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Broad-Scale Monitoring of Live Fuel Moisture

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Abstract

Remote sensing has as a spaceborne informant about Earth system processes become the technology of choice for monitoring the status of fuels and fire at local through global scales. This study reviews techniques and presents an application of remote sensing for monitoring live fuel moistures at broad spatial scales. The text recalls the roots of biophysical remote sensing, reviewing how early work about the spectral behavior of vegetation offered insights that promoted remote sensing as a fire knowledge source. Time-series data from the National Oceanic and Atmospheric Administration and Advanced Very High Resolution Radiometer (AVHRR) are used to map relative live fuel moisture stress for the continental USA. Results of fuel moisture maps produced from the AVHRR protocols compare favorably with those derived from the Landsat 7 Enhanced Thematic Mapper Plus.

Introduction and Background

Climate and vegetation largely determined fire patterns prior to human settlement (Lomolino et al. 2006; Strahler and Strahler 1973); but that was then. Human activity since settlement has through land use and climate change affected the geography of fire significantly. With a legacy spanning the balloon age through the space age, remote sensing technology empowers inquiry into the geography of fire past and present.

The geography of fire (a.k.a. pyrogeography) is the study of space–time relationships between fire and humans (Bowman et al. 2009). It is a rich, synthetic field, spanning the biophysical and social realms – from the physical aspects of vegetative fuels and fire behavior, to the politics and economics of fire (Gantenbein 2003; Pyne 1997). This study considers an increasingly important biophysical part of pyrogeography: monitoring live fuel moisture stress frequently and at broad spatial scales. The study recalls the 'roots' of biophysical remote sensing, recounting how early experiments on the spectral behavior of vegetation contributed insights that thrust remote sensing science into contemporary prominence. The methodological focus is on long time-series data for broad-scale monitoring of live fuel moisture; it features a well-known long-term remote-sensing system (the Advanced Very High Resolution Radiometer, AVHRR) and a well-known vegetation metric (the Normalized Difference Vegetation Index, NDVI). This study opens with theory and definitions, offering an historical perspective on fire as a keystone landscape process and on the remote-sensing science available to support landscape process studies. This is followed by a critical review of some remote-sensing strategies for monitoring variations in live fuel moisture. The review leads to a representative application specific to broad-scale live fuel moisture stress mapping and monitoring using 'legacy' AVHRR data. The study concludes with a summary and recommendations.

THEORY AND DEFINITIONS

Fire is a biochemical reaction between fuel, heat and oxygen (Albini 1976; Pyne et al. 1996; Rothermel 1972). Ignition is mediated by live and dead fuel moisture: The less moisture, the easier it is for a heat source to raise the fuel to ignition temperature. Lower fuel moistures thus increase the likelihood of ignition. Live fuel moisture is determined largely by interannual variations in rain or snow. Live fuel moisture is accessible indirectly via spectral interrogation of vegetation canopies. Spectral retrieval of live fuel moistures is discussed in the following section. Live fuels draw on stored soil moisture, affecting the spectral response. Dead fuel moisture in contrast varies in accord with shifts in local meteorological conditions (e.g. relative humidity), and topography (e.g. aspect, elevation, wind patterns).

CONNECTING FUEL MOISTURE, FIRE AND EARTH SYSTEMS SCIENCE

Earth system science is focusing increasingly on fire contributions to greenhouse gas emissions: fire emissions promote formation of smoke palls that affect Earth's radiant energy budget (heat and sunlight) and contribute atmospheric CO_2, influencing climate on regional and global scales (Houghton and Woodwell 1989). Climate effects may promote earlier springs, accelerating fuel moisture loss and spurring increasingly large, high-intensity fires until a new climate–fuel–fire equilibrium is reached (Westerling et al. 2006). Maps of the global distribution of fuels and fire prompt questions of how climate–fire interactions explain earth surface patterns and processes (Moritz and Krawchuk 2008). Fuels and fire are a CO_2 sink and a source, respectively, underscoring the importance of fuels monitoring in terms of land–atmosphere feedbacks. This sink–source duality places fuels and fire centrally in the realm of earth system science. Forest fires, brush fires, and slash and burn agriculture – all varieties of biomass burning – were and are significant earth system processes.

