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Estimation of fuel moisture content towards Fire Risk Assessment: A review

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ABSTRACT: Recent studies have demonstrated that surface wetness can be inferred when thermal infrared measurements are coupled with a spectral vegetation index (VI) that is linearly related to percentage vegetation cover. Even though it has later been shown that a proper interpretation of this relationship requires additional information of soil evaporation and the fractional vegetation cover, the 'temperature-vegetation' index has been proven useful for assessment of surface environmental conditions such as, for example, water content and drought/ fire risk. One of the methodologies shows that the slope of the relationship between surface temperature and the Normalized Difference Vegetation Index (NDVI) is strongly correlated to surface moisture status. Methodologies applied on low-resolution sensors offer a higher temporal resolution compared to high spatial resolution sensors and due to this are more likely to be used operationally for fire risk assessment. The goal of this paper is to present an assessment of the as yet developed or proposed fire risk assessment methodologies dependent upon remote sensing and climatologic data. Methodologies are cross-referenced and their applicability under a range of environmental conditions (land cover, climatology, topography, etc.) is analyzed, resulting in an indication on what the immediate future will hold with respect to fire prediction modelling. It will moreover be shown that an optimized integration of fire weather forecast data, lightning prediction information, and fire risk indices can result in a robust fire prediction model.

1 INTRODUCTION

The world's forest ecosystems are in a state of permanent flux at a variety of spatial and temporal scales. Monitoring techniques based on multi-spectral satellite acquired data have demonstrated potential as a means to detect, identify, and map fire danger in vegetation. Fire danger estimation demands frequent monitoring of vegetation stress. Vegetation moisture is particularly difficult parameter to estimate as it accounts for little spectral variation with respect to other environmental factors (Cohen 1991). Among the fire behavior factors affected by fuel moisture are the preheating and ignition of unburned fuels, rate of fire spread (or fire growth), rate of energy release, and production of smoke by burning and smoldering fuel. High moisture content increases the heat required to ignite a fuel, since some of this energy is used to evaporate water (Chuvieco et al. 2002). Additionally, high values of fuel moisture imply a slow propagation, because part of the heat released by the fire front is used to absorb water from adjacent fuels, and since the air has more water vapor, less oxygen will be available for combustion. Some authors observed a 50% reduction in heat output of burning matter when moisture content increases from 100% to 200% of dry matter. Additionally, moisture content has also been directly related to the energy required to ignite a fuel, and its role is critical for converting a surface fire into a crown fire (Chuvieco et al. 2002). The heat demand can be estimated by Eq.(1). (Wilson 1990)

$$Q_t = Q_f + MQ_M \tag{1}$$

The heat required for the onset and completion of volatilization of the fuel is called the heat of ignition Q_t (kJ kg^{-1}). Q_f (kJ kg^{-1}) is the heat required to raise unit mass of dry fuel from ambient temperature to 400°C, Q_M (kJ kg^{-1}) is the energy to heat unit mass of water to 100°C and to vaporize it, and M is the fractional moisture content (a fuel particle or layer average expressed on an oven dry weight basis). Thus, an increase in M increases the amount of heat required to raise the temperature of unit mass of fuel and increases the preheating time (Johnson et al. 2001).

If we are to improve our understanding of these and other aspects of fire behavior, we must be able to quantify fuel moisture content (FMC) within reasonable bounds. Several measures of FMC have been proposed (Desbois et al. 1997), the most common being the ratio of water to dry weight:

$$FMC = \left(\frac{W_w - W_d}{W_d} \right) \times 100 \tag{2}$$

where W_w is wet weight and W_d is dry weight of the same sample. Other measurements of plant water content (such as Relative Water Content, RWC, that is a function of actual versus potential maximum moisture content) are more common than FMC in plant physiology.

For estimating FMC several methods have been proposed for fire danger applications. The most common are fieldwork (Desbois et al. 1997), the use of calibrated sticks and the computation of meteorological indices (Viegas et al. 2000). None of them are completely satisfactory (Chuvieco et al. 2002). The use of remote sensing methods may overcome some of these difficulties, since they provide temporal and spatial coverage without costly and intense fieldwork, omitting interpolation methods and the data is directly linked to vegetation dynamic processes. The main challenge in this case is to demonstrate that the effect of moisture content on plant reflectance and temperature is clearly distinguishable from other factors of spectral variation, such as leaf area index, soil background, canopy geometry, and atmospheric effects (Chuvieco et al. 2002). The most sensible variable for FMC estimation is based on short-wave infrared bands, and the combination of vegetation indices and surface temperature (Illera et al. 1996).

