Evaluating Remotely Sensed Live Fuel Moisture Estimations for Fire Behavior Predictions

Swarvanu Dasgupta, John J. Qu, and Xianjun Hao

Abstract— **Contemporary research has shown that remote sensing techniques can be used for estimating live fuel moisture content (FMC) from space. These remote sensing based live FMC measurements must conform to some accuracy requirements to be of any practical use in fire behavior predictions. This paper thus investigates the potential errors in live FMC estimations using two simple established techniques and analyzes the implications of such errors in fire behavior predictions using a sensitivity analysis. We study the sensitivity of fire behavior to live fuel moisture content under dry no-wind, no-slope conditions using the FARSITE surface fire behavior model with the objective of evaluating the current satellite based FMC estimation techniques and presenting a basis for accuracy requirements of live FMC retrievals using more sophisticated remote sensing techniques in the future.**

I. Introduction

FUEL moisture content (FMC) in vegetation is one of the most critical factors driving wildfire susceptibility and wildfire behavior. Contemporary research has shown that remote sensing techniques can be used for estimating live FMC from space. Remote sensing techniques utilizing optical and thermal infrared sensors have resorted primarily to two ways of measuring live FMC (ratio of the moisture content weight to the dry weight of the fuel expressed as a percentage): (i) estimating vegetation status or vegetation stress as a proxy for estimating live FMC and (ii) the direct estimation of live FMC. The former indirect methods seek to exploit the obvious correlation between vegetation greenness (chlorophyll content) and its moisture content. Consequently vegetation indices, like the Normalized Difference Vegetation Index (NDVI) (Chuvieco et al 1999, 2002), or its variations like relative greenness (RG) (Burgan & HartFord, 1997; Chuvieco et al 2002) have been found useful in estimating live FMC. Potential improvements in live FMC estimations has been observed by incorporating satellite derived Surface Temperature (ST), since ST would be expected to increase in drier plants on account of reduced evapotranspiration (Chuvieco et al 1999, 2004). Specifically the ratio NDVI/ST was found to be very useful (Chuvieco et al 1999, 2004). However vegetation indices have limitations in estimating vegetation water content since the relation between chlorophyll content and moisture content is not always straightforward and has been found to be plant species dependent (Jackson et al 2004). Apart from water stress, variations in chlorophyll content can be caused by phenological status of the plant, atmospheric pollution, nutrient deficiency, toxicity, plant disease and radiation stress (Larcher 1995). Moreover NDVI saturates at intermediate vales of leaf area index (LAI), and therefore is not responsive to the full range of live FMC (Gao 1996, Jackson et al 2004). Direct methods of vegetation water estimations typically utilize water absorption channels in the shortwave infrared (SWIR) and contrast it with near infrared (NIR) channels to account for the variations in reflectance due to leaf internal structure and dry matter content. Several indices based on SWIR and near infrared (NIR) reflectances have been proposed for this purpose such as NDWI Normalized Difference Water Index (Gao 1996); SRWI, the Simple ratio water index (Zarco-Tejada & Ustin 2001, Zarco Tejada et al 2003); LWCI, the Leaf water content index (Hunt et al 1987); GVMI, the Global vegetation water moisture index (Ceccato et al 2002). An inherent feature of these SWIR-NIR based indices is that they are more related to quantity of water per unit area (equivalent water thickness (EWT) per unit area) rather than the FMC, the quantity of water per unit of dry vegetation weight (Ceccato et al 2002, Jackson et al 2004). Various empirical and semi-empirical relationships have been used to estimate live FMC with reasonable accuracy. However if live FMC is to be estimated with greater accuracy, it would be necessary to fully understand the relative contribution that the spatial and temporal variation in the biophysical (leaf area index, leaf orientation, leaf size), geometric (solar and view zenith and azimuth angles), background (soil and or non-photosynthetically active vegetation) and atmospheric factors make to reflectance variability at the canopy or leaf level (Cohen 1991, Jacquemond & Ustin 2003, Bowyer and Danson 2004). In the perspective of all these imminent challenges, remote sensing based live FMC estimation techniques must conform to some accuracy requirements to be of any practical use in fire conditions monitoring. An obvious use of live FMC measurements would be to estimate the potential burnt area in event of a real or a prescribed fire. Fire behavior models are key tools that are used to estimate the extent of the burn and the intensity and duration of burning in event of a fire (Burgan and Rothermel 1984, Penny 1998). Live fuel moisture is one of the key input parameters to these fire behavior models since it has a strong control on initial probability of ignition, burning efficiency, and the rate of fire propagation (Rothermel

Manuscript received April 25, 2005

S. Dasgupta and Xianjun Hao are with the Center for Earth Observation and Space Research, George Mason University, Fairfax, VA 22030 USA (phone: 703-993-4695; e-mail: sdasgupt@gmu.edu).

J. J. Qu, is with NASA GSFC and the Center for Earth Observation and Space Research, George Mason University, Fairfax, VA 22030 USA (e-mail: jqu@gmu.edu).

1972, Cohen et al 1990, Bowyer and Danson 2004). This paper thus investigates the potential errors in live FMC estimations using two simple established techniques and analyzes the implications of such errors in fire behavior predictions by employing a sensitivity analysis. We study the sensitivity of fire behavior to live fuel moisture content using the FARSITE surface fire behavior model (Finney 1998) with the objective of evaluating the current techniques and presenting a basis for accuracy requirements of live FMC retrievals using more sophisticated remote sensing techniques. We focus our study on the Georgia region, in south eastern USA.

II. FIRE BEHAVIOR MODEL

Since we intend to do the sensitivity analysis using the FARSITE surface fire behavior model, a very brief overview of the model becomes pertinent to our current discussion. Surface fire spread rates at a particular time are typically a function of fuel model, live and dead fuel moisture content, wind and slope. Fuel models such as Anderson's fuel model (Anderson, 1982) or the NFDRS fuel model (Bradshaw et al 1984) were introduced for mapping a heterogeneous and discontinuous fuel bed and can be defined as a set of the fuel type parameters that best describes the fuel bed and can serve as input to a fire behavior model. Fuel moisture is the more dynamic component of fire spread rate computations. Live fuel moisture is controlled by the physiological processes of the plant (Bradshaw et al 1984) and are much less dependent on atmospheric conditions given their mechanisms to extract water from the soil reserve and reduce evapotranspiration (Chuvieco et al 2004). Live fuels are classified into herbaceous plants (grasses, forbs, ferns etc) and woody shrubs. Moisture content in dead fuels on the other hand is exclusively controlled by environmental conditions such as temperature, radiation, relative humidity, wind and precipitation and their variation can be modeled from these factors (Bradshaw et al 1984). Dead fuel is classified into 1 hour, 10 hour and 100 hour classes depending on the time required to lose approximately two-thirds of their initial moisture content under constant conditions (Rothermel et al, 1986).

