Thermal Infrared Remote Sensing for Analysis of Landscape Ecological Processes: Current Insights and Trends

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Introduction:

Landscape ecology as a field of study requires data from broad spatial extents that cannot be collected using field-based methods alone. Remote sensing data and associated techniques have been used to address these needs, which include identifying and detailing the biophysical characteristics of species habitat, predicting the distribution of species and spatial variability of species richness, and detecting natural and human-caused change as scales ranging from individual landscapes to the entire world (Kerr and Ostrovsky, 2003). This has been exemplified in a growing number of special issues of journals and journal articles that have focused on remote sensing applications in landscape ecology (Cohen and Goward, 2004; Gillanders et al., 2008; Newton et al., 2009; Rocchini, 2010a and b). Howvever, we believe that thermal remote sensing data have not been widely exploited to their full potential in landscape studies. Thermal data have important characteristics that can be used to derive quantitative measurements of surface energy balances and fluxes across the landscape, but wide-spread use of these data in landscape ecological research may still be somewhat enigmatic to some investigators.

In an article published in 1999, we examined the direct or indirect uses of thermal infrared (TIR) remote sensing data to analyze landscape biophysical characteristics to offer insight on how these data can be used more robustly for furthering the understanding and modeling of landscape ecological processes (Quattrochi and Luvall, 1999). As we noted at the time our article was published, we believed there was a perception that TIR data were difficult to use for applications in landscape characterization and analysis. Here we present a review and update of the literature related to TIR remote sensing in landscape ecological process studies to further illustrate both how the literature has grown, and to expand upon research area themes that were not included in our original article. Additionally as we noted in our 1999 article, accessing the literature related to TIR data and landscape ecological processes was difficult because of its fragmentation across a wide spectrum of journals or other scientific resources. Because of the interdisciplinary nature of research on TIR data and landscape processes, this is still true to some extent today; the literature on TIR remote sensing applications for land surface process analysis is being published in a wide range of publications, such as those focused strictly on remote sensing, or spread across numerous inter- or multidisciplinary publications such as hydrometeorology, climatology, meteorology, or agronomy.

As we related in 1999, and expounded upon in our edited volume *Thermal Remote Sensing in Land Surface Processes* (Quattrochi and Luvall, 2004), we foresaw that the applications of TIR remote sensing data to landscape ecological studies has been limited for three primary reasons:

1) TIR data are little understood from both a theoretical and applications perspective within the landscape ecological community;

2) TIR data are perceived as being difficult to obtain and work with to those researchers who are uninitiated to the characteristics and attributes of these data in landscape ecological research;

3) The spatial resolution of TIR data, primarily from satellite data, is viewed as being too coarse for landscape ecological research, and calibration of these data for deriving measurements of landscape thermal energy fluxes is seen as being problematic.

Given the increase from 1999 (and even from 2004 when our book was published) in the TIR literature that has been published, these three issues have been considerably mitigated, but not entirely mollified. It, therefore, is still useful to examine examples of the literature that has been published post-1999 to provide further evidence and review of how TIR data has been applied to landscape ecological and land processes research. As was described in our article and book, there are two fundamental ways that TIR data can contribute to an improved understanding of landscape processes: 1) through the measurement of surface temperatures as related to specific landscape and biophysical components; and 2) through relating surface temperature with energy fluxes for specific phenomena or processes. This is not an exhaustive review; we wish only to provide further credence using selected selected studies taken from the literature that highlight and support the utility of TIR data to quantify and model land surface processes. We do so by providing citations that generally fall within several applications areas that we believe are most critical for illustrating the virtues of TIR data and associated analysis methods.

Some Background on NASA TIR Satellite Instruments

Evaluation of the earth's radiation energy balance has been a primary design function of the meteorological and other earth-sensing satellites since the launch of Explorer VII in 1959 (Diak et al., 2004). There has been considerable progress In estimating components of the land surface energy balance from orbit, particularly beginning with the NASA Landsat series of satellites carrying the Thematic Mapper (TM) instrument first launched in 1984 and its successors. The TM sensor aboard Landsat 4 and 5 had spectral bands positioned between .45-12.5 micrometers (µm) in the electromagnetic spectrum. Six of these bands are in the visible and reflective infrared wavebands of the electromagnetic spectrum (between .45-2.35 µm); and there is one TIR spectral band in the 10.40-12.5 µm waveband range. All of the bands except for the TIR band have a spatial resolution of 30m; the TIR has a 120m spatial resolution. The Enhanced Thematic Mapper+ (ETM+) which was launched onboard Landsat 7 in 1999, has the same spectral band configuration as the TM except the TIR band has a spatial resolution of 60m. Landsat 8 launched in February 2013 has a sensor that is equivalent to the ETM+ both in spectral bandwidth and spatial resolution, except for the TIR band which has e a spatial resolution of 100m[1].

[1] For complete information on the Landsat series of satellites, see http://landsat.usgs.gov/about_ldcm.php. Additional information on Landsat 8, known as the Landsat Data Continuity Mission (LDCM) prior to launch, can be accessed at http://ldcm.nasa.gov/.

The collection of TIR data from space has been further augmented via the launch of the NASA Terra and Aqua missions in 1999 and 2002, respectively. Terra carries 5 sensor instruments including the Moderate-Resolution Imaging Spectroradiometer (MODIS) and the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), both of which have capabilities for imaging in TIR wavelengths. MODIS has multiple TIR bands as does ASTER; The MODIS TIR bands are in the 3.1-4.0 nm and 10.7-12.2 µm ranges, and ASTER's are in the 8.1-10.9 µm range The NASA Aqua mission also carries a MODIS instrument. Terra collects data twice daily at approximately 10:30 a.m. and 10:30 p.m. local time, while Aqua collects data twice daily at approximately 1:30 a.m. and 1:30p.m. local time. MODIS TIR data has a spatial resolution of 1km while ASTER thermal data is collected at 90m spatial resolution. In-depth information on Terra and Aqua can be obtained at http://www.nasa.gov/mission_pages/terra/index.html and http://aqua.nasa.gov/index.php, respectively.

One recently launched (December 2011) joint NASA/NOAA (National Oceanic and Atmospheric Administration) mission also offers TIR capabilities is the Visible and Infrared Imaging Radiometer Suite (VIIRS) instrument onboard the National Polar-orbiting Operational Environmental Satellite System (NPOESS), now called the Suomi National Polar-orbiting Partnership or NPP space platform. Although it has a coarse spatial resolution (approximately .39km), VIIRS bears mention because it has 4 TIR spectral bands and it extends and improves upon a series of measurements initiated by the NOAA Advanced Very High Resolution Radiometer (AVHRR), which has been used in many past and present studies of land surface energy balance fluxes. NPP collects data at about 1:30 p.m. and 1:30 a.m. local time, similar to the temporal cycle of Aqua. More information on NPOESS/VIIRS is available at http://npp.gsfc.nasa.gov/index.html.

