Design of a Fire Susceptibility Index for fire risk monitoring

Swarvanu Dasgupta, John J. Qu, and Xianjun Hao

Abstract—**Wildfire risk assessment has traditionally been carried out using models based on meteorological parameters measured at spatially sparse weather stations. Remote sensing techniques can offer a cost effective way of esimating the required parameters such as fuel moisture and fuel temperature in near-real time. Moreover remote sensing can provide wide area coverage and thus circumvent errors introduced due to spatial interpolations of weather station data. In this paper we present a new remote sensing based Fire Susceptibility Index (FSI) based on the susceptibility of the underlying live fuel to burn. The proposed index is based on the concept of heat energy of pre-ignition and thus allows a physical meaning to be associated to the index values. Heat energy of pre-ignition is the heat energy required to bring a fuel from its current temperature to ignition temperature and can be estimated as the heat required in evaporating the moisture content plus the heat required to raise the temperature of the dry fuel to ignition temperature. The computation of the index requires inputs of fuel temperature and fuel moisture content, both of which can be estimated using remote sensing techniques. While MODIS surface temperature is used as a proxy for fuel temperature, fuel moisture is estimated by a linear regression technique utilizing the correlation between ground observations and the ratio of normalized difference vegetation index and surface temperature. Results are shown for the Georgia region during the spring and summer months of 2004.**

I. Introduction – The Role of Remote Sensing

WILDFIRE risk can be defined as the probability of fire initiation and is typically estimated through fire risk indices that integrates the effect of relevant fire favoring variables. Such estimations of fire risk are useful in orienting local policies not only in terms of fire prevention but also in the management of prescribed fires, the latter becoming increasingly important for controlling fuel buildup and revitalizing the landscape (Carlson and Burgan, 2003). Fire risk indices can be classified into long term indices and short term or dynamic indices (San-Miguel-Ayanz, 2003). Long term indices are based on variables such as topography or fuel type that change relatively little over a period of time. They are usually computed before the fire season and are meant to identify areas where intrinsic conditions may be more favorable to wildfires. In contrast short term indices are based on more transient variables like fuel moisture content (FMC) of live and dead fuels. The fire risk index proposed in this paper, namely the fire susceptibility index is a short term index based on live woody FMC and fuel temperature. Traditionally such short term fire risk estimations are accomplished through meteorological indices that attempt to model the fire risk using relevant weather variables such as FMC, temperature and humidity measured at spatially sparse weather stations. Apart from the uncertainty inherent in these meteorological indices, such models suffer from errors due to spatial interpolation techniques that may be unsuitable in areas of complex terrain (Camia et al 1999). Examples of meteorological fire danger indices are the Energy Release Component (ERC), the Spread Component (SC) and the Burning Index (BI). These indices are computed by the National Fire Danger Rating System (NFDRS) (Bradshaw et al, 1984) operated by the USDA Forest service using weather variables measured at weather stations located throughout the United States. Today, remote sensing offers a cost effective way for circumventing the spatial interpolation problem, with other obvious advantages of spatial and regular temporal coverage. Although remote sensing is until now not an alternative to weather stations since it cannot measure critical parameters such as dead fuel moisture and wind over land, it certainly can support and reinforce the ground based observations to a large extent. Remote sensing has the potential of measuring vegetation status, stress and moisture content; variables that are critical in estimating fire susceptibility or fire behavior. 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 and primarily use 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). 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

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the ratio NDVI/ST was found to be very useful (Chuvieco et al 1999, 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. Live FMC itself is good measure of fire risk. Several other remote sensing based fire risk indices have also been proposed and investigated in contemporary research. The Fire Potential Index (FPI) (Burgan 1998) combines AVHRR based RG measures with ground measurements of dead FMC to assess fire risk at a scale of 0 to 100. Others examples in current literature are the FIRA (Fire Risk Assessment Algorithm) index which assesses fire risk by combining Tasseled Cap derived measures of wetness and brightness using LandSat-ETM images (Mbow et al 2004).

