USING NORMALIZED MULTI-BAND DROUGHT INDEX FOR HIGH SPATIAL RESOLUTION SOIL MOISTURE MAPPING.

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ABSTRACT

Soil moisture is an important factor as it has tremendous effects on agriculture production, the environment and climate. For the soil moisture estimation, traditionally, direct soil sampling has been done, but this is labor intensive, very slow, and may be very expensive, hence for large regions Remote Sensing technology is a feasible alternative. The Advanced Microwave Scanning Radiometer (AMSR-E) provides global soil moisture product which has a spatial resolution of 25km but the spatial resolution is not good enough to satisfy the demand for agricultural planning or drought monitoring hence it is necessary to find a method to retrieve Soil Moisture (SM) with higher spatial resolution. In this study, AMSR-E soil moisture in combination with Normalized Multi-Band Drought Index (NMDI) derived from Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery is used to generate higher spatial resolution SM in the Central American region for the 2010 dry season. The combination of the advantages of both, high spatial resolution provided by NMDI and physical units of AMSR-E soil moisture products are used to derive a model which can estimate the SM with higher spatial resolution. The model for SM estimation is validated using checkpoints and the validation results reveal satisfactory results. The estimations can serve as a tool for drought monitoring, prevention and mitigation actions especially in regions, such as Pacific region, which are highly vulnerable to drought.

1. INTRODUCTION

Soil Moisture (SM) is one of the most important variables relative to land surface climatology, hydrology, and ecology and its importance has been extensively acknowledged as a significant variable in many environmental studies (Walker 1999). The mapping of SM can help to accurately monitor and estimate spatial and temporal variability of soil moisture (L. Wang et al. 2009) and the information derived can be used as an instrument for the preparation of humanitarian aid to drought affected areas and to assist food security programs. SM mapping can be developed using direct soil sampling in situ, but the use of this method is complex, labor intensive, slow, and therefore very expensive (Hignet et al. 2008). In contrast with the preceding statement, remote sensing techniques for SM mapping are promising because of their spatially distributed information and their low cost. Remote Sensing based research for SM estimation and mapping has been studied since the 1970's (Musick & Pelletier 1988; Engman 1991; Gruhier et al. 2009; Verstraeten et al. 2006; L. Wang & Qu 2009; Kravchenko & Bullock 1999). It has been proved that Microwave remote sensing at low frequencies is one of the most efficient approaches to characterize soil moisture from space, with low atmospheric contribution (Gruhier et al. 2009; Y. H. Kerr et al. 2001; E. G. Njoku et al. 2003). The most common, although very costly, imaging active microwave configuration is the synthetic aperture radar (SAR) (Moran et al. 2004). Also, great progress has been made in mapping regional soil moisture with passive microwave sensors, and one of the available satellite-based passive microwave sensor imagery is the Advanced Microwave Scanning Radiometer (AMSR-E) which was successfully deployed on the NASA Aqua platform in 2003 (Njoku et al. 2003), but the use of passive microwave measurements for soil moisture mapping is limited because the spatial resolution is inherently coarse. This disadvantage can be covered with the use of optical images, but, despite the multitude optical sensors available in orbit, it is only recently when soil moisture conditions and drought has been assessed with the use of visible, near-infrared (NIR), shortwave infrared (SWIR) from MODIS satellite images (L. Wang et al. 2006; L. Wang & Qu 2007; L. Wang & Qu 2009; H. Zhang et al. 2009). The use of optical image, also has disadvantages, among them is that it has limited ability to penetrate clouds and vegetation canopy (Musick & Pelletier 1988). The diverse remote sensing methods for SM mapping have their advantages and disadvantages therefore optical remote sensing and microwave remote sensing observations of surface soil moisture can complement each other and produce a higher spatial resolution SM mapping. In this study, the MODIS surface reflectance data images are used to estimate the Normalized Multiband Drought Index (NMDI) proposed by using three wavelengths, one in the NIR centered approximately at 0.86 µm, and two in the SWIR centered at 1.64 µm and 2.13 µm, respectively (L. Wang & Qu 2007). The potential of NMDI has been deep-rooted by its application in different research topics such as drought monitoring in Henan province of China (H. Zhang et al. 2009). The results show that there is a significant correlation between NMDI and soil moisture. In this study, MODIS surface reflectance data to derive NMDI, MODIS Leaf Area Index (LAI) product and AMSR-E soil moisture products are used. LAI MODIS data is used for eliminating the dense vegetation areas, because NMDI stops responding to soil moisture change gradually as LAI increases (L. Wang & Qu 2007). Also, the high spatial resolution NMDI and the low spatial resolution AMSR-E soil moisture data is used to create a model which can generate a higher spatial resolution SM mapping. This can serve as a tool for drought monitoring, prevention and mitigation actions, especially in highly vulnerable regions to drought such as the Pacific region of Central America.