The surface fire spread rate model used in the FARSITE is the well-known Rothermel spread equation (Rothermel et al 1972) which gives us the steady state fire spread rate (m/min) in a plane parallel with the ground surface at any point on a landscape.

$$R = \frac{(I_p)_0(1+\phi_w+\phi_s)}{\rho_b \varepsilon Q_{ig}} \qquad (1)$$

In the denominator Qig (kJ/kg) is the heat of pre-ignition and is defined as the heat required in bringing a unit weight of fuel to ignition. p_b (kg/m^3) is the actual ovendry bulk density of fuel while the effective heating number ε represents the fraction of the actual bulk density involved in the ignition process. In the numerator $(Ip)_0$ (kJ/m^2-min) is the heat flux absorbed by a unit volume of fuel at the time of ignition under no wind and no slope conditions. Wind and slope increase this basic heat flux by exposing the potential fuel to additive convective and radiant heat from the approaching fire front. Φw and Φs represent this additional propagating flux due to wind and slope respectively. They are dimensionless coefficients depending on wind, slope and fuel conditions. The rate of spread in equation (1) in a sense is a ratio between heat flux received from the source (heat source) in the numerator and the heat required for ignition by the potential fuel (heat sink) in the denominator. Various parameters for the above equation were determined analytically or empirically through carefully conducted experiments (Rothermel, 1972). Fuel Moisture Content enter into fire spread equation through $(Ip)_0$ and Q_{ig} With increase in fuel moisture, $(Ip)_0$ decreases while Q_{ig} increases resulting in an decrease in fire spread rate. A particular fuel model, however, is a heterogeneous mixture of live and dead fuels with a different spread rate for each class. To arrive at a single spread rate value, the FARSITE finds a singular characteristic spread rate by surface area weighting of the spread rates for the different dead and live fuel classes.

Fire growth modeling in FARSITE is carried out using a vector approach as described in Richards, 1990. FARSITE requires various inputs to drive fire simulation. Landscape inputs are described as raster files and include fuel model, slope, aspect, elevation. Weather inputs include daily observations of maximum and minimum temperature and relative humidity, the time of these maximum and minimum readings, and the amount of precipitation. Inputs of latitude, dates and canopy cover and cloud cover are used to estimate the amount of solar radiation reaching the dead fuel. Weather inputs and the estimated solar radiation are used to model the changes in dead fuel moisture over course of the fire simulation period. Predictions of temperature and humidity during the simulation are made using a diurnal weather pattern in which temperature and humidity are assumed to respond inversely over time as approximated by a cosine curve between the maxima and the minima (Finney, 1998). Fuel moisture inputs include initial fuel moistures of 1 hour, 10 hour, 100 hour dead fuels, and herbaceous and woody live fuel for each fuel model within the landscape.

III. EXPERIMENTAL METHODOLOGY

Our study region is one of most fire prone regions of south-eastern USA. It encompasses the state of Georgia and lies within 30^0N to 35^0N and 81^0W to 85^0W (Fig. 1).

The first part of our study is concerned with estimating the amount of errors possible while estimating live herbaceous and live woody FMC using simple linear relations with (i)NDVI/ST and (ii) NDWI. Our approach towards live FMC retrievals is to correlate daily measured values of live woody FMC at selected Georgia Forestry Commission weather stations across the study region with corresponding MODIS derived daily values of NDVI/ST and NDWI. This analysis allows us to construct simple linear regression equations relating NDVI/ST and NDWI to live FMC values. Studies have related foliage moisture content with satellite derived indices. However a significant correlation of about 0.97 between live herbaceous moisture content (ground observations at same stations) and live woody moisture content in this case leads us to presume that live woody moisture content can also be estimated from these indices.

In the first step manual scanning of MODIS-aqua daytime RGB images during the spring and early summer months of 2004 was employed to select 10 cloud free days over the region (Table 1). MODIS/Aqua Calibrated Radiances 5-Min L1B Swath 1km (MYD021KM, Ver 4), MODIS/Aqua Geolocation Fields 5-Min L1A Swath 1km (MYD03, Ver 4) and MODIS Aqua Land Surface Temperature Daily L3 Global 1km (MYD11A1, Ver 4) data products were then acquired for these 10 days.

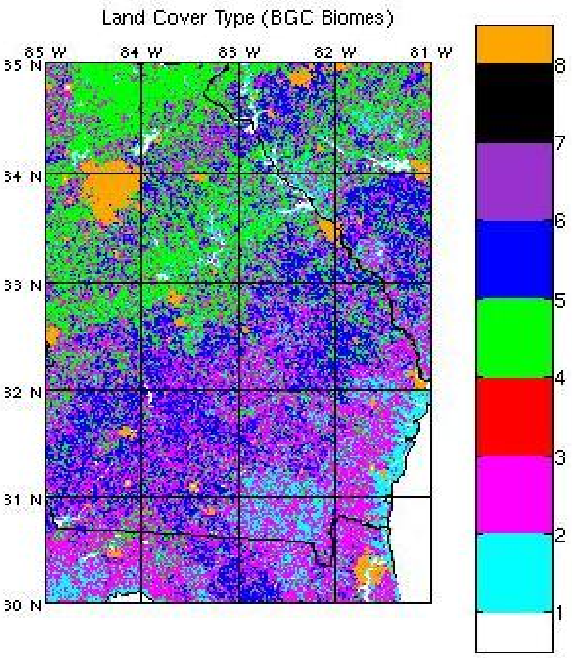


Fig. 1. Study Region in Georgia, USA showing the BGC biome surface types (1-Evergreen Needleleaf Vegetation; 2- Evergreen Broadleaf Vegetation; 3-Deciduous Needleleaf vegetation; 4- Deciduous Broadleaf vegetation; 5-Annual Broadleaf vegetation; 6-Annual Grass Vegetation; 7-Non-vegetated land; 8-Urban)

TABLE 1
CLOUD FREE DAYS SELECTED DURING SPRING AND SUMMER OF 2003, 2004

Year	Selected Dates
2004	*March 22, March 23, April 3, April 4, April 5, April 15, April 17, April 28, May 4, May 5*