2 METHODOLOGIES

Methods of FMC estimation that combine optical and thermal remote sensing are the subject of the current review. Several laboratory and field analyses have been conducted in the last years to improve our knowledge on the effects of water content on vegetation reflectance and temperature, which is the basis for applying remote sensing methods to FMC estimation. Before going into detail on methods, which combine optical and thermal satellite data, an overview of research done in each domain is presented.

2.1 *Optical remote sensing*

Investigations focused on optical bands have tried to estimate water content from variations in leaf reflectance, either from raw spectral data or from synthetic indices (band ratios, tasseled cap transformation). Cohen (1991) stated that water stress effects manifest themselves in such ways as a change in leaf area and architecture, both of which may affect the canopy spectral response in significant ways. As a result, the use of vegetation indices (VI) to predict water stress in leaves appears limited.

Several VI can be used as such, for example the adjusted NDVI, which has the advantage that its value for dry vegetation (or no vegetation) is zero and that it maximizes the contrast in " greenness" for purposes of analysis (Paltridge et al. 1988, Cohen 1991, Chuvieco et al. 1994).

$$VI = B_2 - 1.2B_1 / B_2 + B_1 \tag{3}$$

Here B_1 & B_2 are the near infrared and respectively Red bands. From the VI value, fuel moisture content is estimated according to the following formula:

$$FMC = 250VI(t)/VI(x) \tag{4}$$

Where FMC is the fuel moisture content, VI(t) is the vegetation index at any specific time, and VI(x) is the same measure on a the image of the month with maximum vegetation vigor.

2.2 *Thermal remote sensing*

Thermal studies have related leaf water content to evapotranspiration (ET) rates, which can be detected by the cooling effect produced by the latent heat loss using an energy balance (Nemani and Running 1989, Moran et al. 1994). The techniques involve a combination of atmospheric corrections, energy resistance models, and detailed spatial information of major surface and climate variables. Operational applications of these techniques, however, are often limited due to the inherent complexity of the procedures (Yang 1997). When the plant dries, transpiration is reduced and, consequently, so does latent heat, whereas sensible heat increases simultaneously (Kozlowski et al. 1991). As a result of this relation, the difference between air and surface temperature should be clearly related to plant water content and to water stress.

Current satellite sensors usually contain one or two channels in the thermal region (8 to 12μm), and the emitted radiation provides a basis for calculating a radiometric surface temperature (T_s) (Price, 1989). This method which is called the split-window approach, analyzes the variable response of two thermal channels (Tb_4, Tb_5), one sensitive to water vapor and one not, by empirically assuming the surface emissivity to be 0.96. The empirical approach is designed to reduce atmospheric water vapor attenuation in the thermal infrared radiance (TIR) region, such that (Price 1984):

$$T_s = Tb_4 + 3.3(Tb_4 + Tb_5) \tag{5}$$

Norman et al. (1995) reviewed a variety of methods for computing surface temperatures with satellite thermal-infrared data. Using satellite data to estimate surface humidity is problematic because water vapor in the atmospheric profile is a major cause of attenuated reflectances. One possible approach is to compute a surface temperature during the night overpass of a polar orbiting satellite (12hr opposite the daytime pass) and apply the T_{min} versus T_{dew} relationship (Waring et al. 1998). However, image navigation of nighttime scenes is difficult, so only approximate locations are possible.

Studies by Tucker (1980) among others have shown that direct remote sensing of leaf water content may be possible at wavelengths between 1.55 and 1.75μm (a band not yet incorporated in the AVHRR instrument, but included in the ESA ATSR-2 instrument).