REMOTE-SENSING TECHNOLOGY ENABLES ACCESS TO EARTH SYSTEM PROCESSES

Remote sensing has as the pre-eminent gatherer of intelligence about Earth system processes become a key informant for the status of fuels and fire; a prominent means for mapping fire hazards and effects at local through global scales (Keane et al. 2001; Sampson et al. 2000). From ecologists interested in fire regimes, earth systems' scientists monitoring fire-related carbon fluxes, to geographers investigating the spatial patterns of fire, there is an increasing demand for methods that, powered by human intellect, can coax the pyrogeography from remotely sensed data (Chuvieco and Justice 2004; Yool 2004; Yool et al. 1985). Methods have been developed to map pre-fire live fuel moisture with airborne and spaceborne systems (Ceccato et al. 2002; Cheng et al. 2007; Chuvieco 2003; Chuvieco and Congalton 1989; Cohen 1991; Danson and Bowyer 2004; Dennison et al. 2003; Hardy and Burgan 1999; Nemani and Running 1989; Peterson et al. 2008; Stow and Niphadkar 2007; Yebra et al. 2008); to monitor active fire spread (Morisette et al. 2005); and to map post-fire effects (Kasischke et al. 1993; Key and Benson 2005; Lentile et al. 2007; Medler and Yool 1997; Miller and Yool 2002; Miller et al. 2003, 2009; Patterson and Yool 1998; Rogan and Yool 2001; Yool 2001). Landscape response to fire effects is more or less resilient (Bouchon and Arseneault 2004; Keeley et al. 2005; Lentile et al. 2007). The value of remote sensing technology for such applications derives from surface spectral responses – for this study, variations in spectral responses mediated by live fuel moisture content.

THE SPECTRAL BASIS FOR VARIATIONS IN LIVE FUEL MOISTURE CONTENT

Live fuel moisture content is the moisture level (expressed in percentage) found in grass, brush and trees. Related theory, linking plant moisture to its spectrum, was forged by Gates et al. (1965), Knipling (1970), Carlson et al. (1971) and Thomas et al. (1971), among others. Their historical experiments documented that leaf chloroplasts absorb highly in the red (0.6–7.0 μm); that leaf water absorbs in the middle infrared (1.3–2.7 μm); and that near-infrared reflectance was mediated by cell structure (Figure 1). These early studies were confirmed by Kleman (1985), Ripple (1986), Hunt et al. (1987), Westman and Price (1988) and Carleton et al. (1994), then revisited in a more recent work cited later in this study.

Live fuel moisture co-varies with surface temperature, which derives from the balance between incoming and outgoing energy fluxes. This observation has motivated predictive models that obtain regional-scale surface moisture patterns from spaceborne infrared measurements [Carlson et al. 1981; Wetzel and Atlas (1983) in Carlson 1986]. But a persistent unresolved issue has been whether spectral response patterns collected by satellites can distinguish variations in vegetation moisture characteristics from among other sources of spectral variation (e.g. leaf area index, soil background, sensor degradation, atmospheric effects and viewing geometry). Such patterns are sensitive to variations in solar zenith angle and sensor-viewing angle (e.g. Justice et al. 1985; Tucker and Sellers 1986). These