TABLE 2
GEORGIA FORESTRY COMMISION WEATHER STATIONS, LOCATIONS AND SURFACE TYPES AT 3X3 PIXELS AROUND THEM

Station	Location	Surface Type
Adel	31.11N , 83.43W	Evergreen Broadleaf, Annual Broadleaf
Byromville	32.17N, 83.97W	Deciduous Broadleaf, Annual Broadleaf, Annual Grass
Dallas	33.83N, 84.74W	Deciduous Broadleaf
Metter	32.39N, -82.04W	Evergreen Broadleaf, Deciduous Broadleaf, Annual Broadleaf
Athens	33.90N, -83.37W	Evergreen Broadleaf, Deciduous Broadleaf, Annual Broadleaf
Camilla	31.21N, 84.24W	Evergreen Broadleaf, Annual Broadleaf
Dawsonville	34.38N, 84.06W	Evergreen Broadleaf, Deciduous Broadleaf, Annual Broadleaf
Sterling	31.26N, 81.61W	Evergreen Needleleaf, Evergreen Broadleaf

The top of atmosphere reflectances at band 1 at 0.65µm ($\rho_{0.65}$), band 2 at 0.86µm ($\rho_{0.86}$) and band 7 at 2.1µm ($\rho_{2.1}$), were then corrected for sensor zenith angle using sensor zenith angle values from the MYD03 datasets. These corrected reflectances were then combined as $(\rho_{0.86}-\rho_{0.65})/(\rho_{0.86}+\rho_{0.65})$ and $(\rho_{0.86}-\rho_{2.1})/(\rho_{0.86}+\rho_{2.1})$ to derive NDVI and $NDWI_7$ images respectively. The 2.1 µm band has been identified as a water absorption band and the corresponding LandSat band has been used to retrieve vegetation water content information in the past (Chuvieco et al 1999,2002). Fuel temperature images are also computed for these 10 days using MODIS-Aqua land surface temperature as a proxy for fuel temperature. While this may not be an optimum way to retrieve fuel temperature especially in non-forested areas, in forested areas surface temperature can serve as an approximate measure. There have been instances of using satellite derived surface temperature as measures of leaf temperature in the current literature (Chuvieco et al 1999, 2003, 2004).

Four Georgia Forestry commission stations were selected so that together they may represent all the major surface types relevant to the forested regions in Georgia. We intend to build a surface type independent model for FMC estimation. Four other stations were selected to test the regression model for estimating live FMC from satellite indices. The names, locations, and the surface types in the 3x3 pixels surrounding the station location for all these eight are given in Table 2. The first four were used to construct the regression models, while the next four were used for testing the model. Fig 1 shows the BGC biome surface type (Running et al 1994) derived from MODIS Terra Yearly 1km Land Cover Type (MOD12Q1, Ver 4) data of 2001. Live woody and live herbaceous daily data were acquired from the Georgia Forestry Commission Weather /NFDRS data Retrieval System at http://weather.gfc.state.ga.us/Getwxdata/Getwxdata.aspx. The FMC measurements at these stations were taken at around 1.30pm (EST) at around the same overpass time of Aqua (1pm local time).

NDVI/ST and $NDWI_7$ were then computed for each of the 4 stations on each of the 10 days by averaging over 3x3 pixels centred on each of the station locations (to minimize the consequences of residual misregistrations) and then correlated with live woody FMC measured on the same day. NDVI/ST and $NDWI_7$ values of pixels having scan angles greater than 30^0 were not considered for deriving the regression equation since larger pixel sizes at such scan angles would deteriorate the validity of the regressed equation. Pixels identified as water by the land sea mask image derived from the MODIS geolocation product were not considered for computing the averages. Residual analysis was then performed to estimate the potential errors inherent in these techniques.

The second part of our study is to investigate the sensitivity of fire behavior to live herbaceous and live woody fuel moisture. This would allow us to analyze the implications of errors in satellite-based estimations of live FMC towards predictions of fire behavior. For this purpose we have selected one of the most fire-prone regions in Georgia, the Okefenokee National Wildlife Refuge area between 30.5N-31.5N and 82W-83W (Fig 1(a)). The Blackjack Bay Complex fire as it is called burnt around 95000 acres of the refuge during the summer of 2002 (Source: USGS; National Burn Severity Mapping Project). Simulating fire behavior using FARSITE requires us to define the landscape. Generating the landscape for FARSITE requires us define the fuel model, elevation, slope, aspect and canopy cover layer for the Okefenokee region (Fig 2a). For topography we use GTOPO30 data which is a global DEM dataset with a horizontal grid spacing of 30 arc seconds (approximately 1 kilometer) and was derived from several raster and vector sources of topographic information by the US Geological Survey. Fig 2b shows the elevation image of Okefenokee. We also used the Moderate Resolution Imaging Spectroradiometer (MODIS) continuous vegetation cover data product (MOD44B) for the year 2000 to estimate a mean canopy cover over our study region. The MOD44B product is a level 4 dataset with 500m spatial resolution and provides yearly estimates of percent tree cover for all regions of the earth (Hansen et al 2003). Fig 2c shows the percent tree cover distribution for the Okefenokee region. For fuel model distribution we used the NFDRS fuel model dataset from Wildland Fire Assessment System (WFAS, http://www.fs.fed.us/land/wfas/nfdr_map.htm) operated by the National Interagency Fire Center (NIFC), Boise, Idaho. National Fire Danger Rating fuel models have been mapped across the lower 48 states at 1 km resolution [14]. Figure 2d, shows the fuel model distribution for the study region.