In this paper we propose a new fire risk index, which we call the fire susceptibility index or FSI. We compute these indices for the spring and summer months of 2004 for the Georgia region of south-eastern USA using MODIS Aqua observations and subjectively evaluate the results.

II. FIRE SUSCEPTIBILITY INDEX

Remote sensing based fire risk indices generally have no physical meaning and are basically measures of vegetation dryness. The proposed fire susceptibility index is a step in that direction and is based on a physical measure of heat energy required for the fuel to ignite. Heat energy of pre-ignition (Q_{ig}, J/kg) as it is called, can be defined as the heat energy required to bring a fuel from its current temperature to ignition temperature and can be estimated as the heat required to raise the temperature of moisture contained to the boiling point (373K under standard atmospheric pressure) plus the latent heat required in evaporating the moisture content plus the heat required to raise the temperature of the dry fuel to ignition temperature (Bradshaw et al 1984). Heat energy of pre-ignition is an important parameter of Rothermel's fire spread rate model (Rothermel, 1972) and can be expressed as

$$Q_{ig} = C_{pd}\,(T_{ig} - T_f) + [C_{pw}\,(373\text{-}T_f) + V] \text{ KJ/kg} \qquad (1)$$

where C_{pd} and C_{pw} are the specific heat of dry wood ($\approx$1.7KJkg^{-1}K^{-1}) and water ($\approx$ 4.187KJkg^{-1}K^{-1}) respectively, while T_{ig} and T_f are the ignition temperature of wood (assumed to be $\approx$ 600K after Rothermel, 1972) and the fuel temperature respectively. M_f is the fractional moisture content (=FMC/100) and V is the latent heat of vaporization of water ($\approx$2258KJkg^{-1}). If we substitute the values of the various constants, we are left with two variables FMC and fuel temperature both of which can be potentially measured by remote sensing. We believe Q_{ig} can serve as a measure of fire risk. With the objective of defining a unitless index we fix a FMC, fuel temperature pair that can describe an average fire risk condition. We arbitrarily set the average fire risk FMC at 120% and fuel temperature at 300K. Substituting these average risk FMC and fuel temperature value in (1) we get an average risk pre-ignition energy, Q_{igavg}. The fire susceptibility index (FSI) is then defined as

$$FSI=(Q_{igavg} - Q_{ig}) / Q_{igavg} * 100 \qquad (2)$$

FSI thus turns out to be an open ended index that measures the percentage less energy required for ignition than in the average case. For example a pixel FSI value of 80 would imply that woody material in that pixel would require 80% less heat energy than a pixel with woody material that has a FMC of 120% and a fuel temperature of 300K. Positive values would indicate a fire risk higher than the defined average risk while negative values would indicate otherwise. In fig 1 we show the sensitivity of FSI to FMC with the fuel temperature fixed at 300K. It shows that at 300K FSI can drop from 40 to -40 for an increase of FMC from 60% to 180%. Fig 1 also shows the variation of FSI with fuel temperature with FMC fixed at 120%. At this FMC an increase of fuel temperature