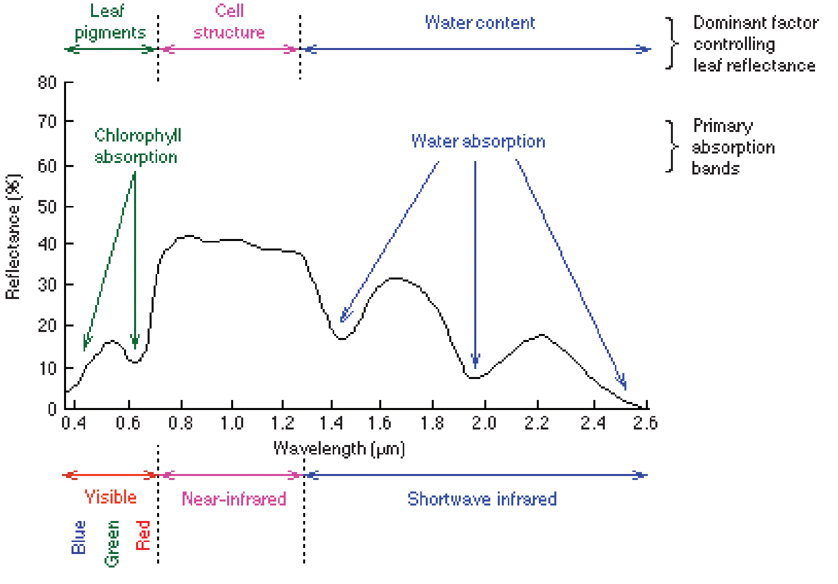

Fig. 1. The visible, near-infrared and shortwave infrared portion of electromagnetic spectrum, showing the spectral response pattern of live vegetative fuels: absorption by leaf pigments (chiefly chlorophyll) controls reflectance in the 'visible' portion of the spectrum (0.4–0.7 μm). Leaf cell structure controls reflectance in the near-infrared portion of the spectrum. Live fuel moisture content controls reflectance in the shortwave infrared, producing peaks in this graph at about 1.7 and 2.2 μm. The 'valleys' in the shortwave infrared represent absorption of energy in these wavelengths by water vapor in the atmosphere (source: Jensen 2000). Though not shown in this graph, the thermal infrared portion of the spectrum is sensitive also to changes in live fuel moisture.

findings underscore the interactions between surface and sensor characteristics that inform the choice of remote-sensing systems.

REMOTE-SENSING SYSTEM TRADE-OFFS

Trade-offs among the spatial, spectral and temporal resolution domains are distinctive, if unwelcome, characteristics of remote-sensing systems. Consider the AVHRR: in designing a protocol for mapping live fuel moisture stress, analysts could, in light of the coarse AVHRR nominal spatial resolution (about 1 km^2), select instead the Landsat, Quickbird and IKONOS systems, given they all carry comparatively higher nominal spatial resolution than the AVHRR. Now consider Landsat: although the selection of Landsat favors spatial resolution (30 m) and spectral resolution (6 bands in the reflective wavelengths), there is a *temporal* resolution trade-off (i.e. 16-day Landsat revisit interval) – a significant limitation for tracking live fuel moisture variations. What of commercial systems (e.g. Quickbird; IKONOS)? These systems carry higher nominal spatial resolution than either Landsat or AVHRR – but they lack both spectral resolution and temporal resolution – key requirements for mapping live fuel moisture over long spans of time. Such commercial systems emerged to fill market niches for applications requiring finer spatial and broader temporal scales – both strengths of private sector remote sensing. It is in fact difficult if not impossible to map broad-scale fuel moisture patterns with high-resolution commercial systems because of spectral and temporal resolution limitations; thus we must rely on comparatively coarse operational systems like AVHRR or the Moderate Resolution Imaging Spectroradiometer (MODIS). Although the AVHRR is favored in particular for its historically long time series, there are technical constraints on continuous data quality of the 1-km resolution AVHRR, including orbital drift.