Thermal Inertia Method

Current method is explained aiming on combining it with remotely sensed vegetation indices such that it can be used in operational fire risk assessment models for the frequent estimation of FMC. The daily rise and fall of temperatures is investigated by the thermal inertia method using night and day remote sensing images (e.g. from the AVHRR sensor). Similar with the concept of "inertia" in mechanics, an index, thermal inertia (TI), is introduced to describe soil moisture. Under the condition of high moisture, soil thermal inertia is high, so the variation of soil temperature is small. On the other hand, if soil moisture is low, which means that thermal inertia is low too, soil temperature may change violently when compared under the same thermal condition. (Norman 1995, Qianguang 1997).

$$\frac{\partial T}{\partial t} = k\frac{\partial^2 T}{\partial z^2} \tag{6}$$

The method to monitor bare soil moisture by thermal infrared remote sensing is based on the following thermal conduction equation. Where k= λ/ Cap, λ is thermal conductivity, Cap is thermal capacity, T is soil temperature, t is time and Z is soil depth. The boundary condition for the daily rise and fall of temperatures is:

$$T_0(t) = T + T_0 Sin(\omega t) \tag{7}$$

T is mean daily soil temperature and T_0 is daily range of soil temperature, which can be retrieved from thermal infrared channel.

$$TI = \frac{c(1-A)}{T_{day} - T_{night}} \tag{8}$$

Here c is an experimental coefficient, related to soil type, and A is the albedo of land surface calculated as A=0.526Ch1+0.47Ch2+d. Ch1, Ch2 are the first and second channel albedo of NOAA/AVHRR and d is a constant. Using Eq. 9 instead of TI, soil moisture (Y) is a function of the estimated thermal inertia (TIest(X)). The function can be established by a regression method as Y=F (X).

$$TIp = \frac{T_{day} - T_{night}}{(1-A)} \tag{9}$$

This method has two limitations: Firstly, it is only efficient in the area with less vegetation cover, because vegetation cover reduces the temperature difference between day and night, the relationship between thermal inertia and soil moisture is not so close. Secondly, to detect the soil moisture situation in a certain place and a certain time, the temperature difference derived from AVHRR/ Ch4 is needed. As a consequence, it's not easy to get cloud-free AVHRR images both in day and night on the same day if the area is quite large, so this method cannot be used in real-time monitoring. The advantages are that this method tends to reduce errors from differences between radiative and aerodynamic temperatures because it depends on the difference between two radiative temperatures (Norman 1995). Most likely, thermal inertia and moisture availability are empirical parameters that provide a reasonable solution to the surface energy budget.

The combination of day and night coarse resolution imagery using the thermal inertia method can close a part of the gap towards a solid FMC estimation method. Several sensors can be used and each has his advantage. As such, long-term time series (15 years) of the AVHRR sensor exist, combined with the advanced exploration of data and developed methods for extracting information. Currently the new AATSR sensor is launched, which has a dual look feature leading to a superior atmospheric correction module and an extra water sensitive band (Table 1:1b)

Table 1. ATSR-2 and AVHRR Channels

ATSR-2/AATSR		AVHRR	
Band	Range (µm)	Band	Range (µm)
V1	0.545-0.565		
V2	0.649-0.669	1	0.5-0.68
V3	0.855-0.875	2	0.725-1.1
1b	1.58-1.64		
1a	3.55-3.93	3	3.55-3.93
2	10.4-11.3	4	10.3-11.3
3	11.5-12.5	5	11.5-12.5

2.3 *Combining thermal and optical remote sensing*

2.3.1 *Single ratio of NDVI and T_s and surface resistance computation*

When NDVI and surface temperature are plotted together in a two-dimensional graph, a predictable pattern emerges. After screening out pixels of clouds and snow, we see that forest have the coolest temperatures, and bare surface the warmest. (Fig.1)

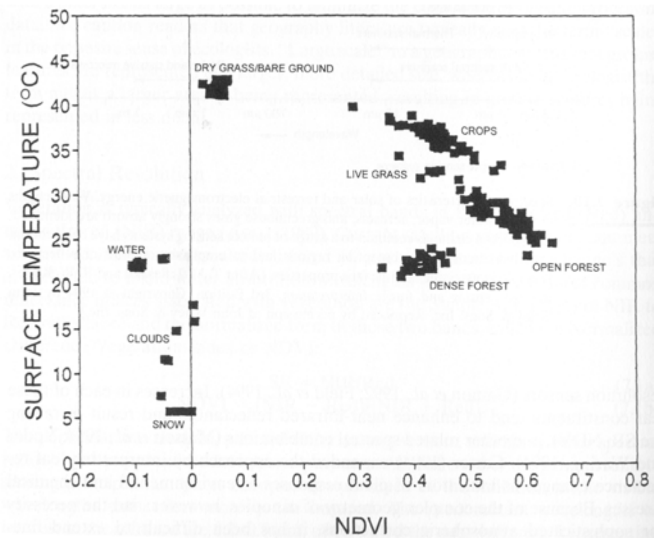

Figure 1. Variation in radiometric surface temperature observed by AVHRR for 14 July 1987, 1430hr local time, for a complex 106,000-km^2 region with farmland, range land, and forestland in Montana (Nemani et al. 1989 and Nemani et al. 1993). The 40°C range in surface temperatures observed across the region result from varying albedo and energy partitioning to latent or sensible heat. Original graph by Nemani et al. 1989.