It must be noted that NASA or NOAA Earth Observing satellites are not the only space-based TIR platforms. The European Space Agency (ESA), the Chinese, and other countries do have in orbit, or plan to launch, TIR remote sensing systems. However, a discussion of these systems will not be presented here for the sake of brevity[2].

The Use of TIR Data in Analysis Landscape Ecological Characterization

Solar and thermal radiation within the earth-atmosphere regime governs the energy available at the earth's surface for heating and cooling of the air (i.e., sensible heat), the evaporation of water from soil and vegetation (i.e., latent heat) and heating or cooling of natural (e.g., soil) and non-natural (e.g., pavement) land surfaces. The earth's only significant source of energy is solar radiation, which is partitioned into various energy fluxes at the surface (Diak et al., 2004). The ultimate driving factor controlling surface characteristics such as soil moisture, land cover, and vegetation conditions, is the energy transfer that occurs in land-atmosphere interactions. The simplest form of the surface energy balance (assuming no advection of energy across the land surface) is given by:

[2] Quattrochi et al. 2003 gives a listing of the characteristics of U.S. and international imaging satellites either launched at that time or planned for future launch.

$$R_{net} = G + H + LE \tag{1}$$

where R_{net} is the net radiation balance, G refers to the soil heat flux (i.e., the energy used to warm the near surface soil layers, H is sensible heat flux and LE is the latent heat flux The ability to quantify the partitioning of available energy at the land surface into sensible and latent heat flux is key to understanding the impact of the land surface on atmospheric processes (Czajkowski et al., 2000). Understanding land-atmosphere energy exchange processes is important for improving short-term meteorological conditions (i.e., the weather), and in predicting the impacts of natural and anthropogenic changes in the land surface on long-term climate variability (Humes et al., 2000). Although land-atmosphere energy fluxes can be measured using *in situ* methods via surface thermal radiation measurements and soil moisture instruments, the synoptic view provided by remote sensing data from satellites can measure land surface temperatures and energy fluxes over a wide area repetitively for multiple temporal periods (i.e., hours, days, weeks) for the same geographic area on earth. This facilitates the modeling of surface energy fluxes for different land covers across the heterogeneous land surface, for developing an understanding how individual land covers with different thermal characteristics force energy exchanges between the land and atmosphere. There are numerous references that explain thermal IR theory and how it can be used to derive surface thermal energy balances using remote sensing data (see for example Quattrochi and Luvall, 2009 and Quattrochi et al., 2009) and this will not be explained here.

Estimating Land Surface Energy Budgets Using Remote Sensing Data

Satellite remote sensing provides an excellent opportunity to study land-atmosphere energy exchanges at the regional scale. Many algorithms have been developed and tested using satellite TIR data to measure regional distributions of land surface temperature (LST), land surface reflectance, particularly that from vegetation, using the Normalized Vegetation Index (NDVI), and fluxes of net radiation, soil heat, and sensible and latent heat flux. The NDVI has been used extensively to measure canopy density (or biomass content) to develop better regional estimates of energy fluxes for vegetation at the regional scale (see Quattrochi and Luvall, 1999, 2004). The NDVI has also been used to compare the energy fluxes of vegetation with other types of land covers (e.g., non-natural surfaces), and to assess how energy dynamics of vegetation, especially evapotranspiration, affects surrounding land covers (NASA, 2013; (Quattrochi et al., 2009).

Landsat TM and ETM data have been used extensively to derive land surface temperatures in conjunction with NDVI's. Fan et al., 2007) used ETM+ data to derive regional distribution of surface energy fluxes in conjunction with NDVI over a watershed in Inner Mongolia China. Distribution maps revealed strong contrasts in thermal energy responses of surface characteristics as a function of landscape features. Southworth (2004) investigated the utility of integrating Landsat data for differentiation between successional stages of forest growth in the Yucatan, Mexico. He found that the Landsat ETM+ thermal data contains considerable information for the discrimination of land cover classes in the dry tropical forest ecosystem. Li et al., (2004) used Landsat TM and ETM+ data to derive land surface temperatures as part of the Soil Moisture Experiments in 2002 (SMEX02) in central Iowa. Results from the study show that it is possible to extract accurate LSTs that vary from 0.98 ^{o}C to 1.47 ^{o}C from Landsat 5 TM and Landsat 7 ETM+ data, respectively. Julien et al. (2006) used LST algorithms and NDVI values to estimate changes in vegetation in the European continent between 1982 and 1999 from the Pathfinder AVHRR (NOAA Advanced Very High Resolution Radiometer) NDVI dataset[3]. These data show a well confirmed trend of increased NDVI values over Europe, with southern Europe seeing a decrease over the whole continent except for southern areas which show an increase of in NDVI. LST averages stay stable or slightly decrease over the whole continent, except southern areas which show an increase. These results provide evidence that arid and semi-arid areas of southern Europe have become more arid, while the remainder of Europe has seen an in increase in vegetated lands. Wloczyk et al., 2011 used ETM+ data in conjunction with a temperature-vegetation index method (TVX) for area-wide mapping of instantaneous air temperature. The TVX method was applied to a multi-temporal data set of nine ETM+ scenes covering large parts of northeastern Germany. These satellite-derived measurements were compared with *in* situ measurements showing an average error of about 3 K[4] whereas the mean error in LST estimation was about 2 K. These results are comparable with previously reported results for the TVX method.

[3] The Pathfinder AVHRR NDVI dataset is available from the NASA Goddard Earth Science Data and Information Services Center (GES DISC) at http://disc.sci.gsfc.nasa.gov/about-us

[4] Kelvin is a measurement of heat energy or temperature, which advances in the same increments, as does Celsius. Its principle difference is that Kelvin measurements are written as K, and have a much lower starting point; 0K or 0 Kelvin is measured at -273.15 ^{o}C which is the point at which no heat energy exists in a substance (called absolute zero). Celsius converts to K by adding 273.15 to the Celsius number.

The MODIS and ASTER sensors have been a critical tool for providing regional estimates of LSTs. LST are warmer in the early afternoon than in the morning because this is a peak time for solar insolation. MODIS Data from the Aqua mission, therefore, are more likely to be closer to the maximum daily LST than that acquired earlier in the day by Terra. Coops et al. (2007) investigated the differences in LST between Aqua and Terra to get an assessment of how large these differences are across Canada. Using MODIS Aqua and Terra data for 2000 through mid-2002, they found there are statistically significant differences between AM and PM LSTs ranging from 1.2 ^{o}C and 5 ^{o}C, depending on the time of year. On the average, over 90% of the variation observed in the PM data can be explained by the AM LST land cover type and location.