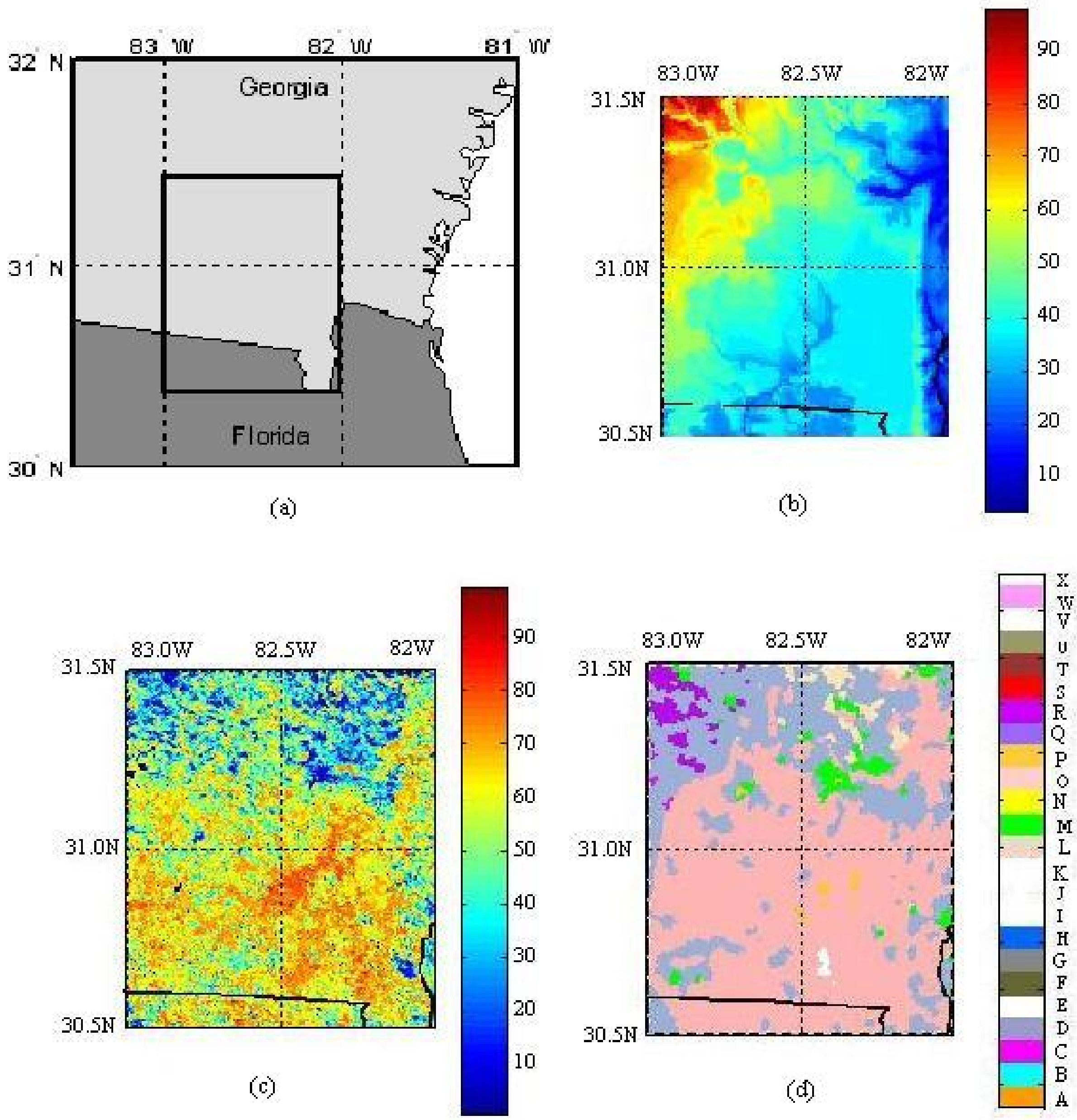


Fig. 2. (a) Location of the Okefenokee National Wildlife Refuge Area (b) Elevation (c) Percent Tree Cover (d) NFDRS Fuel Model

TABLE 3
PRIMARY FUEL MODELS IN STUDY REGION

Fuel Model	%Area	Fuel Loading (tons/acre)					Surface Area to Volume (ft^{-1})			Fuel bed depth (ft)	Dead Fuel moisture of extinction (%)	Heat Content (all fuels) Btu/lb
		1hr	10hr	100hr	Live woody	Live herb.	1 hr	Live Woody	Live Herb.			
High Pocosin (O)	61.12	2.0	3.0	3.0	7.0	-	1500	1500	-	4.0	30	9000
Southern rough (D)	30.83	2.0	0.5	-	3.0	.75	1250	1500	1500	2.0	30	9000

TABLE 4
EXPERIMENTAL LANDSCAPES

Landscape	Fuel Model	Canopy Cover	Elevation (m)	Latitude
LandscapeO	O (High Pocosin)	61%	41	31^0N
LandscapeD	D (Southern Rough)	61%	41	31^0N

TABLE 5
NOMINAL VALUES AND RANGES FOR LIVE FUEL MOISTURE

Fuel Moisture Content (%)	Range	Nominal Value
Live Herbaceous	30 – 235	50
Live Woody	50 - 185	80

TABLE 6
NOMINAL VALUES FOR DEAD FUEL MOISTURE & WEATHER VARIABLES

Variable	Nominal Value
1hour and 10 hour dead FMC	6
100 hour dead FMC	6
Temperature (^{0}F)	85
Relative Humidity (%)	30
Wind speed (m/h)	0
Rainfall	Nil
Cloud Cover (%)	0

The error estimates inferred from our study would be dependent on the accuracy of the FARSITE model. The most important result of the *FARSITE* tests to date has been that spread rates for all fuel models tended to be over predicted by the Rothermel spread equation (FARSITE technical documentation, Sanderlin and Sunderson, 1975). This over prediction have been attributed to data and model inaccuracies. For example, the time and space-averaged winds (e.g. hourly), spatially homogenized fuels within rasters, topographic representations may be too coarse to capture the true fine-scale variability in fire environment (temporal or spatial) that keeps fire actually spreading at variable rates. This could force the average fire spread rate over large areas and long time spans to be over predicted. The nonlinear relationship between wind speed, fire acceleration, and fire spread rate means that the average wind speed cannot be expected to predict the average spread rate (Richards 1993).

The use of real landscapes thus would be a hindrance in making meaningful inferences from the sensitivity analysis since fire behavior simulation results in such case would depend on the topography, fuel model distribution, canopy cover distribution and the starting point of ignition. Instead what we need for our proposed study are experimental flat landscapes with constant fuel models and constant canopy cover that are representative of the study region. The wind is kept at zero, while the simulation period is set to 24 hours for our simulation. A no-wind, a flat (no-slope) homogenous single fuel model landscape assumption along with a short simulation period is expected to keep the over predictions limited to a reasonable extent.

The region elevation derived from GTOPO30 data ranges from 3m to 98m with a mean elevation of about 41m and a standard deviation of 14.2 m implying that a flatland approximation would not be inappropriate for our experiments. The mean tree cover derived using MOD44B is 54% which we use as our constant landscape canopy cover percentage. As for fuel model distribution, the NFDRS fuel model data shows that two fuel models viz – fuel model O (Southern rough) and fuel model D (High Pocosin) cover almost 90% of the wildlife refuge area. Fuel type parameters pertaining to these two fuel model parameters are given in Table 3. Two experimental landscapes most representative of the study region are therefore used for our sensitivity studies. Details of these experimental landscapes are given in Table 4.

The variables for which we conduct the sensitivity analysis are live herbaceous fuel moisture and live woody fuel moisture, since these are the ones that remote sensing techniques would retrieve. Our experiments would be 'One At a Time' experiments in which the impact of changing the values of each live fuel moisture factor is evaluated while keeping the other factor fixed at some nominal value. The value range for each live fuel moisture variable and their nominal values are specified in Table 5. The 1978 NFDRS technical documentation (Bradshaw et al, 1984) mentions the ranges of live herbaceous fuel moistures from 30% to 200%, while for live woody fuel moisture the ranges are from 50% to 250%. Towards the lower end of the moisture scale herbaceous plants are considered cured at 30% moisture content and woody plants dormant if their moisture content dropped to 50%. In keeping with these ranges our experiments span the range 50% to 185% for live woody fuel moisture and 30% to 235% for live herbaceous fuel moisture. Burgan, 1979 estimated the live fuel moisture content for wet, normal and dry seasons. His work indicated that live fuel moistures of 80% and 50% are reasonable estimates for woody and herbaceous fuel respectively during a very dry season.

