MAPPING SPATIAL VARIATION IN SURFACE MOISTURE USING REFLECTIVE AND THERMAL ASTER IMAGERY FOR SOUTHERN AFRICA

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ABSTRACT

An uneven distribution of rainfall and the higher rate of evaporation cause frequent droughts in southern Africa. Previous studies have shown that it is difficult to monitor droughts in real time by monitoring rainfall anomalies. Alternatively, a method to estimate the variation of surface soil moisture would be useful to help monitor droughts. This research explored the potential of using ASTER imagery to map the variation in moisture conditions in crop fields at a given time. ASTER imagery acquired on April 18, 2004 (i.e., around the harvesting time) near Pretoria, South Africa was used for this study. Thermal and reflective data were combined and used in the Vegetation Index (VI) - Land Surface Temperature (LST) triangular method to map the relative variation in moisture conditions in the study area. Modified Soil Adjusted Vegetation Index (MSAVI) from the Visible and Near Infra Red (VNIR) bands and land surface temperature from the Thermal Infra Red (TIR) bands were used as VI and LST respectively. The initial results were compared with the South African Development Community (SADC) precipitation data and US Geological Survey regional Water Requirement Satisfaction Index (WRSI). These results indicate that ASTER imagery has the potential to be used in a decision support system to estimate surface moisture.

INTRODUCTION

Drought is a regular and recurrent feature of South African climate (Rouault and Richard, 2003) and is one of the most important natural disasters in southern Africa (Unganai, 1994). Almost every year some parts of this region are affected by drought. The 1991-92 droughts ravaged more than 80% of southern Africa (Unganai, 1994).

A short and intense rainy season, with erratic and unreliable rainfall (Rockstorm, 2000) and higher rate of evaporation can lead to frequent droughts (Amaral and Sommerhalder, 2004). Studies of the normalized vegetation index dataset (Los and others, 1994) show that the impact of droughts on vegetation (Farrar and others, 1994) is particularly strong where annual rainfall amount varies from 300 to 500 mm (Richard and Poccard, 1998). Since 1970, most of southern Africa has been characterized by strong interannual rainfall variability, that leads to more intense and more widespread droughts (Richard and others, 2001).

There are many indicators and indices used to predict and monitor drought. However, these indices may give conflicting information as to the extent and severity of drought conditions (Brown and others, 2002). Commonly used drought indices in the U.S. include the Palmer Drought Severity Index (PDSI), Crop Moisture Index (CMI), and Standardized Precipitation Index (SPI), each with its own recognized strengths and weaknesses (Brown and others, 2002).

The PDSI, a meteorological drought index, was the first comprehensive drought index developed in the United States (Palmer, 1965). The PDSI provides a measure of the departure of the moisture supply from its normal. The PDSI is the most used index in the USA but this index does have some limitations (Guttman, 1998; McKee and others, 1995). The SPI is a simple calculation solely based on rainfall with a temporal flexibility. It is a statistical measure on the surplus or lack of precipitation during a given period as a function of the long-term average precipitation (McKee and others, 1993; McKee and others, 1994). Although it is a relatively recent index, the SPI
was used in Turkey (Komuscu, 1999), Argentina (Seiler et al.; 2002), Canada (Anctil and others, 2002), Spain (Lana and others, 2003), Korea (Min and others, 2003), Hungary (Domonkos, 2003), China (Wu and others, 2001) and Europe (Lloyd-Hughes and Saunders; 2002) for real time monitoring or retrospective analysis of droughts. Rouault and Richard (2003) used SPI to monitor drought in South Africa at different time scales.

The CMI is an indicator of soil moisture in the topsoil. It uses a meteorological approach to monitor week-to-week crop conditions. It was designed to evaluate the short-term moisture conditions across major crop-producing regions and is based on the mean temperature and total precipitation for each week within a climate division, as well as the CMI value from the previous week. The CMI responds rapidly to changing conditions.

The precipitation pattern in the whole southern Africa regime is very complex, and it is difficult to monitor drought in real time with a chart showing percentage from normal or anomaly in total rainfall (Rouault and Richard, 2003). Sometimes severe drought is caused by a sudden drop in the amount of required precipitation. CMI can then be used to determine the potential for short term drought in an area; however, one must collect data for sixteen variables to calculate CMI. CMI is not widely used because of the large amounts of data required.

Remote sensing is now widely used to both monitor and predict drought. Normalized Differential Vegetation Index (NDVI) and other recently developed vegetation indices have been used to determine vegetation conditions for the assessment of crop yield. Limited studies have been conducted using remotely sensed data to estimate the available moisture content in a crop field for the prediction of potential drought. The current project was designed to evaluate the potential of high resolution multispectral satellite imagery to determine the moisture content of a crop field for the use as a substitute of CMI.