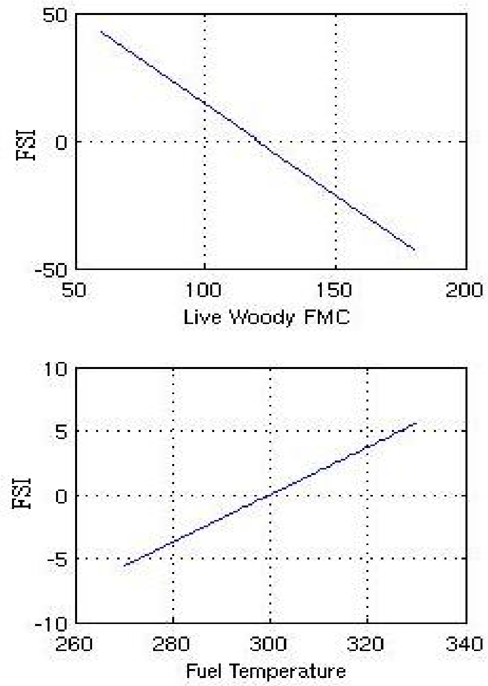

Fig. 1. Sensitivity of FSI to Live Woody FMC and Fuel Temperature

from 270K to 330K results in an increase of FSI from about -6 to about 6. Thus the contribution of FMC to FSI is relatively higher than fuel temperature.

FSI can be localized to a vegetation type by setting the average risk FMC and fuel temperature to appropriate values. This baseline FMC can also be set as the live FMC of extinction for the vegetation type. Live fuels can act as a heat sink or a heat source depending on whether its moisture content is above or below this extinction moisture content. If the moisture content remains above this critical value, live fuels do not burn and act as a heat sink (Bradshaw et al 1984). This implies that if we use this extinction moisture content as the baseline FMC for computing FSI, locations with negative values of FSI would have negligible fire risk. Further the physical theory underlying the concept of FSI lends itself to computations of probability of ignition. The 1978 NFDRS technical documentation (Bradshaw et al 1984) defines the probability of ignition P(I) by a firebrand as the probability that the firebrand will start a fire after landing on receptive fuels. This probability of ignition of a fuel with a certain Q_{ig} was proposed to be a product of the probability that a firebrand of specific size will cause an ignition of the fuel and the probability that the firebrand will be of that size. Moreover previous investigations of ignition probability caused by lightning (Fuquay et al 1979, Latham & Schlieter 1989) also used an energy argument in which the available energy density in the lightning continuing current was compared to the fuel's heat of pre-ignition. In this perspective FSI could be potentially prove to be useful in computing these probabilities of ignition either by fire-bands or by lightning. Obviously the feasibility of this claim needs to be further investigated.

A particular limitation of FSI is that it does not take moisture content of dead fuel into consideration. Dead fuel moisture content is an important factor in fire ignition and spread. Unfortunately remote sensing cannot suitably measure dead fuel moisture content since in forested areas optical signals from dead fuel on the forest floor may not penetrate the canopy. However interpolated values of dead fuel moisture measured at weather stations can be used to calculate a FSI for dead fuel. The FSI of live fuel (FSI_L) and dead fuel (FSI_D) can then be linearly combined with proper weighting to compute a reinforced combined FSI. Relative greenness (RG), a measure of fractional vegetation cover of the pixel can be used for this weighting

$$FSI = RG.FSI_L + (1\text{-}RG).FSI_D \qquad (3)$$

Here (1-RG) serves as a measure of the fractional amount of dead fuel. In this paper, however we only restrict ourselves to the computation of FSI for live fuels.

III. FSI RETRIEVALS IN GEORGIA

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. 2).

FSI retrievals in our study region would require us to retrieve fuel temperature and live FMC. 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. This analysis allows us to construct a simple linear regression equation relating NDVI/ST to live FMC values. Studies have related foliage moisture content with NDVI/ST, since the relation between leaf (bearing chlorophyll) moisture content and NDVI is more obvious. 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 NDVI/ST.