2. STUDY AREA

The study area selected is Central American region, formed by Guatemala, El Salvador, Honduras, Nicaragua, and Belize (figure 1). This study area in particular has an area of: 394,881 km² in total, including the 5 countries.

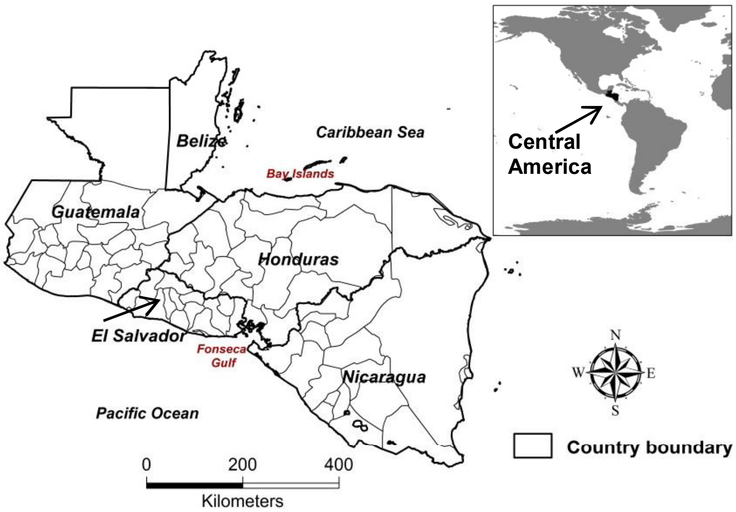

Figure 1. Study area which includes five countries of the Central American Region: Nicaragua, Honduras, El Salvador, Guatemala and Belize.

The rainfall in Central America is variable, depending on the wind direction and the position of the tropical and intertropical convergence zones. In the Central American region, SM presents strong variability caused by the volcanic origin of the terrain, and the climatic differences of the Pacific seasonal rains and Caribbean coasts year-round rains (Georgakakus 2001). In the region, there is an elevated mountain system in the central part of Honduras, Guatemala and Nicaragua which creates a climatological contrast originating a very humid Caribbean region which is subject to floods, and a Pacific region with a long dry season that provokes an intense drought in the most populated regions in Central America (Birkel 2005).

3. REMOTE SENSING DATA

The data used in this study includes the MODIS multi-spectral image for NMDI estimation, MODIS LAI/FPAR product and the AMSR-E soil moisture data. The image acquisition period is the dry season of the year 2010 which ranges from January to April. The MODIS product used is MOD09A1 which provides MODIS band 1-7 surface reflectance at 500 m resolution. It is used because each product pixel contains the best possible L2G observation during an 8-day period (Justice et al. 2002). NMDI is estimated using the NIR band 2 (0.86 μm) and two SWIR bands (band 6, 1.64 μm and 7, 2.13 μm). The AMSR-E instrument provides sea surface temperature, sea ice concentration, snow water equivalent, soil moisture, surface wetness, atmospheric cloud water, and water vapor (JAXA 2006). The AMSR-E L3 soil moisture is the product used in this study. It is also called AE_Land3 and has a daily temporal resolution. LAI data is also required for eliminating areas with dense vegetation. The product used in this study is the MODIS LAI/FPAR which is produced at 1 km spatial resolution (MOD15A1) and composited over an 8-day period based on the maximum FPAR value.

4. METHODS

In this study, NMDI is calculated for each date of the MODIS images collected for the 2010 dry season. MODIS LAI/FPAR (Leaf Area Index) is used as the vegetation cover reference to separate high density vegetation areas from low density vegetation areas. NMDI and AMSR-E soil moisture data sets are used for lineal approximation analysis to estimate SM with 1 km spatial resolution. Validation of the SM estimated is carried out using 10%

check points selected initially from the AMSR-E soil moisture data, points which are not used for lineal approximation analysis. The methodology flowchart is illustrated in figure 2.