AVHRR ORBITAL DRIFT

Given the potential historical significance of AVHRR for monitoring fuel moisture and other biophysical variables, a key issue is continuous data quality. Orbital drift of the AVHRR gradually pushes the overpass time later in the day, introducing a bias that reduces the value of these data for broad-scale mapping (Trishchenko et al. 2002). One example is surface temperature (T_s), which varies with live fuel moisture content: A number of studies have associated AVHRR orbital drift with a cooling trend in retrieved T_s (Gleason et al. 2002; Goetz 1997; Traore et al. 1997). Documented cooling trends of 4–6°K were recorded over desert targets, which appear to be most sensitive to drift as a result of rapidly changing afternoon temperatures. Drift effects are more significant over bare ground than over vegetated surfaces (Gleason et al. 2002; Traore et al. 1997). Jin and Treadon (2003) found, for example, that orbital drift from a local overpass time of 2 PM to an overpass time of 5 PM in July over Northern Hemisphere middle latitude desert areas decreases the temperature by 5–10°C; in contrast, grassy areas cooled 1–2°C. Global Inventory Modeling and Mapping Studies (a.k.a. GIMMS, a 25-year AVHRR NDVI record) data are post-processed for such orbital drift. Analysts requiring finer spatial resolution should note that the GIMMS data have a spatial resolution of 8 km.

THE AHVRR AS A SOURCE OF NDVI TIME-SERIES DATA

The NDVI is an established metric for vegetation condition, including inferred live fuel moisture stress. Developed in the early 1970s (Rouse et al. 1974), the NDVI is the most used (and likely most debated) metric in remote-sensing science. The NDVI uses the reflectances from the near infrared (NIR) and red spectral bands, as follows:

$$\mathrm{NDVI} = \frac{\rho\mathrm{NIR} - \rho\mathrm{Red}}{\rho\mathrm{NIR} + \rho\mathrm{Red}}, \tag{1}$$

producing values from −1 to 1. Positive values indicate greater and negative values less greenness. It is important to note NDVI is not a direct measure of vegetation moisture stress: NDVI measures photosynthetic activity and cell turgor. The internal structure characteristic of hydrated plant leaves reflects NIR strongly. As vegetation loses moisture, NIR reflectance decreases, due likely to the difference between the index of refraction of air vs. water occupying the space within these cells (Chuvieco et al. 2002). As vegetation dries (i.e. as fuel cures), red reflectance rises and NIR reflectance falls, decreasing the NDVI and signaling a loss of fuel moisture. We can by examining the NDVI time-series data detect fluctuations in live fuel moisture.

The AVHRR NDVI have been shown to be sensitive spectrally to vegetation condition (Anyamba and Tucker 2005; Chuvieco and Martin 1994; Holben 1986). But the chief asset of the AVHRR is its daily duty cycle and decades long history of service (Eidenschink and Faundeen 1994). Although the AVHRR 'yields' some spatial and spectral resolution to most other sensors, it has 'seen' the world twice daily for decades. These qualities combine to provide a hypertemporal sampling of broad-scale live fuel moisture.

The AVHRR provides a nearly complete hypertemporal stream of maximum value composite (MVC) datasets (since 1989): are these data timely for live fuel moisture monitoring? Ground reference measurements show live fuel moisture should be sampled semi-monthly during the fire season (http://www.fl-dof.com/wildfire/live_fuel_moisture/lfm_pdfs/procedures.doc). This sampling interval matches the NDVI MVC, which is selected from each (roughly) 2-week interval of daily observations. The MVC sampling protocol produces over this interval a MVC NDVI for each pixel. The MVC is rescaled from its normal range (−1 to +1) to 0–200 (Eidenshink, 1992). Effects of clouds, directional and off-nadir viewing effects, atmospheric attenuation, sun angle and shadow effects are minimized in MVC images (Holben 1986). We have seen these NDVI MVC images used as metrics that associated greenness with live fuel moisture.