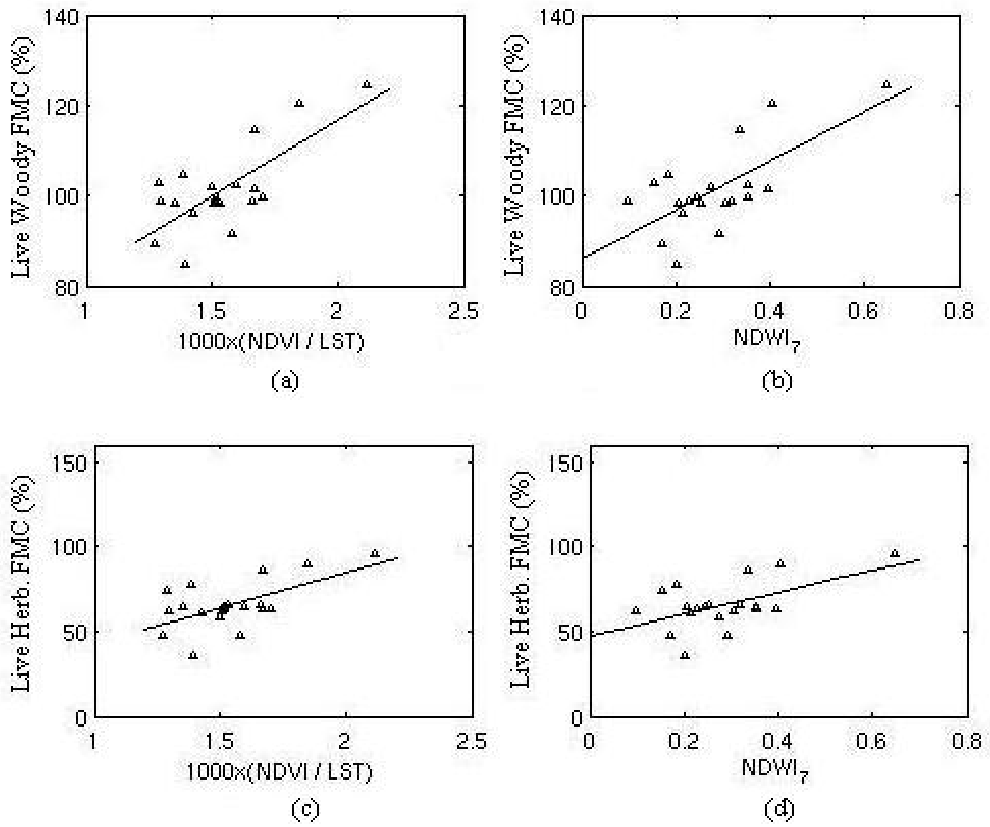


Fig. 3 (a) NDVI/LST versus Live Woody FMC ; (b) $NDWI_7$ versus Live Woody FMC; (c) NDVI/LST versus Live Herbaceous FMC ; (d) $NDWI_7$ versus Live Herbaceous FMC;

Nominal values for the dead fuel moisture factors and weather factors during the simulation experiments are specified in Table 6. The nominal values for dead fuel moisture in the 1 hour, 10 hour and 100 hour classes are set at 6%, 6% and 8% representing high burning conditions. The nominal values of temperature, relative humidity and wind speed are representative of a hot (80^0 F), dry (30% relative humidity) and windless (wind speed of 0m/h) day. Overall the nominal values represent moderately high burning conditions.

TABLE 7
LEAST SQUARE REGRESSION

Variable pair	R^2	Regression equation	Standard Error
NDVI/LST (x), Live Woody FMC (y)	0.54 (p= 0.0002)	y=33760x +49	6.6
$NDWI_7$ (x), Live Woody FMC (y)	0.47 (p= 0.0008)	y=54.35x+85.91	7.04
NDVI/LST (x), Live Herbaceous FMC(y)	0.37 (p= 0.005)	y=41496x+2	11.49
$NDWI_7$ (x), Live Herbaceous FMC(y)	0.30 (p= 0.01)	y=64.59x+47.3	12.06

IV. Results and Discussion

Fig 3 shows the scatter plot and derived least square regression lines of NDVI/ST and $NDWI_7$ with live woody FMC values live herbaceous FMC values. The equations were derived from 20 pairs which survived the scan angle restriction ($<30^0$). The Pearson determination coefficients (R^2), significance of correlation values (p), least square regression equation and the standard error are shown in Table 7. R^2, also called the goodness of fit, represents the fraction of variance in the satellite derived indices explained by live FMC (woody or herbaceous). Given the host of biophysical to geometrical factors that serve to confound the relationship between satellite derived indices and live FMC, the R^2 values are quite consistent with expected results. Bowyer and Danson, 2004 found R^2 values of 0.42 and 0.47 between PROSAIL and PROGEOSAIL simulated NDWI and FMC under site specific conditions. Their NDWI was defined using 1.24 µm SWIR band instead of the 2.1 µm SWIR band. Using an empirical model to estimate live FMC from NDVI, ST and the day of the year in different Spanish sites, Chuvieco et al 2004 reported R^2 values ranging from 0.665 to 0.857 and standard errors ranging from 11.34 to 17.58 between observed and estimated live FMC. Of course the estimation capability of live woody FMC in our case depends closely on the quality of data used, the range of conditions under which the data was collected and the data range used in building the model.