PREVIOUS STUDIES

Nemani and Running (1993), Carlson and others (1994), Moran and others (1994), and Gillies and others (1997) combined thermal and reflective data to determine either soil water status or surface water availability.

In those studies a scatterplot of vegetation cover and surface temperature results in a characteristic triangular or ‘trapezoid’ envelope of pixels. The surface temperature response is a function of varying vegetation cover and surface soil water content (which can be defined as surface moisture availability). Lambin and Ehrlich (1996), explained the vegetation index (VI) and Land Surface Temperature (LST) space in terms of evaporation, transpiration and fractional vegetation coverage based on previous studies. According to Lambin and Ehrlich (1996), the variations in surface brightness temperature are highly correlated with variations in surface water content over base soil. The space diagram will be discussed in detail in the methods section.

Ray and others (2003) used the triangle method developed by Gillies and Carlson (1995) and Gillies and others (1997) to estimate available soil moisture using satellite data in conjunction with the Soil Vegetation Atmospheric Transfer (SVAT) model. The SVAT model is used to determine the available soil moisture fraction (defined as the ratio of the soil water content to that at field capacity) and surface energy fluxes. The SVAT model requires atmospheric information such as temperature, dew point temperature, pressure, height, wind speed, and direction as inputs along with soil moisture data.

The triangle method is based on the interpretation of observed triangular shape in a scatterplot between satellite-derived NDVI values and surface radiant temperatures. Ray and others (2003), used ASTER and MODIS imagery to calculate NDVI, and TIR bands of ASTER imagery for surface radiant temperature.

The scatterplot of NDVI and surface radiant temperature values (Figure 1) derived from the ASTER image used by Ray and others (2003) shows this characteristic triangular pattern, with the range of surface radiant temperature variation decreasing with increasing values of NDVI. The points along the edge on the right side of this triangle correspond to pixels with low soil moisture and thus indicate low surface moisture availability, while the points along the left side of this triangle correspond to pixels with high soil moisture content and hence indicate high surface moisture availability.

Ray and others (2003) also showed that for specified atmospheric conditions, the variation of surface radiant temperatures and surface energy fluxes can be simulated for a range of surface moisture availabilities (0–1.0) and fractional vegetation covers (0–1.0) using the SVAT model. The satellite-observed NDVI can be related to fractional vegetation cover (Fr) as Fr = N*2, where N* is the scaled NDVI and it is defined as follows:
\[ N^* = \frac{(NDVI_h - NDVI_l)}{(NDVI_h - NDVI_l)} \]  

where, \( NDVI_l \) and \( NDVI_h \) are the NDVI values at the base and the top (Figure 1a) of the triangular shaped scatterplot.

\[ \frac{R_{1600}}{R_{220}} = 0.666 + \frac{1.0052}{1+1159 \times X} - 6.976 \times X \]  

where, \( X \) is the unit g/cm². Although this is not very sensitive to the high water content, the fitted \( R^2 \) value may be as high as 0.92.

**OBJECTIVES**

The main objective of current research was to evaluate the potential of ASTER imagery to map the variation of crop moisture within a given area in a specific time. The research used two approaches and then compared the results.

**Approach 1:** Combining the thermal and reflective imagery in the VI-LST Triangular method to map the relative variation of crop moisture in a field. Modified Soil Adjusted Vegetation Index (MSAVI) from VNIR image and land surface kinetic temperature from the TIR image were used as the Vegetation Index (VI) and as the Land Surface Temperature (LST) respectively. MSAVI was used instead of NDVI (which was used in previous triangular methods as VI) to eliminate the effects from background soils in VI calculation. The signal-to-noise ratio is higher than that of other vegetation indices, such as, NDVI and Soil Adjusted Vegetation Index (SAVI). It not only increases the vegetation dynamic responses, but also further reduces the soil background variations (Liang, 2004).

**Approach 2:** Creating suitable index image using the reflective and shortwave imagery to map the relative variation of crop moisture in a crop field. In this case, the Normalized Differential Water Index (NDWI) was calculated using band 2 of the VNIR image and band 1 of the SWIR image.
STUDY AREA

A portion of the Limpopo River basin, in southern Africa (Figure 2) was selected as the study area for this project. The Limpopo River basin is located in the arid to semi-arid region of the world and drains part of Botswana, Mozambique, South Africa and Zimbabwe. The project site is the part of the Limpopo River basin located inside South Africa (Figure 2). The extent of the selected area is approximately 160 square miles.