Yang et al. (2011) employed several land cover indices, the Soil-Adjusted Vegetation Index (SAVI), the Normalized Multi-band Drought Index (NMDI), the Normalized Difference Built-up Index (NSBI), and the Normalized Difference Water Index (NDWI) to investigate four land cover types (vegetation, bare soil, impervious, and water) in a suburban area of Beijing, China. They applied these indices to MODIS and ASTER data acquired in May 2001. The study was designed to evaluate differences in LST as function of spatial scale differences between the 1km MODIS TIR and 90m ASTER TIR data. They applied a disaggregation method for subpixel temperature analysis using a remote sensing endmember index based technique to derive land surface temperature[5]. It was found that there was good agreement in LSTs between the two spatial resolutions. Another scaling study by Liu et al., 2006 used different scaling approaches to compare LSTs for MODIS and ASTER data over a part of the Loess Plateau in China. ASTER 90m TIR data were scaled up to match the 1km spatial resolution of the MODIS sensor to compare LST values between the two instruments. They found that upscaled ASTER LSTs achieved an agreement of -0.2 $\pm$ 1.87 K in comparison to the MODIS LSTs.

As part of Soil Moisture-Atmosphere Coupling Experiment (SMACEX) experiment (Kustas et al., 2005) conducted over Oklahoma, Kansas and surrounding states, French et al. (2005) used ASTER data to detect and discern variations in surface temperature, emissivities, vegetation densities, and albedo for distinct land use types. They combined ASTER observations with two physically based surface energy flux models, the Two-Source Energy Balance (TSEB) and the Surface Energy Balance Algorithm for Land (SEBAL) models, to retrieve estimates of instantaneous surface energy fluxes. Intercomparison of results between all flux components indicated that the two models operate similarly when provided identical ASTER data inputs. Further assessment of a multiscale remote sending model for disaggregating regional fluxes, is given in Anderson et al., 2004. Here thermal IR data from 6 remote sensing satellites (including the NOAA Geostationary Operational Environmental Satellite or GOES) are used in conjunction with the Atmosphere-Land Exchange Inverse (ALEXI) model and

[5] Spectral mixture analysis provides an efficient mechanism for the interpretation and classification of remotely sensed multidimensional imagery. It aims to identify a set of reference signatures (also known as 'endmembers') that can be used to model the reflectance spectrum of at each pixel of the original of a finite number of ground components (Plaza et al., 2002).

associated disaggregation technique (DisALEXI), in effecting regional to local downscaling of these data. An excellent reference that provides an overview of advances in thermal infrared-based land surface models is also provided by Kustas and Anderson, 2009.

<u>Evaporation/Evapotransipiration/Soil Moisture</u>

A predominant application of TIR data has been in inferring evaporation, evapotranspiration (ET), and soil moisture. This is verified by the numerous references in the literature relating to this application as we noted in our 1999 article and Quattrochi and Luvall, 2009. A good overview of remote sensing research in hydrometeorology and evapotranspiration, with particular emphasis on the major contributions that have been made by the U.S. Department of Agriculture's, Agricultural Research Service (ARS), is given by Kustas et al., 2003. A review of surface temperature and vegetation indices remote sensing-based methods for retrieval of land surface energy fluxes and soil moisture is also proved by Petropoulos et al., (2009). An additional overview of remote sensing of evapotranspiration is given in Kustas, Diak, and Moran (2003).

Landsat ETM+, MODIS, and ASTER data have been successfully used to derive parameters, such as surface temperature and emissivity, for input into soil moisture and ET models. Liu et al. (2007) used ETM+ and meteorological data were used in a regional ET model for the Beijing, China area. Comparisons of energy balance components (net radiation, soil heat flux, sensible and latent heat flux) with measured fluxes by the model were made, integrating the remotely sensed fluxes by the model. Results show that latent heat flux estimates with errors of (Mean Bias Error [MBE] $\pm$ Root Mean Square Error [RMSE]) of -8.56$\pm$23.79 Wm^{-2}, sensible heat flux error of -8.56$\pm$23.79 Wm^{-2}, net radiation error of 25.16$\pm$50.87 Wm^{-2}, and soil heat flux error of 10.68$\pm$22.81 Wm^{-2}. The better agreement between the estimates and the measurements indicates that the remote sensing model is appropriate for estimating regional ET over heterogeneous surfaces.

Another study conducted as part of SMACEX by Su et al., (2005) used the Surface Energy Balance System (SEBS) to estimate land surface fluxes using remote sensing and meteorological data. SEBS consists of several separate modules to estimate the net radiation and soil heat flux, and to partition the available energy into sensible and latent heat fluxes. Results from using SEBS show that the model can predict ET with accuracies approaching 10-15% of that of in situ measurements. To extend the field-based measurement of SEBS, information derived from Landsat ETM+ data and data from the North American Land Data Assimilation System (NLDAS)[6] were combined to determine regional surface energy fluxes for a clear day during the field experiment. Results from this analysis indicate that prediction accuracy was strongly related to crop type, with corn prediction showing improved estimates compared to those of soybean. This research found that differences between the mean values of observations and the SEBS Landsat-based predictions at in situ data collection sites were approximately 5%. Overall, results from their analysis indicate much potential

[6] Information on the NLDAS can be found at http://ldas.gsfc.nasa.gov/

toward routine prediction of surface heat fluxes using remote sensing data in conjunction with meteorological data.

In water-deficient areas, water resource management requires ET at high spatial and temporal resolutions. The use of remote space-borne sensing data to do so, however, requires the assessment of trade-offs between spatial and temporal resolutions. The sharpening of remotely sensed data is one potential way to obviate the limitations posed by data from satellite platforms, to derive surface temperature and NDVI at the spatio-temporal scales needed for water resources management applications. Yang et al., 2010 used the triangle algorithm to sharpen Landsat ETM+ data. Sharpened surface temperatures and reference temperatures were compared at 60m and 240m spatial resolutions. The reflectance measurements are used to calculate the NDVI. NDVI is then plotted as a function of surface temperature radiation (T_r) to evaluate the relationship between these two variables, as well as providing and overlaying index of moisture availability to establish a ‘warm edge’ and a ‘cold edge’ index (Figure 1). (A good overview of the triangle method is presented in Carlson, 2007). It was found that