NDVI, RELATIVE GREENNESS AND LIVE FUEL MOISTURE

The Relative Greenness (RG; Burgan and Hartford, 1993) and Departure from Average (DA; Hartford and Burgan, 1994) are AVHRR NDVI-based metrics designed to measure the moisture stress in live fuels. These metrics relate current NDVI observations to a historical range or mean. RG compares NDVI maximums and minimums for the same period since 1989 to the current NDVI value:

$$\mathrm{RG} = \frac{\mathrm{NDVI} - \text{min since 1989}}{\text{max since 1989} - \text{min since 1989}}. \tag{2}$$

Departure from Average divides current NDVI value by the mean for the same period since 1989:

$$\mathrm{DA} = \frac{\mathrm{NDVI}}{\text{mean NDVI since 1989}}. \tag{3}$$

Relative Greenness and DA related well to fires in the Northern Rocky Mountains, for example, but threshold values are difficult to define for these metrics (Leblon 2001). There is moreover continued debate about the value of the NDVI as a spectral metric for vegetation condition.

THE NDVI DEBATE

There is noteworthy debate about the merits of the NDVI as a proxy for vegetation moisture stress (Leblon 2001). Multiple studies have confirmed a functional relationship between NDVI and the moisture condition of grasses, shrubs and forest understory species (Alonso et al. 1996; Burgan et al. 1998; Chladil and Nunez 1995; Deshayes et al. 1998; Paltridge and Barber 1988). The relationship between the NDVI and reflectance from canopies of conifer forests has, however, not been well characterized (Hardy and Burgan 1999). Such uncertainty is due likely to the number of complex factors contributing to the spectral response of each pixel within a mixed conifer forest – including diverse species, morphology, as well as the obscuring of the understory by the overstory signal, which may reflect a very different moisture condition (Eidenshink et al. 1990; Hardy and Burgan 1999; Leblon, 2001). Questions about sensitivity of the visible and NIR wavelengths to vegetation moisture prompted investigations of the shortwave infrared (SWIR).

LIVE FUEL MOISTURE STRESS AND THE SWIR

Previous work has shown that foliar moisture produces strongest differences in the SWIR portion of the electromagnetic spectrum, which spans 1.4–2.0 μm (Bowman 1989; Cohen 1991; Hunt et al. 1987; Jackson and Ezra 1985; Tucker 1980). Water strongly absorbs SWIR wavelengths, producing negative correlations between SWIR and, for example, leaf water content (Chuvieco et al. 1999). Handheld radiometry has supported relationships between vegetation moisture content and SWIR reflectance (Cibula et al. 1992, Westman and Price 1988). Other trials showed leaf geometry (e.g. wilting), shadows and background soil can overwhelm spectral variations related to foliar moisture (Cohen 1991). This observation has, however, been challenged at least for conifers, which, because of leaf shape, do not wilt under water stress (Nemani et al. 1993). Still other studies report reflectance decreases because of moisture stress are mixed with reflectance increases because of chlorophyll loss, differences in species and soil variations (Chuvieco et al. 1999; Hardy and Burgan 1999).

Although satellite measurements are few, some authors have reported satisfactory results for grassland fuel moisture (Chladil and Nunez 1995; Paltridge and Mitchell 1999). Ceccato et al. (2002) described why most spectral proxies for vegetation water content cannot retrieve it at leaf level. They used instead a combination of SWIR and NIR. Results showed that the longer SWIR wavelengths are more sensitive to leaf area index, fractional vegetation cover and solar zenith angle than the shorter SWIR wavelengths and NIR. A later study confirmed the importance of the SWIR, noting that useful empirical relationships between vegetation moisture content (grass fuels particularly) and remotely sensed vegetation indices are possible (Bowyer and Danson 2004). What emerges from this diversity of findings is the importance of matching system capabilities with information requirements. The diversity of findings has implications for the design of AVHRR follow on systems, and spurs investigations into other spectral realms. AVHRR lacks SWIR resolution, but does support the thermal infrared. Riggs and Running (1991) demonstrated the complementarity of the NIR and thermal infrared for the assessment of vegetation moisture stress, supporting past and present studies of the thermal infrared.