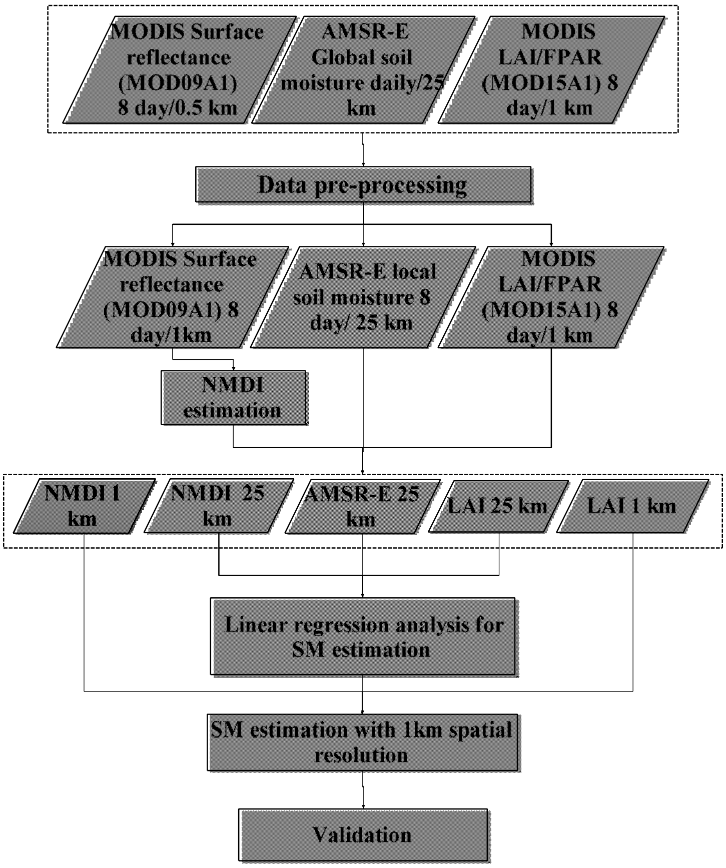

Figure 2. Analytical framework of the study

4.1 Data pre-processing

The raw data of MODIS images use the Sinusoidal projection (Equal Area Projection) and it is converted to UTM coordinate system using the MODIS Reprojection Tool (MRT). The MODIS surface reflectance images have 500 meters spatial resolution hence they are resampled to match the spatial extent of the MODIS LAI/FPAR product which has a spatial resolution of 1 km. Using vector data of the country boundaries a water mask is applied, and finally clouds are removed. Both MODIS datasets have a 1 km spatial resolution, for the subsequent calculations and analysis, this datasets need to match the spatial extent of the of AMSR-E soil moisture data which is 25 km. To resample from 1 km to 25 km one main criterion is considered: a minimum of 80% of the MODIS data pixels which conform one equivalent AMSR-E soil moisture data pixel of 25 km resolution should correspond to same class. If not, this pixel is not considered. NMDI is calculated for 1 km spatial resolution and afterwards, NMDI and LAI/FPAR are resampled to 25 km for modeling. Raw data of the global soil moisture products of AMSR-E has an EASE-Grid (Equal-Area Scalable Earth Grid) projection and coordinate system. The AMSR-E soil moisture image of the study area is then converted to UTM projection coordinate system. AMSR-E provides data on a daily basis, and for the purpose of matching the temporal resolution of MODIS datasets, an 8 day average is used.

4.2 NMDI

In this study, NMDI is used for the soil moisture assessment. NMDI uses the 0.86 μm channel as the reference instead of using a single liquid water absorption channel; however, it uses the difference between two liquid water absorption channels centered at 1.64 μm and 2.13 μm as the soil and vegetation moisture sensitive band. NMDI is defined as:

$$\text{NMDI}=\frac{R_{0.86\mu m}-(R_{1.64\mu m}-R_{2.13\mu m})}{R_{0.86\mu m}+(R_{1.64\mu m}-R_{2.13\mu m})} \tag{1}$$

Where $R_{0.86\mu m}$is Band 2, $R_{1.64\mu m}$ Band 6 and $R_{2.13\mu m}$Band 7 of MODIS satellite image. NMDI is used for assessment of SM (L. Wang & Qu 2007). Numerous research has applied the index to test its sensitivity to monitor drought, soil moisture, vegetation moisture, forest fire risk and to detect forest fires (L. Wang et al. 2009; H. Zhang et al. 2009; L. Wang et al. 2008) and from the results the index has proved an enhanced sensitivity compared with other indexes and that it is a suitable index to assess soil moisture and vegetation water content.