Figure 2. A. Limpopo River basin in Southern Africa, B. Extent of the study site.

DATA USED

Imagery from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) imagery was acquired from NASA. ASTER L1b product and ASTER Level-2 Land Surface Kinematic Temperature (AST_08) products were used for this study. The imagery was acquired on April 18, 2004 and georectified and projected in WGS 84 projection. This date was chosen to study the crop (maize or sorghum) condition near the harvesting period. The general characteristics of ASTER imagery are shown in Table 1.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Resolutions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectral Bands</td>
<td>14 (4 VNIR, 6 SWIR and 5 TIR)</td>
</tr>
<tr>
<td>Spatial Resolution</td>
<td>VNIR: 15 m X 15 m</td>
</tr>
<tr>
<td></td>
<td>SWIR: 30 m X 30 m</td>
</tr>
<tr>
<td></td>
<td>TIR: 90 m X 90 m</td>
</tr>
<tr>
<td>Swath</td>
<td>60 km X 60 km</td>
</tr>
<tr>
<td>Revisit</td>
<td>16 days</td>
</tr>
</tbody>
</table>

Table 1. Characteristics of ASTER Imagery

METHODS AND RESULTS

Five crop fields were selected in the study site (Figure 3). The crop fields were selected on the basis of assumed uniform growth of canopy within a single crop field. The selected crop fields were grouped into four zones. Figure 3 shows the acquired VNIR ASTER imagery with the location of the selected crop zones. According to the regional crop zones the selected crop fields were occupied by maize or sorghum. The time of the image acquisition was close to the harvesting period of the crops (according to the FAO 1999 crop calendar of South Africa).

Figure 3. Selected crop fields
Vegetation Index

A Modified Soil Adjusted Vegetation Index (MSAVI), proposed by Qi and others (1994) was created using ASTER VNIR image. The following equation was used to calculate the index image.

\[
MSAVI = \rho_n + 0.5 - \frac{1}{2}(\sqrt{(\rho_n + 0.5)^2 - 2(\rho_n - \rho_r)})
\]  

(3)

Where, \(\rho_n\) is reflectance at Near Infra Red (NIR) (ASTER Band 3n) band and \(\rho_r\) is reflectance at Red (R) band (ASTER Band 2).

The index image was normalized to 8 bit (0-255) and classified into two classes: healthy crop (195-255) and stressed crop (0-195) using a thresholding technique. The thresholds were determined using general vegetation curves for healthy and stressed crops. In this case it has been assumed that the pattern of general vegetation curves would be similar for the crops in the crop field. The purpose of this classification was to determine the uniformity of the selected crop fields and the crop condition. Figure 4 shows the classified index images.

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ZONE 1  ZONE 2
ZONE 3  ZONE 4
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**Figure 4.** Classified MSAVI images.

ESTIMATION OF CROP MOISTURE

First Approach: VI-LST Triangular Space Method

The Vegetation Index (VI) – Land Surface Temperature (LST) Triangular Space Method proposed by Lambin and Ehrlich (1996) was used to map the relative variation of crop moisture within a crop field. The MSAVI created from ASTER VNIR image was used as VI and land surface kinetic temperature (in degree centigrade) from ASTER TIR image was used as LST. The flow chart shown in figure 5 illustrates the procedures followed to generate the crop moisture map.

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Figure 5. Procedure for creating crop moisture map using MSAVI-LST Triangular method.

The MSAVI image and LST image were stacked to create a two layer image that was then classified into 50 classes using unsupervised classification method. A feature space image was created using the two layer image. The MSAVI image layer was used along X axis and the LST image layer was used along Y axis. The feature space image was used to identify the signatures of the classified image on the basis of Lambin and Ehrlich’s (1996) interpretation (Figure 6). Figure 7 shows the feature space image created using the ASTER imagery and the comparison with Lambin and Ehrlich’s (1996) interpretation. Figure 8 shows the feature identification procedure using the created feature space image. The initial classified image was recoded into three classes: normal crop moisture, low to moderate crop moisture and low crop moisture. Pixels located around the line BD and AC were assigned ‘normal moisture’ and ‘low moisture’ classes respectively. Pixels located between the lines BD and AC were assigned ‘low to moderate moisture’ class. Figure 9 shows the classified crop moisture image for all four zones.

Figure 6. Lambin and Ehrlich’s (1996) Feature space interpretation
Figure 7. Feature space image created using ASTER imagery showing comparison with Lambin and Ehrlich’s (1996) interpretation.