If this analysis is repeated through the growing season, a trend emerges. In the spring, the ground is wet, so bare soil surface temperatures are relatively low and differ little from forest temperatures. As summer progresses and the landscape dries out, bare soil and dry grasses heat up faster than forests, and so the trend line between T_s and NDVI becomes steeper (Fig.2). Nemani and Running (1989) related the change in T_s versus NDVI with a simulated canopy resistance to evapotranspiration. They call it surface resistance, because it operates as a landscape-level measure of canopy resistance as well as that associated with evaporation from the ground (Waring 1998).

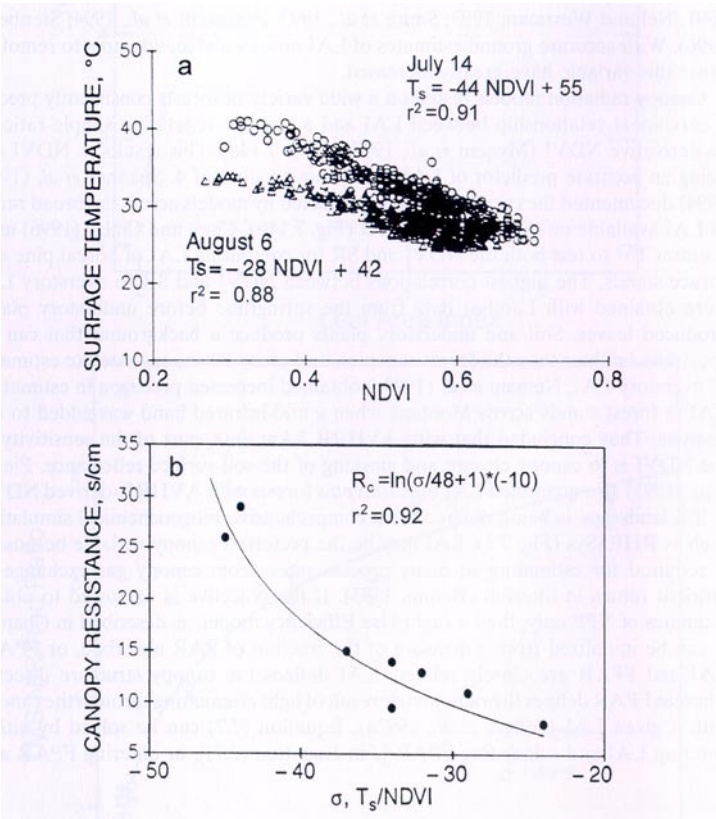

Figure 2. (a) As the land surface dries, exchange of latent energy declines, and the slope of the scatter of points in Fig.1 become steeper as sensible heat exchange and surface temperatures (T_s) increase. (b)This change in the T_s/NDVI scattergram was expressed as a regional surface resistance to evapotranspiration by Nemani and Running (1989). The change in slope of T_s/NDVI computed for 8 clear days during the summer of 1987 was closely related to canopy resistance. Graph free after Nemani et al. 1989.

A substantial change in the slope of T_s/NDVI relation between wet and dry days was observed over forests for a 50-pixel × 50-pixel target area. However, vegetation type and topography are important in determining the size of the target-area grid size. Grasslands, because of their general lack of topographic and ecological variability relative to forests, require a larger grid size to adequately define a slope of the T_s/NDVI relationship.

The satellite-derived surface resistance calculated by Nemani and Running (1989) and Nemani et al. (1993) can be translated into a fire danger index that provides an automated and spatially continuous mapping of the danger of fire ignition, integrating both the surface meteorology and the vegetation energy partitioning condition related to stress and fuel flammability. Vidal et al. (1994) applied a derivation of the algorithm used to evaluate fire ignitions during the summers of 1990 and 1991 (where 537,000 ha burned in the Mediterranean region). The satellite-derived fire risk corresponded with the dates of observed fire ignitions in two study areas of southern France.