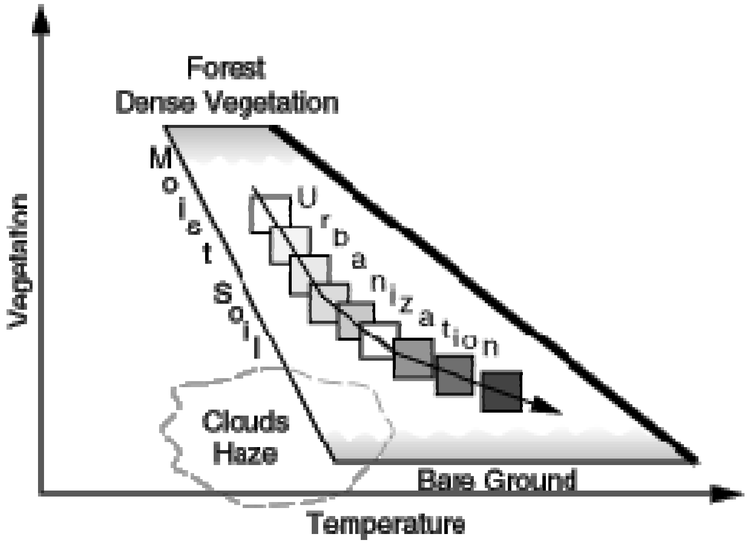

Figure 1. Schematic of the triangle concept that illustrates the relationships between temperature and vegetation within the overall perspective of NDVI, where the % of vegetated land cover and canopy density increases vertically, and the % of bare ground increases horizontally. The example here shows that as % of urbanized land cover and vegetation decreases, there is a corresponding increase in bare ground and higher surface temperatures (Quattrochi and Luvall, 2009).RMSE with the triangle algorithm is smaller than those with a functional relationship between surface temperature and NDVI.

In another study focused on a water deficient area, Landsat ETM+ data were used as input to a remote sensing based ET algorithm called METRIC (Mapping Evapotranspiration at High Resolution using Internalized Calibration) to provide accurate ET maps on actual crop water use over the Texas High Plains (THP) (Gowda, et al., 2008). The performance of the ET model was evaluated by comparing the predicted daily ET with values derived from soil moisture budget at four commercial agricultural fields. Daily ET estimates resulted in a prediction error (RMSE) of 12.7±8.1% when compared with ET derived from measured soil moisture through the soil water balance. Considering prevailing advection conditions in the THP, these results are good. The investigators note that METRIC offers promise for use in mapping regional ET in the THP region.

In a study over the U.S. central Great Plains, Park, Feddema, and Egbert, 2005) used surface temperatures (T_s) derived from MODIS data for correlation with concurrent water budge variables. Using a climate water budget program, four daily water budget factors (percentage of soil moisture, actual/potential ET ratio, moisture deficit, and moisture deficit potential ET ratio) were calculated at six weather station sites across western and central Kansas. Correlation analysis showed that T_s deviations from air temperature had a significant relationship with water budget factors. To do the analysis on a weekly basis, daily MODIS data were integrated into three different types of weekly composites, including maximum T_s driest-day, and maximum T_s deviation from maximum air temperature or max T_α. Results showed that the maximum T_s deviation (T_s-maxT_α) temperature composite had the largest correlation with the climatic water budget parameters. Correlation for different data acquisition times of MODIS TIR data improved the representativeness of signals for surface moisture conditions. The driest-day composite was most sensitive to time correction. After time correction, its relationship with soil moisture content improved by 11.1% on average, but the degree of correlation improvement varied spatially, but there was not a strong correlation with water budget factors in relation to the maximum T_s deviation composite method.

Three representative studies using MODIS data illustrate the potential of using these data for ET estimation. Modeling of actual daily ET in combination with MODIS data by Sanchez et al., 2007 allowed for the determination of surface fluxes over boreal forests on a daily basis from instantaneous information registered from a conventional meteorological tower, as well as the canopy temperatures (T_c) retrieved from satellite. The comparison between T_c ground measured with a thermal infrared radiometer at the meteorological sites and T_c retrieved from MODIS, showed an estimation error of $\pm 1.4^{o}C$. Their modeling method was validated over the study site using 21 MODIS images from 2002 and 2003. The results were compared with eddy-correlation ground measurements; with an accuracy of $\pm$1.0mm/day and an overestimation of 0.3mm/day were shown in daily ET retrieval. Mallick et al., 2007 used MODIS optical and thermal band data and ground observations to estimate evaporative fraction and daily actual ET (AET) over agricultural areas in India. Five study regions, each covering a 10km x 10km area falling over agricultural land uses, were selected for ground observations at a time closest to MODIS overpasses. Eight MODIS scenes collected between August 2003 and January 2004 were resampled to 1km, and were used to generate surface albedo, land surface temperature, and emissivity. Evaporative fraction and daily AET were generated using a fusion of MODIS-derived land surface variables coincident with ground observations. Land cover classes were assigned using a hierarchical decision rule applied to multi-date NDVI and applied via a triangle method to estimate the relationship between NDVI and surface temperature. Energy balance daily AET from the fused MODIS data was found to deviate from water balance AET by between 4.3% to 24.5% across five study sites with a mean deviation of 11.6%. The RMSE from the energy balance AET was found to be 8% of the mean water balance AET. Thus, the satellite-based energy balance approach can be used to generate spatial AET, but as noted by the investigators, further refinement of this technique should produce more robust results.

Remote sensing with multispectral infrared can improve regional estimates of ET by providing new constraints on land surface energy balance. Current models use visible and near infrared bands to obtain vegetated cover and in some cases utilize TIR data; these data together yield good ET estimates. However, it may be possible to enhance these ET models by using emissivity estimates derived from TIR emissivity, which is a property related to fractional vegetation cover but independent of plant greenness (French and Inamdar, 2010). This is demonstrated in a study using MODIS observations obtained over Oklahoma and Kansas, which were compared with changes in NDVI for winter wheat and grazing land. It was found that emissivity changes were independent of NDVI and sensitive to standing canopies, regardless of growth stage or senescence. Therefore, emissivities were seasonally dynamic, able to detect wheat harvest timing, and helpful for modeling ET.

Data combinations from different satellite sensors potentially provide even more useful information on soil wetness than by using data from one satellite platform alone.

Surface soil wetness determines moisture availability that controls the response and feedback mechanisms between land surface and atmospheric process. Mallick, Bhattacharya, and Patel (2009) performed a study to estimate volumetric surface soil moisture content in cropped areas in India at field ($<10^2$ m) to landscape ($\leq 10^3$ m) scales. In situ data collected at the field scale were used to obtain a soil wetness index (SWI) from which soil moisture content (θ_V) was derived using ASTER data for the field scale and MODIS at the landscape scale.