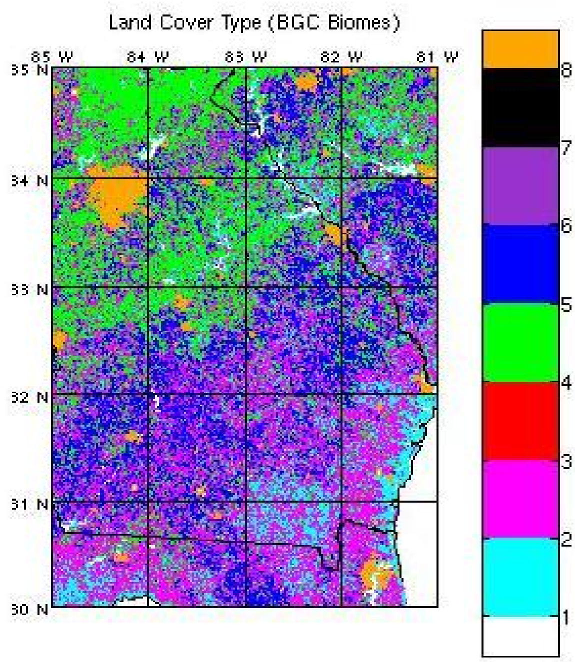

Fig. 2. Study Region in Georgia, USA showing the BGC biome surface types (1-Evergreen Needleleaf Vegetation; 2- Evergreen Broadleaf Vegetation; 3-Deciduous Needleleaf vegetation; 4- Deciduous Broadleaf vegetation; 5-Annual Broadleaf vegetation; 6-Annual Grass Vegetation; 7-Non-vegetated land; 8-Urban)

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. The top of atmosphere reflectances at band 1($\rho_{0.65}$), band 2($\rho_{0.86}$) from the L1B swath products, were then corrected for sensor zenith angle using sensor zenith angle values from the MYD03 datasets. These corrected reflectances were then combined as ($\rho_{0.86}$-$\rho_{0.65}$)/($\rho_{0.86}$-$\rho_{0.65}$) to derive NDVI images. Surface 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 (Chuvieco et al 1999, 2003, 2004).

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

Four Georgia Forestry commission stations were selected so that together they may represent all the surface types relevant to the forested regions in Georgia. The names, locations, and the surface types in the 3x3 pixels surrounding the station location are given in Table 2. Fig 2 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 ground measurements were taken at 1.30pm (EST) at around the same time of Aqua overpass (1pm local time).

NDVI/ST 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 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. Fig 3 shows the scatter plot of the NDVI/ST and live woody FMC values. The equations were derived from 20 pairs which survived the scan angle restriction ($<30^0$). The Pearson determination coefficient R^2 is 0.54 with significance value of 0.0002. The regressed least square equation derived is FMC_{woody}=33760x(NDVI/ST)+49 with a standard error of 6.6. Given the host of biophysical to geometrical factors that serve to confound the relationship between NDVI/ST and live woody FMC, the R^2 value are quite consistent with expected results. 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.

Using the regression equation derived above we compute the live woody FMC images for the 10 selected days. The live

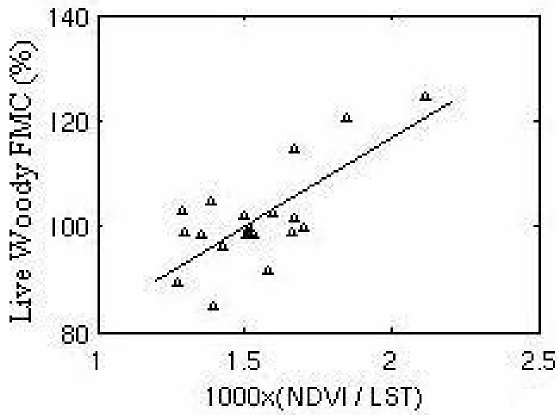

Fig. 3. Scatter plot of MODIS derived NDVI/ST versus ground station observed live woody FMC. The least square line is also shown

Woody FMC retrieval algorithm works fairly well in forested regions, but in urban areas it fails. A low NDVI in urban areas is estimated as low FMC by the NDVI/ST index, when however the low NDVI is caused by a lower fractional vegetation cover. To address this issue we have masked the urban areas in FMC images using the BGC biome surface types. We also build the fuel temperature images which is actually MODIS surface temperature. Corresponding images of live woody FMC and fuel temperature are then combined using the FSI equation to retrieve FSI images. Fig 4 shows the Fuel Temperature, Live Woody FMC and FSI images for three days in 2004 (March 22,April 17,May 4). Urban areas have been masked out. March 22nd represents early spring and it is the start of the growth season. April 17th is in the middle of spring, while May 5th is summer time. FSI captures the fire risk during this time quite well. During the beginning of the growth season, fire risk is higher on the average; it decreases during the middle of spring when vegetation is gaining moisture until during summer vegetation is fully grown reducing the fire risk further.