4.3 Linear regression analysis of NMDI, AMSR-E and LAI datasets for sensitivity analysis

The 25 km resolution NMDI images, AMSR-E soil moisture data and LAI/FPAR data are plotted to observe its sensitivity to vegetation change as shown in Figure 3a and 3b. Horizontal axis corresponds to the AMSR-E soil moisture data, the vertical axis corresponds to NMDI and the color of each point represents the different LAI values. As seen in figure 3a, LAI data points in the scatter plot distribution change gradually from low to high. Linear regression analysis is performed and a regression line plotted for each LAI interval (figure 3b). Line colors represent different categories of LAI and when the LAI values are low, the NMDI, AMSR-E soil moisture data has a higher sensitivity hence the slope of the regression line for the first category is the largest. The slope gradually decreases as the LAI increases and the regression line slope gradually approaches zero. This indicates that the NMDI gradually reduces its sensitivity on the AMSR-E soil moisture data when LAI is increased, an assumption that matches the simulation results in L. Wang & Qu 2007 study.

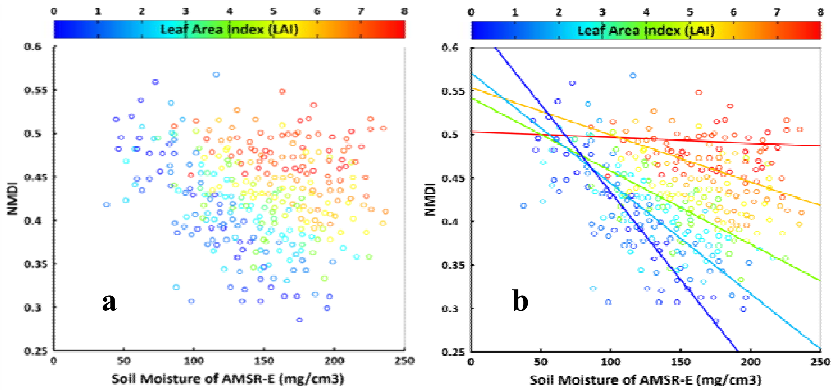

Figure 3. (a) Scatter plot of NMDI, AMSR-E soil moisture and LAI data points (b) Linear regression line for each LAI category

4.4 SM estimation model

4.4.1 Linear regression analysis

NMDI and AMSR-E soil moisture regression analysis is performed in order to model the relationship between these two variables by fitting a linear equation to the observed data. AMSR-E soil moisture products, which are generated by microwave remote sensing technology, have a quantitative physical unit but a very low spatial resolution and NMDI has high space resolution which is calculated using optical images, but does not have quantitative physical units, therefore, in this study the combination of the advantages of both, high spatial resolution provided by NMDI and physical units of AMSR-E soil moisture products provide the SM estimation with higher spatial resolution. The coefficients obtained from the linear regression analysis are derived from 90% of the original dataset leaving the remaining 10% as check points for validation. Once the regression model has been fitted for the group of data, examination of the residuals (the deviations from the fitted line to the observed values) is performed. This allows the validation of the assumption that a linear relationship exists.

4.4.2 Validation

The validation of the model is done by using 10% of the AMSR-E soil moisture data which were randomly selected from the original dataset as checkpoints. These 10% data checkpoints are not used for the linear regression analysis performed previously. The SM estimation model function is used to estimate SM for the 10% dataset. The results of this SM estimation are evaluated by RMSE and examination of the residuals. This allows the validation of the model.

5. RESULTS AND DISCUSSION

The SM is calculated using model acquired from linear regression of the AMSR-E soil moisture datasets and NMDI for the dry season of the year 2010. The model obtained was used to estimate the SM at 1 km spatial resolution (figure 4a). The model generated a fairly consistent SM for the entire region and it visually shows a similar spatial variability when compared to the true values of the AMSR-E soil moisture data (figure 4b). It can also be noticed that in the large urban areas, SM estimated from model is very low, and there is a clear contrast between cities and surrounding areas, characteristic that cannot be observed in the AMSR-E soil moisture true data. This is particularly important to notice because it reveals the level of detail that the SM estimation can provide, confirming visually the effectivity of the model. This similarity in visual spatial variability of SM and AMSR-E as well as other characteristics observed, require quantitative validation.