LIVE FUEL MOISTURE STRESS AND THE THERMAL INFRARED

Leaf and soil temperatures increase as moisture decreases. This fact motivated early studies of remote, broad-scale measurements of surface temperature and moisture (Heilman and Kanemasu 1976; Jackson 1982; Pierce and Congalton 1988; Rhode and Olson 1970). The inverse relationship between the NDVI and temperature was demonstrated in earlier works on crop and forest lands (Bartholic et al. 1983; Goward et al. 1985, Smith and Choudhury 1990), and for arid and semi-arid regions (Jackson and Idso 1975; Vukovich et al. 1987). Several investigators have advanced the importance of the thermal infrared (modeled as surface temperature, T_s), which when combined with NDVI data produces a negative slope that characterizes the range of vegetation water content (Dupigny-Giroux and Lewis 1999; Nemani and Running 1989; Sandholt et al. 2002).

This inverse relationship has direct bearing on the estimation of live fuel moisture stress (Goward et al. 1985; Nemani and Running 1989; Nemani et al. 1996; Taconet et al. 1986), and constitutes the method suggested in this study as a suitable broad-scale monitoring of live fuel moisture stress.

Application: Broad-scale Monitoring of Live Fuel Moisture Stress

The MVC time-series data for the AVHRR NDVI and T_s were combined to model live fuel moisture stress. This protocol differs from the Wildland Fire Assessment System, which uses the NDVI only. The 1-km AVHRR outputs were evaluated against identically processed data from the 30-m Enhanced Thematic Mapper Plus (ETM+). Modeled outputs were not compared with actual live fuel moisture stress measurements; results are thus relative, not absolute. The AVHRR data were not post-processed for orbital drift. I modeled T_s using a split-window technique (Equation 4; Prabhakara et al. 1974). When tested against *in situ* sea-surface temperature, this technique produced a correlation of $R = 0.97$, and an absolute error of <1°C:

$$T_s = 1.764\mathrm{Tb4} - 0.764\mathrm{Tb5} + 0.78. \tag{4}$$

This split-window technique was also used by Nemani and Running (1989), who cited its simplicity, its applicability over both land and sea (because of the similar emissivities of vegetation and water), and its suitability as a relative measure of seasonal surface temperature trends. Other split-window techniques have since appeared.

The NDVI MVC images were acquired within a given year to demonstrate the sensitivity of surface moisture to regional-scale climate variability. The year 1999 was selected from the time series: Southwest US precipitation statistics revealed June 1999 was dry and September 1999 was wet; this contrast served as a test of algorithm sensitivity to live fuel moisture variations The AVHRR NDVI and T_s image data were processed with an iterative self-organizing clustering algorithm (ISODATA; Leica Geosystems ERDAS Imagine®, Hexagon Group, Sweden). These clustered NDVI and T_s data depict dominant regional patterns in relative live fuel moisture stress (Figures 2 and 3).

Modeled live fuel moisture stress for June and September 1999 varies significantly (Figures 2 and 3). We can, for example, see in the September map the 'tongue' of Mexican moisture sitting in the vicinity of the Sierra Madre Occidental (East of the Gulf of