Validation of the FSI was not undertaken since the primary objective of this short paper was to introduce the index. Moreover validation of fire risk indices is generally not straightforward. One way to validate is to verify if the probability distributions of FSI for actual fire locations are significantly different from the probability distributions of the non-fire pixels. Even so the relation between fire occurrence and fire risk is not simple, since fire only occurs when an ignition cause is present even if the FMC is high and fire risk is low (Chuvieco et al 1999). However, validating FSI remains a future task for us.

IV. Conclusion

We have introduced a new short term fire risk index called the fire susceptibility index (FSI). The concept of FSI is rooted in the idea of heat energy of preignition or the heat required to ignite woody fuel. This physical basis endows FSI with the potential of estimating probability of ignition from firebrands or lightning; although this needs to be investigated further. No validation efforts were undertaken in this short paper. We feel that since FSI originates from a physical concept, the estimation of fire risk using FSI is quite reasonable although validation efforts to justify FSI would definitely need to be pursued in the future. Robust techniques estimating FMC and fuel temperature more accurately would

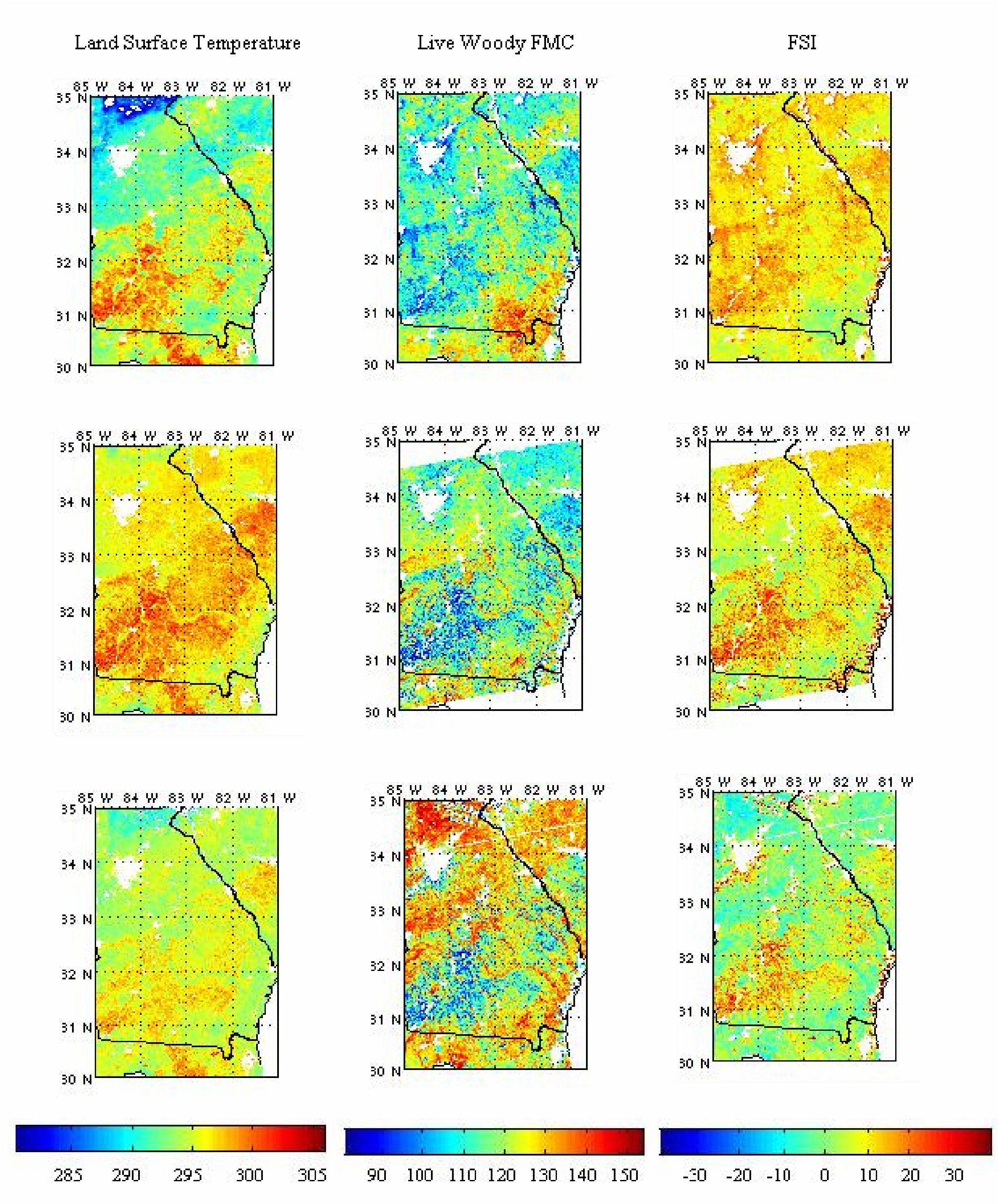

Fig. 4. Surface temperature, live woody FMC and FSI images for three days in 2004; first row : March 23 2004, second row: April 17 2004; third row: May 5 2004. first column represents ST, second column shows live woody FMC and third column shows FSI

obviously reinforce the validity of the FSI. FSI could be computed at a daily scale from MODIS direct broadcast level 1B products or as 16 day products derived from MODIS 16 day NDVI composites and MODIS 8 day LST products and hence can be beneficial to the forest community in better management of wildfires or prescribed fires.

V. REFERENCES

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., 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.