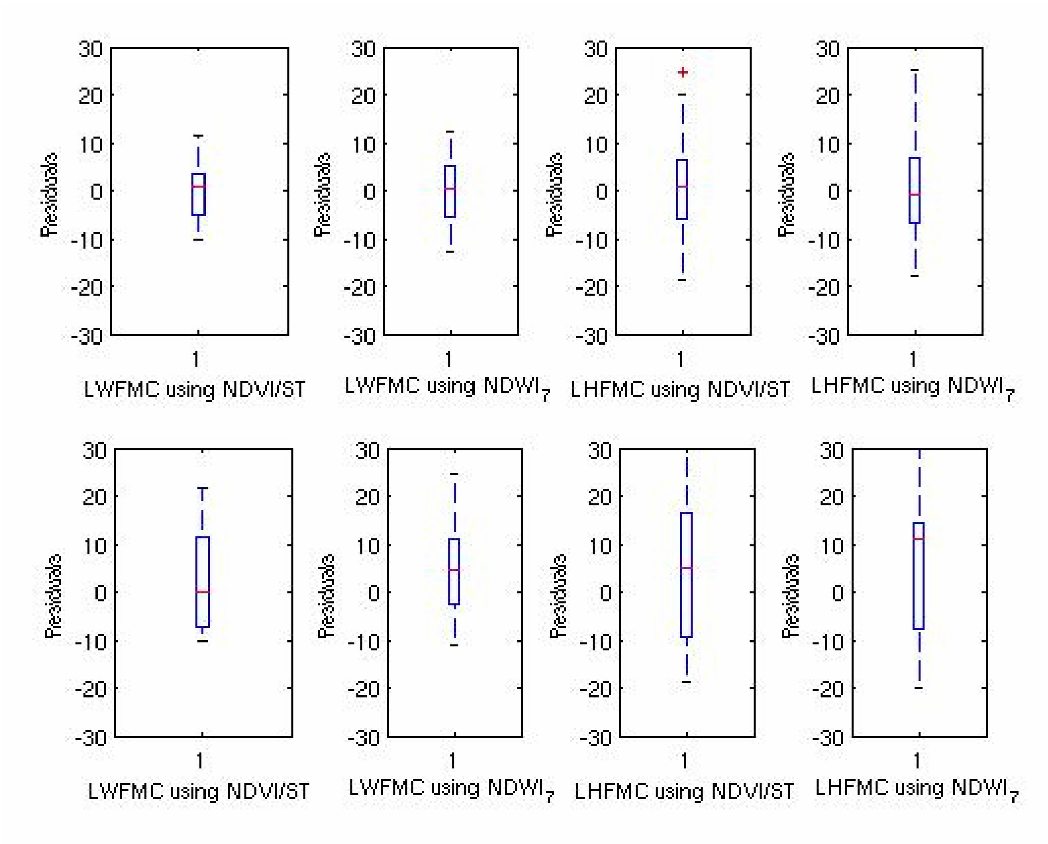
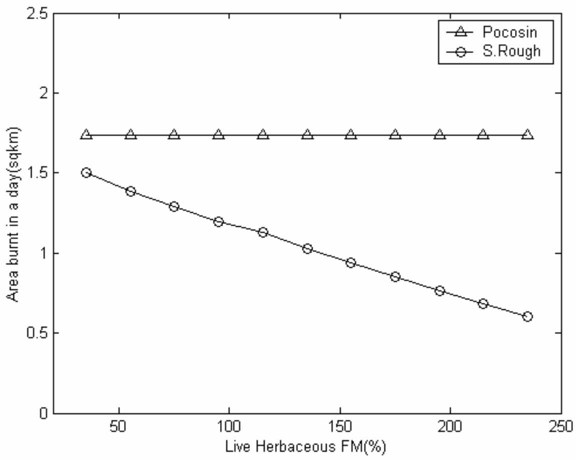


Fig. 4 Top Panel: Box plots of residuals in estimating Live Woody FMC (LWFMC) and Live Herbaceous FMC (LHFMC) using NDVI/LST and $NDWI_7$ in (Adel, Byromville, Dallas, Metter). Bottom panel: Box plots of residuals in estimating Live Woody FMC (LWFMC) and Live Herbaceous FMC (LHFMC) using NDVI/LST and $NDWI_7$ in (Athens, Camilla, Dawsonville, Sterling).

Differences between the modeled values and the actual observations i.e. the residuals are determined separately for the four stations that were used to construct the models, as well the other four stations that were selected for testing the model. The box plots of the residuals in the eight cases, i.e. Live woody FMC and Live Herbaceous FMC estimation using NDVI/ST and $NDWI_7$ in (Adel, Byromville, Dallas, Metter) and (Athens, Camilla, Dawsonville, Sterling) are shown in Fig 4. Residuals play a key role in evaluating model adequacy and can be viewed as realizations of model errors (Montgomery et al 2001). The results of the residual analysis are summarized in Table 8 which shows the mean absolute error and maximum absolute errors in the eight cases. The results show that average expected errors can be about 9 for live woody FMC and about 14 for live herbaceous FMC. The maximum errors can be in the range of 25 for live woody FMC and 35 for live herbaceous FMC. It must be noted that this obviously is a best case estimate of errors since the residuals were computed in the same region and during the same season and year from which the least square model was constructed. Higher errors are very likely if the models were employed elsewhere or even during some other season or year. Estimates of errors in FMC estimation were reported in Chuvieco et al 2003 where live Fuel Moisture Content was estimated by an empirical model using NDVI/ST and RG. The latter model was constructed by correlating NOAA AVHRR data and ground observations in Spanish sites during the period 1996-1997. Their error estimates are a little higher since the model was calibrated over two full years and was thus season independent. The mean absolute errors for grasslands and shrublands for the period 1996-1997 reported in that study were 26.418 and 15.424, while the mean error for grassland and shrubland combined was about 20.921. The mean absolute errors for the period 1998-1999 were a little higher at 32.223 for grasslands and 15.718 for shrublands.

With these estimates of potential errors in satellite derived live FMC, we then investigate the implications of these errors in fire behavior predictions. The next part of the study uses FARSITE to determine the sensitivities of live FMC to fire behavior on the simulated landscapes representative of the Okefenokee region. All the FARSITE runs are done during a typical summer day for 24 hours from morning 8am to 8am on the next day. The diurnal variation in temperature, humidity or wind is not accounted for since we keep these factors constant throughout the 24 hours of simulation. The solar radiation, however, does change depending on the Sun's altitude reaching a maximum at solar noon and dropping to zero after sunset. Dead FMC is modeled in FARSITE to vary in response to the current weather conditions.

Fig 5 shows the effects of changing one live fuel moisture factor while keeping all other fuel moisture and weather factors fixed at their nominal values. They represent the amount of change the factor alone can induce on the burn area over a period of 24 hours. In order to determine the



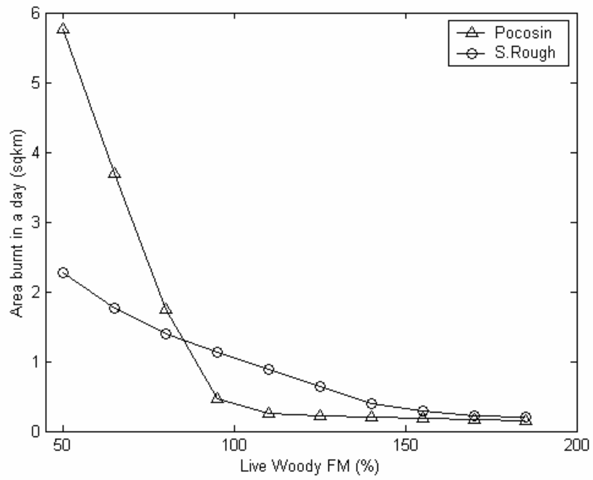


Fig 5. Effect of each live FMC on fire behavior while keeping all other factors at a fixed nominal value (Table 5). Top: Live herbaceous FMC; Bottom: Live Woody FMC

sensitivities, we fit our input FMC and output burnt area pairs to straight lines. The R^2 values give an estimate of the goodness of fit which are all quite high. The slopes of the linear fit serve as a measure of the sensitivity of wildfire behavior to the concerned live FMC factor. Table 9 shows the R^2 values and the slopes for the linear fits for the two fuel model cases. The values under the slope column give us the error in estimating the burn area in m^2 induced by a single ignition point over 24 hours for an error of 1% in estimating the corresponding FMC parameter. These error estimates are under dry, no-wind, no slope conditions.