Integration of satellite data with spatial data on vegetation and terrain features via GIS methods have also been used to map ET. Accurate estimation of ET is difficult to obtain over heterogeneous landscapes with diverse land covers and topographic terrains. Mariotto et al., (2011) performed a study to build advanced remote sensing and land surface energy balance algorithms to map ET in a heterogeneous semi-arid area over the U.S. Department of Agriculture, Agricultural Research Service, Jornada Experimental Range that encompasses parts of southern Arizona, New Mexico, and Texas. ET of 12 different land covers was computed by applying he Surface Energy Balance Algorithm for Land (SEBAL). A GIS raster/vector system was used to integrate multispectral TIR and reflectance imagery from ASTER with meteorological, terrain, and land cover data. The study showed that SEBAL run with all these input data, provided the best agreement with ground measurements, in comparison with SEBAL run without any modification for terrain features and associated data, and it could significantly discriminate ET among 75.8% of vegetation types. SEBAL without ASTER integrated data set could not discriminate any vegetation types.

The influence of spatial scale on ET estimation using multiple satellite sensors collected over heterogeneous land surfaces is a critical research need. McCabe and Wood (2006) used Landsat ETM+ (60m), ASTER (90 m), and MODIS (1,020 m) data to independently estimate ET. The range of satellite sensor resolutions allows for analyses that span spatial scales from in situ measurements (i.e., point-scale) to the MODIS kilometer scale. ET estimates derived at these multiple resolutions were assessed against eddy covariance flux measurements during the SMACEX campaign over the Walnut Creek watershed in Iowa. Together, these data allow a comprehensive scale intercomparison of remotely sensed predictions, that included intercomparison of the ET products from the various sensors, as well as a statistical analysis for the retrievals at the watershed scale. A high degree of consistency was observed between the higher spatial resolution sensors (ETM+ and ASTER). The MODIS-based estimates were unable to discriminate the influence of land surface heterogeneity at the field scale, but did effectively reproduce the average ET of the watershed response, which illustrated the utility of this sensor for regional scale ET estimates.

Further information on the assessment of ET and soil moisture content across different scales of observation that has implications in deriving ET from satellite-based data is given in Verstaeten, Veroustaete, and Feyen (2008). Here they provide a summary of the generally accepted theory of ET, a summary of ET assessment at different scales of observation, a summary of data assimilation schemes for estimating ET using reflectance and TIR remote sensing data, and a summary of soil moisture retrieval techniques at different spatial and temporal scales. Another useful reference on scaling of TIR data for evaporation estimation is given by Li et al., (2009). Here they provide an overview of the commonly applied ET models using remote sensing data at regional scales. They discuss the main inputs, assumptions, theories, advantages and drawbacks of different ET models. They also provide insight into the limitations and promising aspects of the estimation of ET-based remotely sensed data and ground-based measurements.

Drought Monitoring

In addition to using TIR data for ET and soil moisture analysis over vegetated surfaces, there is also a need for using these data for assessment of drought conditions. Anderson and Kustas (2008) illustrate that ALEXI model can successfully be used with TIR data to model ET and drought at local to continental scales. They demonstrate this using GOES AVHRR data to produce ET soil moisture stress estimates at a 10 km grid resolution over the coterminous U.S. They also indicate that in ALEXI run in a disaggregation mode (DisALEXI) can generate moderate to high resolution (10^0-10^3 m) ET flux maps using data satellite platforms such as Landsat and MODIS. This methodology is examined more extensively and reported on in Anderson et al., 2011. Min and Minghu (2010) show that combining a spectral vegetation index (*NDVI*) with TIR data (T_s) in a T_s/*NDVI* triangle model can provide a promising measure for drought monitoring. They use the T_s/*NDVI* triangle method using MODIS NDVI and LST data to explore dryness monitoring in Heilongjiang Province, China. The spatial pattern observed using this method demonstrates that the summer dryness is characterized with extensive and long duration droughty conditions. They find that the $T_S/NDVI$ method can provide near-real time drought monitoring in the study area. Another study conducted in China by Wu et al., (2008) used MODIS TIR data within a GIS format to generate a soil moisture map based on the relationship between thermal inertia and soil moisture. Results indicate that thermal inertia derived from MODIS data is consistent with the actual dryness characteristics that occurred as verified with meteorological data[7].

Karniell et al., 2010 provide an insightful analysis of the merits and limitations of the use of NDVI and LST for drought assessment. Their work investigates the generality of the LST-NDVI relationship over a wide range of moisture and climatic/radiation regimes encountered over the North American continent (up to 60^{o}N) during the summer growing season. Information on LST and NDVI was obtained from long term (21 years) datasets acquired with the AVHRR sensor. It was found that when water is the limiting factor for vegetation growth (which is the typical situation for low latitudes of the study area during the midseason), the LST-NDVI correlation is negative. However, when energy is the limiting factor for vegetation growth (in higher latitudes and elevations, particularly at the beginning of the growing season), a positive correlation exists between LST and NDVI. Multiple regression analysis revealed that during the beginning and end of the growing season, solar radiation is the predominant factor

[7] Thermal inertia is the ability of a landscape to resist change in temperature. Because thermal inertia is related to surface composition or to near-surface moisture, remote sensing can be used to measure this property. We explain the utility of thermal inertia measurements in landscape analysis in our1999 *Landscape Ecology* article on pages 583-584.

driving the correlation between LST and NDVI, whereas other biophysical variables play a lesser role. Air temperature is the primary factor in midsummer. They conclude that there is a need to use empirical LST-NDVI relationships with caution to restrict their application to drought monitoring to areas and periods where negative correlations are observed, primarily to conditions when water – and not energy – is the primary factor limiting vegetation growth.

Desert or Arid Environments

Desert or arid environments occupy a significant portion of the earth's surface and with the prospect of the spatial extent of arid lands possibly increasing due to global climate change, they are important areas for analysis in landscape ecology. In association with drought monitoring, TIR data have been used to study surface temperature characteristics over desert or arid environments. For example, Akbar et al. (2011) used AVHRR and meteorological data to assess drought events in the semi-arid central plains of Iran. Drought recognition is based on the analysis of the Standard Precipitation Index (SPI) derived from meteorological variables and NDVI obtained from AVHRR data. These variables include the Vegetation Condition Index (VCI), LST, Land Surface Moisture (LSM), Temperature Condition Index (TCI), Land Surface Moisture (LSM), and the Vegetation Health Index (VHI). Analysis was restricted to the spring season from 1998 to 2004. Results show that indices derived from the AVHRR thermal band have a higher sensitivity to drought conditions than indices derived from the visible bands. Indices derived from reflective bands such as NDVI and VCI, appear to be better correlated to meteorological parameters than thermal band indices such as TCI. Indices that are calculated from both the reflective and TIR bands like LSM and VHI do not seem to be a reliable measure of drought conditions in the study area.