Burgan R.E., Klaver R.W., & Klaver J.M. (1998) Fuel Models and Fire Potential from Satellite and Surface Observations. International Journal. Wildland Fire 8 (3): 159-170

Camia, A., Bovio G., Aguado I., and Stach N. (1999) Meteorological fire danger indices and remote sensing, Remote sensing of large wildfires in the European Mediterranean Basin, E Chuivieco (Ed), Springer, 39-59

Carlson J.D. and Burgan J.D., (2003), Review of user’s need for estimation: the Oklahama example, International journal of remote sensing, vol 24, no 8, 1601-1620

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 reflectance data: applications in fire danger assessment, International Journal of Remote Sensing, 23,No 11, 2145-2162

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

Fuquay D.M., Baughman R.G., Latham D.J., (1979) A model for predicting lightning-fire ignition in wildland fuels. Research paper. INT 217. Ogden UT:USDA Forest Service, Intermountain Forest and Range Experiment Station 21p

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

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

Latham D.J., Schlieter J.A., (1989). Ignition probabilities of wildland fuels based on simulated lighting discharges. Research paper INT 411, Ogden UT:USDA Forest Service, Intermountain Forest and Range Experiment Station 16p

Mbow C., Kalifa G., Benie, G.B., (2004) Spectral Indices and fire behavior simulation for fire risk assessment in savanna ecosystems, Remote Sensing of Environment 91, 1-13

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.

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

San-Miguel-Ayanz J., Carlson J. D., Alexander M., Tolhurst K., Morgan G., Sneeuwjagt R., Dudley M., (2003) Current Methods to Assess Fire Danger Potential Wildland Fire Danger Estimation and Mapping - The Role of Remote Sensing Data" by E. Chuvieco (editor). World Scientific Publishing Co. Pvt. Ltd., Singapore. Series in Remote Sensing Volume 4. 21-61

Zarco-Tejada, P.LJ., & 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

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