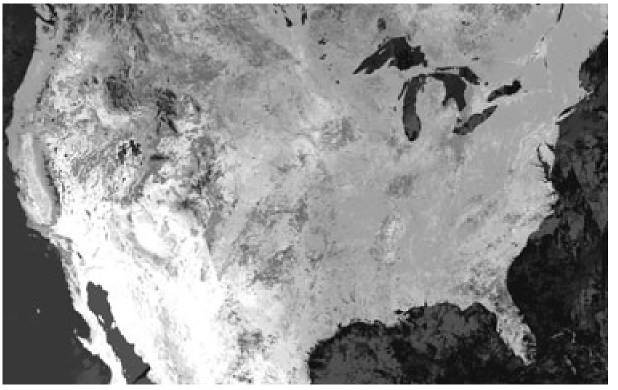

Fig. 2. Vegetation moisture image for the continental USA for the first 2 weeks of June 1999. Dark areas are moister and light areas drier. The Great Lakes are obvious. Those familiar with the western USA can make out Great Salt Lake (Utah), the Salton Sea (Southern California) and Lake Tahoe (Northern California and Nevada). The entire Southwest US Region and Northern Mexico is comparatively dry, confirming the climate record for this period. These data are not perfect: Note the linear seam east of the dark, backwards 'comma' that marks the moist ponderosa pine forest of the Mogollon Rim. The small, darker area at the top of this 'comma' is the Kaibab Forest – part of the north rim of The Grand Canyon.

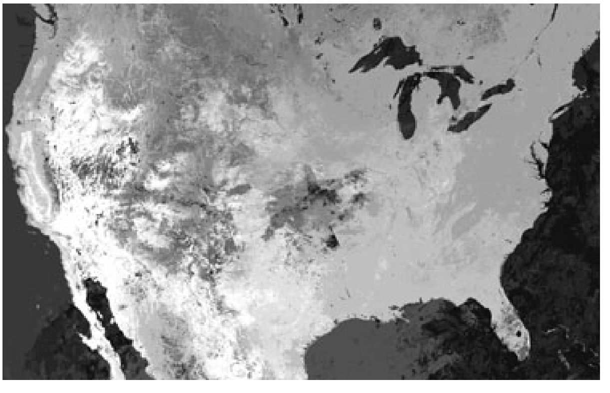

Fig. 3. Vegetation moisture image for the continental USA for the first 2 weeks of September 1999. Dark areas are moister, and light areas drier. Compared with the June 1999 period shown in Figure 2, this September 1999 image expresses the response of the Southwest US Region to summer monsoonal precipitation. The moist uplands that defined the Mogollon Rim in Figure 2 have expanded into a broader band of moisture-laden forests.

California). This moisture was produced by monsoon thunderstorms that typically soak the region July through September. Extending north to Arizona and New Mexico, complex spatio-temporal moisture/dryness patterns emerge: June is typically a dry month in the Southwest – the last month of the 'fire season' before the arrival of monsoon-driven rains. June 1999 was particularly dry. By September 1999, moisture from monsoonal rains has decreased live fuel moisture stress in this region substantially.

CONSISTENCY BETWEEN THE AVHRR AND ETM+

The good news is that AVHRR can be used to map relative live fuel moisture at broad spatial scales. The bad news is that such maps are difficult to evaluate because of the asynchronous relationship between field sampling and the AVHRR overpass: It is impossible

Fig. 4. This ETM+ vegetation moisture image shows an area southwest of the Phoenix, AZ Metropolitan area (visible as grid networks in the right half of this image.) A cluster of dark vs. light (moist vs. dry) agricultural fields can be seen in the lower left portion of this image. The Salt River enters the image from the right as a thin, dark line, joining the broader Gila River (which enters the image from the bottom) in the vicinity of the agricultural area. The dark, braided pattern is produced by vegetation growing in the Gila River channel. Results shown here are consistent with results shown in Figures 2 and 3.

strictly speaking to reconcile *in situ* measurements and the AVHRR data because spectral values are averaged over the 1-km AVHRR spatial resolution; such averaging is not comparable with point-based samples (e.g. the National Fuel Moisture Database).

An alternative to *in situ* validation is to use collateral data as a line of evidence – for example, a higher-resolution sensor system. I selected the 30-m Landsat ETM+. The Landsat ETM+ has a comparatively higher spatial resolution (30 m nominally – about the size of a baseball diamond); ETM+ carries also the spectral resolution required to implement the NDVI/T_s algorithm used for the AVHRR-based live fuel moisture mapping. The ETM+ data have a 16-day temporal resolution and were acquired within a couple of weeks of the September 1999 AVHRR overpass. ETM+ data were processed by the same protocols as used with the AVHRR (Figure 4). Although the spectral resolution of ETM+ and AVHRR does not match perfectly in the red portion of the spectrum (630–690 vs. 580–680 nm), or the near-infrared (780–900 vs. 725–1100 nm), analysts have agreed to label them 'red' and 'near-infrared'. Because 'upscaling' the ETM+ outcomes to AVHRR spatial resolution would complicate analysis of mixed pixels, I evaluated outcome consistency at native resolution; I compared outcomes at ETM+ resolution with outcomes at AVHRR resolution (Figures 2–4).