Figure 8. Procedure of feature identification using feature space image.
Second Approach: Moisture Index

The Normalized Differential Water Index (NDWI) proposed by Tian and Others (2002), was calculated using the VNIR and SWIR ASTER imagery. The equation of NDWI is as follows:

$$NDWI = \frac{P_{SW} - P_R}{P_{SW} + P_R}$$

(4)

Where, $P_{SW}$ is reflectance at Short Wave Infra Red (SWIR) band (ASTER Band 4) and $P_R$ is reflectance at Red band (ASTER Band 2).

The index image was normalized to 8-bit and classified into the same three classes of crop moisture variation as normal crop moisture, low to moderate crop moisture and low crop moisture. Thresholds were determined by general spectral curves for wet and dry areas and by visual inspection of the VNIR image. Table 2 shows the thresholds for the respective classes. Figure 10 shows the classified crop moisture maps for all four zones.
Comparison of Results
The percentage of the area covered by each class in the classified MSAVI, MSAVI-LST and NDWI images were calculated and tabulated to compare the values.(Table 3,4, and 5).

Table 3. Distribution of crop type according to MSAVI

<table>
<thead>
<tr>
<th>Crop Type</th>
<th>Percentage of Coverage Area</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Zone 1</td>
</tr>
<tr>
<td>Healthy crop</td>
<td>99</td>
</tr>
<tr>
<td>Stressed crop</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 4. Variation of crop moisture as determined by VI-LST Triangular method

<table>
<thead>
<tr>
<th>Moisture Level</th>
<th>Percentage of Coverage Area</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Zone 1</td>
</tr>
<tr>
<td>Normal crop moisture</td>
<td>18</td>
</tr>
<tr>
<td>Low to moderate crop moisture</td>
<td>55</td>
</tr>
<tr>
<td>Low crop moisture</td>
<td>27</td>
</tr>
</tbody>
</table>
Table 5. Variation of crop moisture as determined by NDWI method

<table>
<thead>
<tr>
<th>Moisture Level</th>
<th>Percentage of Coverage Area</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Zone 1</td>
</tr>
<tr>
<td>Normal crop moisture</td>
<td>78</td>
</tr>
<tr>
<td>Low to moderate crop moisture</td>
<td>22</td>
</tr>
<tr>
<td>Low crop moisture</td>
<td>0</td>
</tr>
</tbody>
</table>

The classified MSAVI images show that the crop fields of all four zones are occupied by mostly healthy vegetation. The classified MSAVI-LST images show that with the exception of Zone 3, all crop fields have significant variation in crop moisture, where as, the classified NDWI images show insignificant variation in crop moisture in all four zones.

The rainfall estimate image from the Southern African Development Community (SADC) for April 11-20, 2004 (Figure 11) shows that the study site had an average rainfall of approximately 11-25 mm, which is significantly lower than the annual average (about 500 mm). So the rainfall data suggests that the reduced levels of crop moisture in crop fields in April, 2004 is likely. This observation is also supported by USGS Regional Crop Water Requirement Satisfaction Index (WRSI) of April 2004 (Figure 12), where the study site’s water satisfaction index values were ranked as average to poor.

![Rainfall estimate image of SADC, April 11-20, 2004.](image1)

**Figure 11.** Rainfall estimate image of SADC, April 11-20, 2004.

![Regional Crop Water Requirement Satisfaction Index (WRSI), April, 2004.](image2)

**Figure 12.** Regional Crop Water Requirement Satisfaction Index (WRSI), April, 2004.

Source: Regional Food Security Programme Report, Southern African Development Community (SADC), May, 2004
DISCUSSION AND CONCLUSIONS

The results of the analyses of the current research indicate that crop moisture can be estimated using ASTER imagery. Crop moisture estimated using the NDWI method generally agrees with the crop health map generated by MSAVI, but not with precipitation and crop water satisfaction map. Crop moisture estimated using MSAVI-LST Triangular method does not correlate with the crop health map generated by MSAVI, but does correlate with precipitation and crop water satisfaction map. Therefore, it can be concluded that MSAVI-LST Triangular method (using ASTER VNIR and TIR bands) has potential to estimate crop moisture variation more accurately than NDWI method (using ASTER VNIR and SWIR bands).

Field data related to crop moisture may help to calibrate the method for more precise result, and suitable microwave imagery can be used to compare the results obtained from optical imagery. Crop Moisture Index (CMI) can be calculated for the studied crop fields to validate the results of the study, since the research was designed to explore the potential of remote sensing techniques as an alternate of CMI.

REFERENCES