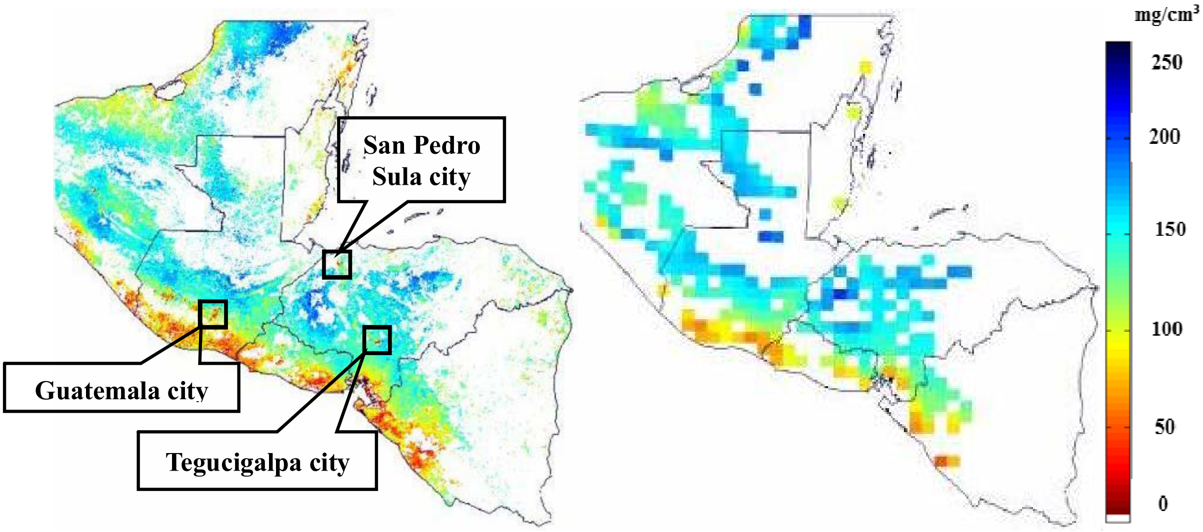

Figure 4. (a) SM estimation with 1 Km spatial resolution on 22 March 2010. The area within the black boxes is the location of urban areas. (b) AMSR-E soil moisture with 25 km spatial resolution

In this study for validation, 10% of the points are selected randomly to be used as the checkpoints, while the remaining 90% of the data are used for the mode estimation. An average RMSE of 10.54 is obtained, for the dry season of 2010. In table 1 RMSE of all dates for the dry season of the year 2010 are shown. It illustrates that the RMSE is consistently low for all dates, proving that the SM estimation model performance is satisfactory.

Table 1. Validation of SM estimation model using 10% of total data for check points

Check points (10% of data) Date acquisition	RMSE of SM estimated results	Check points (10% of data) Date acquisition	RMSE of SM estimated results
01 January	9.54	06 March	12.46
09 January	11.97	14 March	11.29
17 January	8.44	22 March	10.30
25 January	9.89	30 March	9.98
02 February	8.98	07 April	11.09
10 February	7.78	15 April	11.26
18 February	12.50	23 April	10.56
26 February	11.90	**Average**	**10.53**

The SM estimation with 1 km spatial resolution for all dates is illustrated in the figure 5. The driest months in this region fluctuate between January and April hence this period is selected for analysis. The maps are illustrated for every 8 days, starting from the beginning of January until the end of April which marks the start of the rainy season. The time series of SM images in 2010 reflects clearly the development of the dry season in the region. From the spatial variability of the SM estimation in the region it is observed a very strong difference of SM between the Atlantic and central area and the Pacific coastal area, which coincides with the known climatic differences that characterizes both regions.