As expected fire behavior has a negative relationship to live FMC, with burnt areas decreasing with increase in live FMC. In southern rough fuels a 1% error in estimating live herbaceous fuel moisture may lead to an erroneous estimation of 4425.8 square meters for burnt areas over 24 hours. Pocosin fuels do not show any such error due to the absence of any fuel loading of the live herbaceous type. Live woody FMC shows an interesting relationship with fire behavior in pocosin fuels. Fire behavior remains very sensitive to live woody FMC in pocosin in the low FMC range below 95% where a 1% error in estimating live woody FMC translates to an error of around 118983 m^2 in burn area estimation. This error significantly reduces to only 1436.2 m^2 above 95% FMC. For southern rough the sensitivities remain relatively stable over the whole live woody FMC range with errors of 15118 m^2 for every 1% error in live woody FMC estimation. Overall fire behavior seems to be more sensitive to live woody FMC than live herbaceous FMC.

In the light of these sensitivity results and our previous estimates of mean and maximum errors of estimating live FMC from space we could compute the errors in fire area estimations over a day under the simulated dry, no-wind, no-slope conditions. A mean error of about 14 or a maximum error of about 35 in estimating live herbaceous FMC over southern rough fuels could translate to an error of about 0.06 km^2 and 0.15 km^2 respectively in predicting the burn area over a period of 24 hours. For woody fuels the mean and maximum errors are about 9 and 25 implying that the corresponding errors in burn area estimations over southern rough can be about 0.14 km^2 and 0.38 km^2 respectively. For pocosin fuels, a mean error of 9 and a maximum error of 25 in estimating live woody FMC when the actual woody FMC is below 95% would propagate to an error of 1.07 km^2 and 2.97 km^2 in predicting the next 24 hour burn area. When the actual live woody FMC is above 95% in pocosin, the corresponding mean and maximum errors in burn area estimations are much less at 0.01 km^2 and 0.04km^2 respectively. The USDA forest service designates a particular day as a "large fire day" on which a fire of final size over 10 acres (≈0.04 km^2) (Andrews and Bradshaw, 1995) is discovered. The error estimates of burn areas even in the average case are well above this "large fire" consideration implying that errors in current estimation techniques may result in a fire management problem. As such current techniques needs to be further improved by including either more bands or more variables (eg surface type, LAI) into the estimation model.

TABLE 8
ERROR ESTIMATES

Estimation methods	Adel, Byromville, Dallas, Metter		Athens, Camilla, Dawsonville, Sterling	
	Mean absolute error	Maximum absolute error	Mean absolute error	Maximum absolute error
Live Woody FMC using NDVI/LST	5.16	11.62	8.6	21.66
Live Woody FMC using $NDWI_7$	5.42	12.81	8.38	24.55
Live Herbaceous FMC using NDVI/LST	8.36	24.07	13.74	29.80
Live Herbaceous FMC using $NDWI_7$	9.13	24.89	13.80	32.26

TABLE 9
SENSITIVITY ANALAYSIS

Fuel Moisture Content (%) p	High Pocosin (Fuel Model O)			Southern Rough (Fuel Model D)		
	Range	R^2	Slope $\Delta A(m^2) / \Delta p$	Range	R^2	Slope $\Delta A(m^2) / \Delta p$
Live herbaceous FMC	50-235	1.0	0	50-235	0.99	-4425.8
Live Woody FMC	50-95	0.99	-118983	50-185	0.93	-15118
	95-185	0.97	-1436.2			

V. CONCLUSION

We have estimated the potential errors in remote sensing based live FMC estimations and analysed the implications of such errors in fire behavior predictions. The study also gives a basis for the accuracy requirements of present and future remote sensing techniques to estimate live FMC. The study was focused on the Georgia region of south-eastern USA and sensitivity of fire behavior to live FMC was investigated in the Okefenokee National Wildlife Refuge area under dry, no-wind, no-slope conditions. The results show that as far as wildfire behavior estimation in Okefenokee is concerned remote sensing retrievals of live woody FMC should be more accurate in the lower FMC range below 95%. Under the simulated dry, no-wind and no-slope conditions errors in burn area predictions range from 0.06 to 0.15 km^2 for the mean and maximum estimated errors of 14 and 35 in measuring live herbaceous FMC. Errors in burn area predictions could range from 0.01 to 2.97 km^2 for the mean and maximum estimated errors of 9 and 25 in measuring live woody FMC. These error estimates are obviously best case estimates since the empirical regression models are used in the same season, same year and same region from which the models were constructed. Overall the study suggests that remote sensing techniques should be further improved. The results of this analysis apply to the Okefenokee region where pocosin and southern rough fuels are predominant. However they can serve as approximate results for other fuel models as well. Fire behavior prediction has typically utilized the 13 fuel models tabulated in Rothermel, 1972 and Albini, 1976. Anderson, 1982 developed a similarity chart that allows mapping of NFDRS fuel models to the fire behavior fuel model of Rothermel. Based on this similarity chart, we can say that the fire behavior in high pocosin is similar to fire behavior in mature bush (fuel model B), while fire behavior in southern rough resembles that in Alaska black spruce (fuel model Q), intermediate brush (fuel model F), sagebrush (fuel model T) and Tundra (fuel model S). Owing to this similarity the present analysis can be assumed to apply to fuel moisture retrievals in regions where the above mentioned fuel model types are present.

REFERENCES

Albini F.A. (1976) Estimating wildfire behavior and effects, general Technical Report, INT-30, USDA Forest Service.

Anderson H.E. (1982), Aids to determining fuel models for estimating fire behavior, General Technical Report, INT 122, USDA Forest Service, Intermountain Forest and Range Experiment Station Ogden, UT.

Andrews P.L. and Bradshaw L.S., (1995) Fire Danger Rating and the Go/No-Go Decision for Prescribed Natural Fire, NFDRS Reference CD published by Fire Sciences Lab, USDA Forest Service, Missoula MT.