Research by Qin, Karnieli, and Berliner (2001, 2002, 2005) also used thermal data from the AVHRR to estimate LST and the variation of this parameter over the Israel-Sinai peninsula. As they note, the retrieval of LST from AVHRR data with two channels in the 10.5-11.3 µm bandwidth is usually derived using split window algorithm technique. In order to assess the spatial distribution of LST over the study area, they used a modified version of the split window technique that only requires input on emissivity and transmittance, as opposed to other versions of this technique that require atmospheric parameters that are generally difficult to estimate due to absence of in situ atmospheric profile data[8]. An LST image in combination with a pseudo-color image generated from AVHRR reflective wavelength bands (1, 2, and 4). A sharp contrast in arid land characteristics can be identified on both sides of the Israel-Egypt border. This contrast is a direct result of different vegetation cover and biogenic crust percentage on both sides.

[8] Extensive work has gone into the development of algorithms to estimate LST from AVHRR channels 4 and 5. The primary approach is the so-called “split window” technique that uses the difference in brightness temperatures between AVHRR channels 4 and 5 to correct for atmospheric effects on sea surface and land surface temperatures. The split window method corrects for atmospheric effects based on differential absorption in adjacent infrared bands in deriving LST from satellite data. The split window technique works independently of other data sources and takes advantage of the differential effect of the atmosphere on the radiometric signal across the atmosphic window region (Czajkowski et al. 2004.). Two other informative sources on the split window technique and retrieval of LST from satellite data are Wan and Dozier(1996) and Dash, et al. (2001).

Miliaresis and Partsinevelos used monthly night averaged LST derived from MODIS throughout a year-period (2006) in an attempt to segment terrain of Egypt into regions with different LST seasonal variability, and represent them parametrically. Regions with distinct spatial and temporal LST patterns were identified using several clustering techniques that captured aspects of spatial, temporal, and temperature homogeneity or differentiation. Segmentation was augmented by taking elevation, morphological features, and land cover information into consideration. Analyses of these data showed that the lowland northern coast region of Egypt along the Mediterranean Sea corresponds to the coolest clusters, indicating a latitude/elevation dependency of seasonal LST variability. Conversely, for inland regions, elevation and terrain dissection plays a key role in LST seasonal variability, while an east to west variability of spatial distribution in clusters is evident. Lastly, elevation biased clustering revealed annual LST differences among the regions with the same physiographic and terrain characteristics. Thermal terrain segmentation outlined temporal variation of LST during the year period, as well as the spatial distribution of LST zones.

Thermal Energy Theory as Applied to Ecological Thermodynamics

The concept of ecological thermodynamics provides a quantification of surface energy fluxes for landscape characterization in relation to the overall amount of energy input and output from specific land cover types. The concept of ecological thermodynamics was introduced in the Quattrochi and Luvall (1999) *Landscape* Ecology paper, but here we present a more thorough understanding of the techniques and methods embodied within this concept to offer an updated and clearer understanding of its utility and virtues

Terrestrial ecosystem's surface temperatures have been measured using airborne and satellite sensors for several decades. Using NASA's Thermal Infrared Multispectral Scanner (TIMS) Luvall and his coworkers (Luvall and Holbo 1989; Luvall et al 1990; Luvall and Holbo 1991) have documented ecosystem energy budgets for tropical forests, mid-latitude varied ecosystems, and semiarid ecosystems. These data show that within a given biome type, and under similar environmental conditions (air temperature, relative humidity, winds, and solar irradiance), the more developed the ecosystem, the cooler its surface temperature and the more degraded the quality of its reradiated energy. These data suggest that ecosystems develop structure and function that degrades the quality of the incoming energy more effectively; that is they degrade more exergy[9], which agrees with the predictions of nonequilibrium thermodynamic theory (Schneider and Kay 1994a; Kay and Schneider 1994; Schneider and Sagan 2005), This remote sensing work suggests that analysis of airborne remote sensing energy flux data is a valuable tool for measuring the energy budget and energy transformations in terrestrial ecosystems. Given the stated hypothesis, a more developed ecosystem degrades more exergy, the ecosystem temperature, Rn/K*, beta index, and Thermal Response Number (TRN) are excellent candidates for indicators of ecological integrity. The potential for these methods to be used for remote sensed ecosystem classification and ecosystem health/integrity evaluation is apparent.

[9] In thermodynamics, the exergy of a system is the maximum work available through any process that brings the system into equilibrium with a heat reservoir (environment). Exergy is the energy available for use. See Fraser and Kay, 2004 for a discussion of exergy in an ecological context.

Recent advances in applying principles of nonequilibrium thermodynamics to ecology provide fundamental insights into energy partitioning in ecosystems. Ecosystems are nonequilibrium systems, open to material and energy flows, which grow and develop structures and processes to increase energy degradation. More developed terrestrial ecosystems will be more effective at dissipating the solar gradient (degrading its exergy content).

Thermal energy theory results from work to understand ecological development. (See Kay 2000 for an overview.) The research in ecological thermodynamics has focused on linking physics and systems sciences with biology, and especially linking the science of ecology with the laws of thermodynamics. This research follows on the observation that similar developmental processes are observed in ecosystems, from small laboratory microcosms, to prairie grass systems, to vast forest systems and ocean plankton systems. Such similar phenomenology has long suggested underlying processes and rules for the development of ecological patterns of structure and function (Odum 1969). Furthermore, recent advances in nonequilibrium thermodynamics coupled with the investigation of self-organizing phenomena in different types of systems, (from simple convection cell systems to forested ecosystems) has revealed that all self-organizing phenomena (including ecosystem development) involve similar processes, processes which are mandated by the second law of thermodynamics. This conclusion, as discussed below, provides a basis for a quantitative description of ecosystem development. (Fraser and Kay 2004; Kay 1991; Kay and Schneider 1992a, 1992b; Schneider and Kay 1993, 1994a, 1994b, 1994 c; Regier Kay 1996.)

The study of self-organization phenomena in thermodynamic systems is based on systems that are open to energy or material flows, and which reside in quasi-stable states some distance from equilibrium, (Nicolis and Prigogine 1977). Both non-living self-organizing systems (like convection cells, tornadoes and lasers), and living self-organizing systems (from cells to ecosystems), are dependent on exergy (high quality energy) fluxes from outside sources to sustain their self-organizing processes. These processes are maintained by the destruction of the exergy; that is the conversion of the high quality energy flux into a flux of lower quality forms of energy. Consequently, these processes increase the entropy of the larger "global" system, in which the self-organizing system is embedded. Crucial insights, into the dynamics of self-organizing systems can be gained from examining the role of the second law of thermodynamics, in determining these dynamics.