2.3.2 *Water Deficit Index (Vidal et al. 1994 derived by Moran et al. 1994)*

A concept termed the Vegetation Index/Temperature (VIT) trapezoid was proposed by Moran et al. 1994 which combines vegetation indices with composite surface temperature measurements to allow application of Crop Water Stress Index (CWSI) (Jackson et al. 1981) and Water Deficit index (WDI).

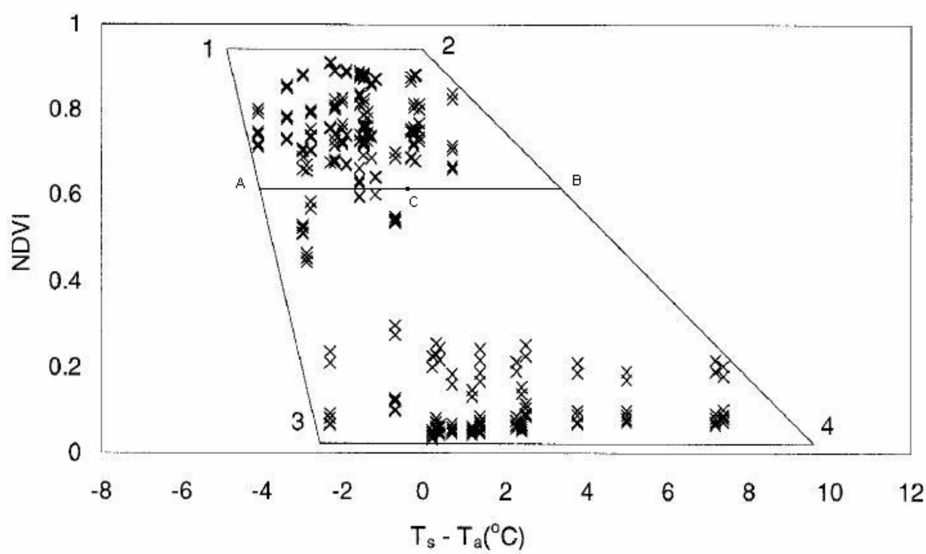

Figure 3. The trapezoidal shape from the relation between (T_s-T_a) and NDVI constructed using field measurements of (T_s-T_a) and NDVI. Graph free after Yang 1997.

The soil moisture availability index (Ma) is defined as (Moran et al. 1994, Yang 1997):

$$Ma = 1 - WDI = \frac{(T_s - T_a)_{\max} - (T_s - T_a)_r}{(T_s - T_a)_{\max} - (T_s - T_a)_{\min}} = \frac{\lambda E_t}{\lambda E_p} \qquad (10)$$

where WDI is the water deficit index, λE_t is the surface ET rate (mmh^{-1}), λE_p is the potential surface ET rate (mmh^{-1}), T_s is the surface temperature, T_a is the air temperature and the subscript *r* refers to the measured value. Measurements of $(T_s\text{-}T_a)_r$ and NDVI for a specific field should fall within the trapezoid (e.g., point C Fig. 3) and the ratio between lengths of CB and AB is equal to the ratio of actual and potential ET rates ($\lambda E_t/\lambda E_p$).

The VIT concept has confirmed to have potential for evaluating field water availability and relative ET rate for Landsat TM images. The VIT trapezoid and WDI have potential for evaluating evapotranspiration rate and relative field water deficit for both full-cover and partially vegetated sites (Yang et al. 1997). This represents an advantage over CWSI which was limited in application to full-cover vegetation. Like CWSI, the WDI requires few input parameters in addition to remotely sensed data, and most input values are either known or can be adequately estimated. Furthermore the technology exists to provide simultaneous measurements of composite surface temperature and spectral reflectance at local and regional scales with ground-, aircraft-, and satellite-based sensors. Goward et al. (1994) and Prihodko (1997) demonstrated that it is possible to estimate ambient air temperatures(T_a), even on a range of lightly vegetated surfaces, by extrapolating the relationship between NDVI and surface temperature (T_s) to conditions equivalent to full canopy closure.

3 VALIDATION

Because direct validation at regional to global scales is extremely difficult, our relative confidence in any prediction is heavily weighted towards models that incorporate principles that have been thoroughly tested at smaller spatial scales where direct measurements were possible (Waring 1998).