Discussion and Recommendations

Live fuel moisture stress is a key metric for assessing the fire potential. Live fuel moisture mediates spectral responses in the visible, NIR, SWIR and thermal infrared wavelengths, making mapping of fuel moisture stress feasible using remote sensing technology. This article described the value of legacy AVHRR time-series data for monitoring relative live fuel moisture stress. The NOAA AVHRR has the spectral resolution, duty cycle and record of service to deliver daily planetary live fuel moisture stress. I provide an example of how the AVHRR NDVI and T_s can be combined using a straightforward clustering protocol, producing a metric that models relative live fuel moisture stress. Outcomes from identical processing of ETM+ and the AVHRR compare favorably. The AVHRR is favorable in particular for monitoring fire hazard at broad scales because climate affects fuel moisture variations at broad spatial scales.

All models are imperfect. The AVHRR is challenged by issues of data quality: the AVHRR has a comparatively coarse nominal spatial resolution (1 km^2), limiting analyses to broad-scale dynamics. The sacrifice of fine spatial resolution, however, favors access to frequent, cloud-free landscape scale live fuel condition and also to open data accessibility: small file sizes enable processing hundreds of images on a personal computer.

The remote-sensing science outcomes from AVHRR technology provide the baseline data that serve as the launch point for the next generation of sensors. Live fuel moisture variations modeled by AVHRR are consistent with measures of vegetation moisture captured at higher resolution by the Landsat ETM+. This finding is encouraging. Perhaps most important is where such findings lead: The deployment of the MODIS (since 2000) opens new pathways for earth system science (Cheng et al. 2007; Peterson et al. 2008; Stow and Niphadkar 2007; Yebra et al. 2008). The MODIS NDVI provides time-series continuity for the AVHRR NDVI legacy data. The MODIS produces in addition to the NDVI an Enhanced Vegetation Index (EVI). EVI is more resistant than NDVI to atmospheric, soil and saturation effects. For live fuel moisture monitoring, the MODIS represents at this time the future of broad-scale monitoring of live fuel moisture stress.

Humans have since their arrival on the planet been the keepers of the flame. Fire is the only natural phenomenon over which humans have had dominion. But fire is today largely out of control, affecting Earth's surface and atmosphere and impacting the current and future quality of life. Conditioned by warmer air temperatures and potential increased duration of live fuel moisture stress, commensurate increases in fire activity could drive a positive feedback cycle that accelerates global warming (Westerling et al. 2006). Remote-sensing science is thus compelled to clarify the dynamics of fuel moisture stress in support of future fire science and management.

Short Biography

Stephen R. Yool is a Professor of Geography and Development, the University of Arizona. He has been engaged in remote-sensing research for three decades. Steve is an applied biophysical geographer and geospatial methodologist. His interests span global change, space–time variability of natural systems at different scales and impacts of human or natural disturbances on Earth's biosphere. He has authored or co-authored papers on these topics in the *Annals of the Association of American Geographers*, *Remote Sensing of Environment*, *Journal of Arid Environments*, *Hydrological Processes*, *International Journal of Wildland Fire*, *Fire Ecology* and *Geocarto International*. He aims to help advance spatial knowledge, in particular the interactions within coupled natural and human systems – work he hopes will translate ultimately into information useful for resource sustainability. Steve holds a PhD in Geography from the University of California, Santa Barbara.

Note

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