Using exergy, the second law of thermodynamics can be applied to nonequilibrium regions and processes. In this systems can be described in terms of the exergy fluxes setting up gradients (e.g., temperature and pressure differences in classical thermodynamic systems). With the establishment of these gradients, the system is no longer in equilibrium. The system responds to these imposed gradients, by self-organizing in a way which resists the ability of the exergy fluxes to establish gradients, and hence move the system further away from equilibrium. More formally, a restatement of the second law says that as systems are moved away from equilibrium, they will utilize all avenues available to counter the applied gradients. As the applied gradients increase, so does the system's ability to oppose further movement from equilibrium (Schneider and Kay, 1994a). As a system self-organizes, the more effective it will become at exergy utilization. Kay and Schneider (1994c) have focused on the application of this thermodynamic principle to the science of ecology. Ecosystems are viewed as open thermodynamic systems with a large gradient impressed on them by the exergy flux from the sun. Ecosystems, according to the restated second law, develop in ways that systematically increases their ability to degrade the incoming solar exergy, hence counteracting the sun's ability to set up even larger gradients. It is clear that for forested ecosystems by far the majority of the energy is processed through sensible and latent heat fluxes as exampled by the measurements form the Hubbard Brook Forest (Figure 2).

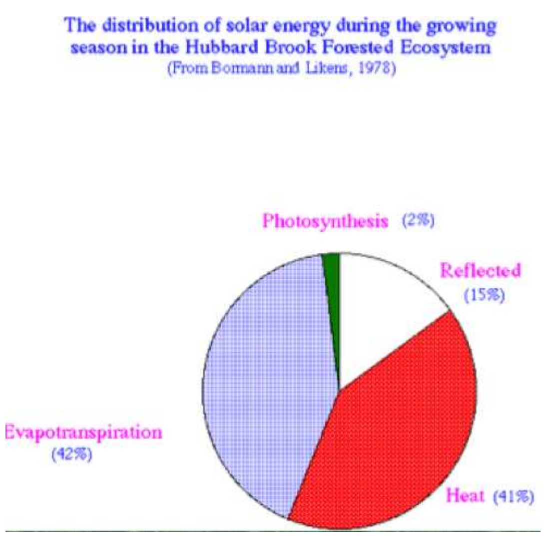

Figure 2. Partitioning of surface energy fluxes in Hubbard Brook (Bormann and Likens 1978, lecture notes J. Kay)

Thus it can be predicted that more mature ecosystems will degrade the exergy they capture more completely than a less developed ecosystem (Table 1). The degree to which incoming solar exergy is degraded is a function of the surface temperature of the ecosystem. (See Fraser and Kay 2004 for details.) If a group of ecosystems receives the same amount of incoming radiation, we would expect that the most mature ecosystem would reradiate its energy at the lowest quality level and thus would have the lowest surface temperature.

Beta Index as a Measure of Surface Temperature Spatial Variation

Three measures to characterize the thermodynamic performance of the ecosystem, the ratio Rn/K*, the Beta Index and the TRN. The average temperature for a forest canopy cannot express the spatial variability. However, as demonstrated by Holbo and Luvall (1989), the frequency distributions of temperatures can be used as a powerful model in differentiation and identification of land surface cover types and their properties. They found that a beta distribution closely resembles the observed temperature frequency distributions from forested landscapes. An advantage of using the beta distribution, as a model is that it utilizes the pixel frequency distributions directly, and no high-order, measurement-error- magnifying statistics are used (Figure 3). From this they developed the Beta Index by which these forested landscapes could be classified and quantify the spatial temperature variability of the ecosystem. As ecosystems develop, nonequilibrium thermodynamic theory suggests that they would tend toward internal equilibrium. Therefore we would expect the spatial variability of temperature to decrease as an ecosystem develops (Table 1). Thus a large beta index should indicate a more developed ecosystem. These data are consistent with viewing ecosystems in terms of nonequilibrium structures and processes. Nonequilibrium thermodynamic theory suggests dissipative systems tend toward steady state and develop homeostatic methods for maintaining steady state and thus we expect temperature variability to decrease with ecosystem development.

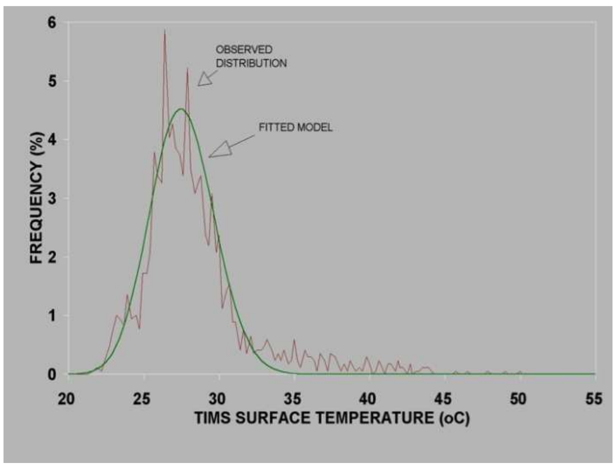

Figure 3. Fitting BETA probability distributions to observed frequency distributions. (Holbo and Luvall 1989).

Thermal Response Number

The second characterization measure, the Thermal Response Number (TRN), can be applied where ever there are overlaps in adjacent flight lines. The TRN was developed in Luvall and Holbo (1989, 1991) as a remote sensing based technique for describing the surface energy budget within a forested landscape. This procedure treats changes in surface temperature as an aggregate response of the dissipated thermal energy fluxes (latent heat and sensible heat exchange; and conduction heat exchange with biomass and soil). The TRN is therefore directly dependent on surface properties (canopy structure, amount and condition of biomass, heat capacity, and moisture). Surface net radiation integrates the effects of the non-radiative fluxes, and the rate of change in forest canopy temperature presents insight on how non-radiative fluxes are reacting to radiant energy inputs. The ratio of net radiation to change in temperature can be used to define a surface property referred to as the Thermal Response Number (TRN).