Bowyer P. and Danson F.M., 2004 Sensitivity of spectral reflectance to variation in live fuel moisture content at leaf and canopy level, Remote Sensing of environment 92, 297-308

Bradshaw L.S., Deeming J.E., Burgan R.E., Cohen J.D. (1984) The 1978 National Fire-Danger Rating System: Technical Documentation, General Technical Report INT-169, USDA Forest Service, Intermountain Forest and Range Experiment Station, Ogden, UT.

Burgan, R..E.., (1979) Estimating live fuel moisture for the 1978 National fire danger rating system, Research Paper INT-226, USDA Forest Service, Intermountain Forest and Range Experiment Station, Ogden, UT

Burgan, R.E. and Rothermel, R.C. (1984). BEHAVE: Fire behavior prediction and fuel modeling system – FUEL subsystem, General Technical Report INT-167. USDA Forest Service, Intermountain Forest and Range Experiment Station.

Burgan, R.E., Hartford R.A. (1997) Live vegetation moisture calculated from NDVI and used in fire danger rating. 13th Conf. on Fire and For. Met., Lorne, Australia, Oct. 27-31, 1997. Jason Greenlee, ed. IAWF, Fairfield, WA 99012.

Ceccato, P., Gobron, N., Flasse, S., Pinty, B., & Tarantola, S. (2002) Designing a spectral index to estimate vegetation water content from remote sensing data: Part 1. Theoretical approach. Remote Sensing of Environment, 82, 188-197

Chuvieco, E., Deshayes, M., Stach, N., Cocero, D., & Riano, D. (1999) Short-term fire risk: foliage moisture content estimation from satellite data. Remote Sensing of Large Wildfires in the Eiropean Mediterrranean basin, E. Chuvieco (Ed). Berlin:Springer-Verlag.

Chuvieco, E., Riano, D, Aguado., I, Cocero, D. (2002) Estimation of fuel moisture content from multitemporal analysis of Landsat Thematic Mapper

Chuvieco, E., Aguado., I, Cocero, D., & Riano, D. (2003). Design of an empirical index to estimate fuel moisture content from NOAA-AVHRR images in forest fire danger studies. International Journal of Remote Sensing, 24(8), 1621-1637

Chuvieco E, Cocero D., Riano D., Martin P., Martinez-Vega J., de la Riva J., Fernando P. (2004) Combining NDVI and Surface Temperature for the estimation of live fuel moisture content in forest fire danger rating. Remote Sensing of Environment 92 322–331

Cohen , W.B.., Omi, P.N., and Kaufman, M.R. (1990). Heating related water transport to intact Lodgepole pine branches. Forest Science, 36, 246-254.

Cohen W.B. (1991), Temporal versus spatial variation in leaf reflectance under changing water stress conditions, International Journal of Remote Sensing, 12, 1865-1876

Finney M.A. (1998) FARSITE: Fire Area simulator – Model development and evaluation, Research Paper, RMRS-RP-4, USDA Forest Service, Rocky Mountain Research Station, Ogden, UT

Gao, B.C. (1996) NDWI- a normalized difference water index for remote sensing of vegetation liquid water from space. Remote Sensing of Environment, 58, 257-266

Hansen M.C., DeFries R.S., Townshend J.R.G., Carroll M., Dimiceli C., Sohlberg R.A., (2003) Global percent tree cover at a spatial resolution of 500 meters: first results of the MODIS vegetation continuous fields algorithm, Earth Interactions, Vol. 7, 10, 1–15.

Hunt, E.R., Rock, B.N., & Nobel, P.S. (1987). Measurement of leaf relative water content by infrared reflectance. Remote Sensing of environment, 22, 429-435

Jackson T.J., Chen D., Cosh M., Li F., Anderson M., Walthall C., Doriaswamy P. and Hunt E.R. (2004) Vegetation water content mapping using Landsat data derived normalized difference water index for corn and soybeans, remote Sensing of Environment 92, 475-482

Jacquemond S. and Ustin S.L. (2003) Application of radiative transfer models to moisture content estimation and burned land mapping, Proccedings of 4th International Workshop on Remote Sensing and GIS Applications to Forest Fire Management (E. Chuvieco, P.Martin and C. Justice eds), Ghent, Belgium, 5-7 June 2003, pp 3-12

Larcher W. (1995) Physiological plant ecology. Ecophysiology and stress physiology of functional groups. (3rd ed) p 528. New York:Springer

Montgomery D.C. Peck, E.A., Vining G.G., (2001),Introduction to linear regression analysis, 3rd ed, Wiley Series in Probability and statistics

Perry, G.L.W. (1998). Current approaches to modeling the spread of wildland fire: A review. Progress in Physical Geography, 22, 222-245.

Richards G.D. (1990). An elliptical growth model of forest fire fronts and its numerical simulation. International Journal of Numerical Methods Engineering, 30, 1163-1179

Richards, G.D. (1993). The properties of elliptical wildfire growth for time dependent fuel and meteorological conditions. Comb. Sci. Tech. 92:145-171.

Rothermel R.C. (1972) A mathematical model for predicting fire spread in wildland fuels, Research Paper, INT-115, USDA Forest Service, Intermountain Forest and Range Experiment Station, Ogden, UT.

Rothermel R.C., Wilson R.A.. Morris G.A., Sacket S.S. (1986) Modeling moisture content of fine dead wildland fuels :input to the BEHAVE fire prediction system. USDA Forest Service Research paper, INT-359

Running, S.W., Loveland, T.R., and Pierce, L.L., (1994) A vegetation classification logic based on remote sensing for use in global scale biogeochemical models, Ambio, 23, 77-81

Sanderlin, J.C. and Sunderson J.M. (1975). A simulation for wildland fire managment planning support (FIREMAN): Volume II. Prototype models for FIREMAN (PART II): Campaign Fire Evaluation. Mission Research Corp. Contract No. 231-343, Spec. 222. 249 pages.

Zarco-Tejada, P.L.J., & Ustin, S.L. (2001). Modeling canopy water content for carbon estimates from MODIS data at land EOS validation sites. International Geoscience and Remote Sensing Syposium, 2001. IGARSS '01, Vol. I, 342-344

Zarco-Tejada, P.LJ., Rueda C.A. and Ustin, S.L. (2003). Water content estimation in vegetation with MODIS reflectance data and model inversion methods, Remote Sensing of Environment, 85, 109-124

Swarvanu Dasgupta completed his bachelor's degree in Mathematics from the University of Calcutta, Calcutta, West Bengal, India in 1998 and graduated with a Master's degree in Computer Applications from Bengal Engineering College (Deeemed University), Howrah, West Bengal, India in 2001. Currently he is enrolled as a PhD student in the School of Computational Sciences, George Mason University with a major in Earth observing and Remote Sensing. He is working as a research assistant in the Center for Earth Observing and Space Research and his research area is the remote sensing of wildfire conditions.