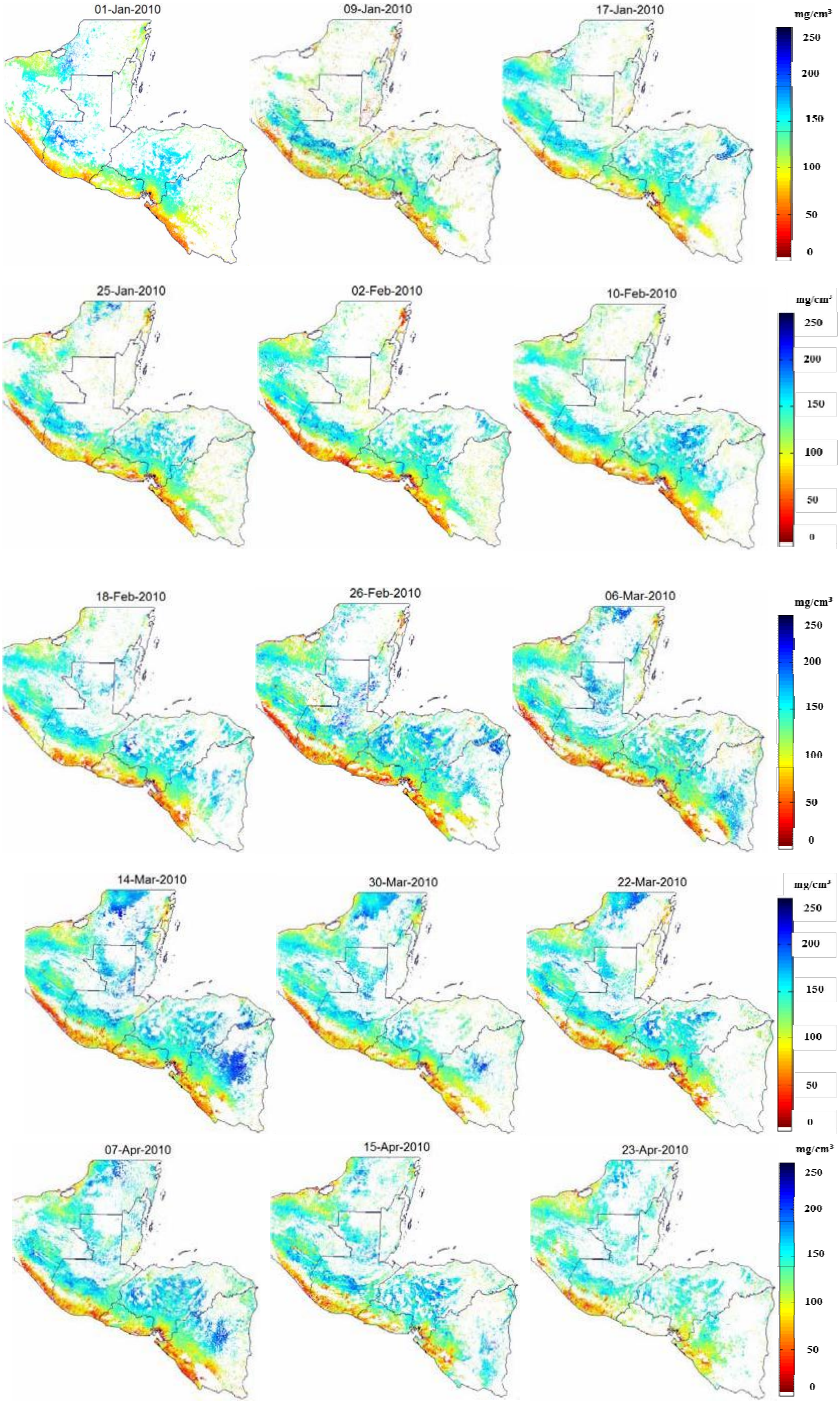

Figure 9. SM estimation from model at 1 km spatial resolution for the dry season of the year 2010 in the Central American region.

6. CONCLUSIONS

The main objective of this study was to generate a higher spatial resolution SM estimation and mapping using NMDI, LAI/FPAR and AMSR-E soil moisture datasets for every 8 days. NMDI was estimated using MODIS land surface reflectance bands 2, 6 and 7 and have a 500 meters resolution (resampled to 1 km). LAI/FPAR data have a 1 km spatial resolution and was used to separate highly dense vegetation areas. AMSR-E data was acquired and averaged for every 8 days. Linear approximation was developed to make use of the advantages of NMDI and AMSR-E soil moisture datasets, coefficients calculated and the function acquired, applied to obtain SM at 1 km spatial resolution. Validation of the model using 10% checkpoints revealed satisfactory SM estimation results. The average RMSE obtained for 2010 dry season dates is 10.53 mg/cm^3 , the lowest RMSE was 7.78 mg/cm^3 obtained in February 10th. The results obtained indicate a clear differentiation between the drought conditions in the Pacific region compared to Atlantic and Central region. The SM content in Pacific coastal area reveals strong drought conditions during the whole dry season, which can directly affect the sustainability of agriculture and the food security in the region. The results from this research can be used as an instrument for agriculture planning and can also be a key variable to develop an early warning system in regions which have a high vulnerability to drought.

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