file transfer protocol (ftp-pull) procedure.

APPENDIX 2: SCRIPT DEVELOPED USING ILWIS 3.6 FOR CALCULATING THE DEVIATION IN NDVI.




```
// calculate (T)NDVI and WSVI for 12.00 UTC image map list and create
// a 10 day maximum composite
// cloud mask from Band IR_108, <280K
// Use MSG Data Retriever to load as muliple times in one file
// Transform to Reflectance and temperature
// Input bands VIS_006, VIS_008 and IR_108
// Use Simple Filename

//NDVI
%4.mpl:=maplistcalculate("iff(@3>280,(@2-@1)/(@2+@1),?)",0,9,%1.mpl,%2.mpl,%3.mpl)
calc %4.mpl
%5.mpr:=mapmapliststatistics(%4.mpl,Max)
calc %5.mpr

//TNDVI (Transformed NDVI)
%6.mpl:=maplistapplic(%4.mpl,"(sqrt(##)+0.5)*10")
calc %6.mpl
%7.mpr:=mapmapliststatistics(%6.mpl,Max)
calc %7.mpr

//WSVI (Water Supply Vegetation Index)
%8.mpl:=maplistcalculate("(@1/@2)*10000",0,9,%4.mpl,%3.mpl)
calc %8.mpl
temp.mpr:=mapmapliststatistics(%8.mpl,Max)
calc temp.mpr

%9.mpr:=iff((%5 ge 0)and(temp>1.5),temp,?)
calc %9.mpr

del temp.mpr -force

closeall
```