Various methods of fire danger evaluation, based on meteorological parameters can be used for validating the above-explained remote sensing based methods. Viegas et al. (1999) concluded, after a thorough evaluation of fire danger methods based on meteorological factors, that the Canadian and the modified Nesterov methods showed the best overall performance.

An assessment of above-cited fire risk assessment methods, which use coarse resolution imagery, can be performed by;

(1) Historical Fire occurrence

(2) Remote Sensing based Fire Scar and Active Fire Detection programs

(3) Interpolated drought & stress indices calculated from climate data

(4) Interpolated Fire Danger Indices (FDI) from metrological fire danger models

(5) Results from developed models applied on high resolution satellite data

Actual field estimations of FMC are not performed due to high cost and amount of measurements needed. As such, for example, it is unrealistic measuring daily FMC at a regional scale. Approach (1) & (2) may be considered an indirect validation of the methods, since fire occurrence is not always related to FMC. Fire danger is a conjunction of different factors, both physical and human caused. Satellite data can only assess vegetation dryness (or, to be precise, moisture content), but other factors related to fire ignition or fire propagation cannot be directly derived from satellite observations. Fire only occurs when an ignition cause is present, even if FMC is not critically low. On the other hand, critical levels of FMC may not necessarily lead to fires, if other factors of risk don't appear.

4 CONCLUSIONS

In general, satellite data provide a higher confidence to estimate Fuel Moisture Content (FMC) in grasslands than in shrub lands, although in both cases, some variables provide significant correlation. The FMC is estimated with a higher confidence for grasslands because grasses are easier influenced by weather conditions due to a mostly less deep rooting systems. Consequently the FMC of grasses is better linked with the "leaf moisture content" assessed by reflectance values.

A very sound approach is the integrated analysis of fire danger based on the combination of satellite data and meteorological danger indices. The former would inform on live fuel conditions, while the latter would provide an estimation of FMC for dead fuels. Theoretical frameworks are available, but additional research is required to obtain a proper integration of these two sources of information.

In the future, possible manipulations of fuel type, load and arrangement could be used to help protect local areas of high value (Pyne et al. 1996). By using two transient general circulation models (GCMs), namely the Hadley Center and the Canadian GCM's, Flannigan (2000) estimated fire season severity in the middle of the next century. The results suggest that the seasonal severity rating (SSR) will increase by 10-50% over most of North America. At the larger scale, however, fuel management would not be feasible. A fine balancing act is required by land managers to protect values (people and resources) from fire. In this context fire danger indices and susceptibility maps will become more and more important.

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Improvements for the future

(1) Linking the thermal inertia method to vegetation dynamics

Keeping in mind that the thermal inertia method is difficult to realize, due to the selective availability of cloud free night & day images and arduous geometrical correction, the possible concept that will be tested in the future is:

$$\frac{VI}{(T_s - T_a)_{day} - (T_s - T_a)_{night}} \tag{11}$$

Eq. 11 is derived by combining the thermal inertia Eq. 6 principle and the vegetation index (VI)/T_s-T_a relationship. In that way the thermal inertia method will be adjusted for full cover vegetation types aiming on using it for the estimation of FMC, as part of an operational coarse resolution remote sensing Fire Risk assessment model.

(2) Using time series of AVHRR /ATSR-2

A good approach to estimate vegetation stress has been the analysis of NDVI multi-temporal series. NDVI composites have been successfully correlated to accumulated evapotranspiration, rainfall and crop moisture indices leading to an operational application in the area of fire danger estimation. In climatology, weather refers to the shorter-term atmospheric conditions (and their variations) – those that occur during individual days or months in individual climatic years. Climatic statistics represent a synthesis or average of this weather over a period of many years. The resulting climatic description thus serves to indicate the range of weather that may be expected at future times. Something similar can be created with remote sensing if data is available of periods of many years. Like this we can start predicting the future and develop early warning systems.

As such, for example the average value of NDVI/T_s-T_a (or other adjusted Vegetation index) is derived for the period from 1995-2000 as background information and compared to the present monthly NDVI/T_s-T_a data. By adding new monthly data the background database is always to ensure it can represent the normal situation.

$$AVIT = \frac{NDVI}{T_s - T_a} - \left(\overline{\frac{NDVI}{T_s - T_a}} \right) \tag{12}$$

Where $\overline{\frac{NDVI}{T_s - T_a}}$ is the average of NDVI at the same time in previous years and AVIT is the average vegetation index approach.

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