$TRN = \sum_{t_1}^{t_2} Rn\Delta t / \Delta T$ (in kJm-2 K); where $\sum_{t_1}^{t_2} Rn\Delta t$ represents the total amount of net radiation (Rn) for that surface over the time period between flights ($\Delta t = t_2 - t_1$) and ΔT is the change in mean temperature of that surface. Experiments by the P.I. using the Thermal Infrared Multispectral Scanner (TIMS) showed that 15-30 minutes between over-flights is sufficient time difference to obtain measurable and useful changes in forest canopy temperature due to the change in incoming solar radiation. The mean spatially averaged temperature for the surface elements at the times of imaging is estimated from $T = \frac{1}{n\sum T_p}$; where each T_p is the temperature of a pixel in the thermal image, and n is the number of pixels of the surface element. The TRN provides an analytical framework for studying the effects of surface thermal response for large spatial resolution map scales that can be aggregated for input to coarser scales as needed by climate models. The utility of TRN is that (1) it is a functional classifier of land cover types; (2) it provides an initial surface characterization for input to various climate models; (3) it is a physically based measurement; (4) it can be determined completely from a pixel by pixel measurement or for a polygon from a landscape feature which represents a group of pixels; (5) surface topography and orientation of observation are not handicaps where adequate digital elevation data are available. The TRN can be used as an aggregate expression of both environmental energy fluxes and surface properties such as forest canopy structure and biomass, age, and physiological condition; urban structures and material types.

Table 1. *Radiative transfer estimates, surface temperatures, Beta Index, and TRN measurements for several surface types at the Andrews Experimental Forest, Oregon. (Modified from Luvall and Holbo 1989, Holbo and Luvall 1989, Bishop et al. 2004).*

	QUARRY	***CLRCUT 2 yr Doug-Fir***	***NATREG 25 yr. Doug-Fir***	***PLANT 25 yr. Doug-Fir***	***MATUREF 400 yr Doug-Fir***
K^{*} W m^{-2}	718	799	895	854	1,005
L^{*} W m^{-2}	273	281	124	124	95
Rn W m^{-}	445	517	771	730	830
Rn /K* %	62	65	86	85	90
T ^{o}C	50.7	51.8	29.4	29.5	24.7
delta T	4.5	2.2	1.7	0.8	0.9
Beta	-12.9	6.3	17.2	34.4	130.7
TRN	168	406	788	1631	1549
kJ m^{-2}					

K* = net incoming solar radiation, L* = net long wave, Rn = net radiation, Rn/K* = percent of net incoming solar radiation degraded into non-radiative processes.

A similar index, thermal buffer capacity (TBC) was later proposed by Aerts et al. 2004 as a dissipation indicator:

$$TBC = \frac{(t_2 - t_1)}{(T_s(t_2) - T_s(t_1))} = \frac{\Delta t}{\Delta T_s}$$

Ecological Complexity and Ecological Health

The use of ecosystem exergy theory with thermal remote sensing observations is beginning to be used to study other ecosystems throughout the world. Maes et al. 2011 research used a series of DAIS (Digital Airborne Imaging Spectrometer) images collected over various forests, orchards, croplands, grazing lands, and urban areas in Northern and Central Belgium. They found that TRN and TBC have the highest discriminative power of all dissipative indices and were particularly suited for distinguishing differences in latent heat flux among the vegetation types. They also determined that TBC and TRN were the dissipation indicators that were least influenced by prevailing meteorological conditions.

Additional work by Lin et al 2009 used TRN, TBC, and Rn /K* to quantify plant community self-organization in a tropical seasonal rainforest, an artificial tropical rainforest, a rubber plantation, and two *Chromolaena odorata* (L.) R.M. King & H. Robinson communities aged 13 years and 1 year. These transects sampled the typical vegetation complexity and land use in Xishuangbanna, southwestern China. They concluded that these thermodynamic indices could discriminate differences in complexity among ecosystems studied both in the dry and wet seasons.

Norris et al. 2012 studied the application of ecological thermodynamics theory to ecosystem climate change adaptation and resilience. They concluded using ecological thermodynamic indicators would significantly enhance the understanding of the characteristics of resilient and adaptable natural environments.

Concluding Remarks

In our final remarks in our 1999 paper, we noted that the incorporation of TIR data into landscape studies offers the prospect to measure the state and dynamics of energy fluxes across and between landscapes, from the patch to the regional levels. The utilization of TIR remote sensing in landscape ecological research has indeed, as illustrated buy the numerous references cited herein, made meaningful and significant progress since the publication of our *Landscape Ecology* article. The utility of TIR data is now commonplace and a “known quantity” for application to landscape ecological research. This is a product of the increased amount of references in the literature to TIR data in landscape studies, but even more so because of the number of satellite platforms that have been launched in the last 14 years since our article was published. Of principle importance have been the TIR sensors onboard the NASA Terra Earth Observing platform (i.e., MODIS and ASTER) where the thermal data from these instruments have been widely used for analysis of a variety of landscape characteristics. Moreover, the launch of the VIIRS instrument in 2011 and Landsat 8 in 2013, has increased the overall availability of TIR data. New NASA missions that will be launched with TIR instruments are outlined in the National Research Council’s report on

"Earth Science and Applications from Space: National Imperative for the Next Decade and Beyond" (better known as the "Decadal Survey") (NRC, 2007) which established a roadmap for developing a suite of Earth observing satellites in the future. The NRC provided further direction for NASA's Earth science missions in its recently published report on "Earth Science and Applications from Space: A Midterm Assessment of NASA's Implementation of the Decadal Survey" (NRC, 2012).

One future mission in particular is important for furthering the use and analysis of TIR data for landscape assessment – the Hyperspectral Infrared Imager (HyspIRI). This will be a combined hyperspectral/thermal instrument with 213 spectral channels between 380 and 2500 nm on 10nm centers, and the TIR sensor will have 8 spectral channels (7 between 7.5-12 µm and 1 at 4 µm). Both instruments will have a spatial resolution of 60 m and the revisit time for HyspIRI will be 19 and 5 days for the Visible/Shortwave Infrared (VSWIR) and TIR instruments, respectively.[10] The HyspIRI mission, therefore, will offer an unprecedented opportunity to obtain high spatial resolution multispectral TIR data that can be used in landscape ecological and land surface processes research, at revisit times wherein observations of the land surface can be made at repeat times that to date, are unattainable by current NASA Earth science missions.

In the spirit of the Decadal Survey, HyspIRI is designed to address a number of thematic topics and underlying science questions related to the observation,

[10] More in-depth information on the HyspIRI mission can be accessed at the HyspIRI Mission Study website at http://hyspiri.jpl.nasa.gov/.

measurement, and analysis of land surface characteristics and ecosystem functioning. Although the HyspIRI science questions, at least in part, all focus on land surface issues, three overarching science question in particular, are of significance to furthering and fostering data analysis and modeling with TIR data from a landscape ecological perspective:

- How does urbanization affect the local, regional, and global environment? Can we characterize this effect to help mitigate its impact on human health and welfare?
- What is the composition and temperature of the exposed surface of the Earth? How do these factors change over time and affect land use and habitability?
- What is the composition of the exposed terrestrial surface of the Earth, and how does it respond to anthropogenic and non-anthropogenic drivers?

Correspondingly, each of these overarching science questions has underlying science sub-questions that elucidate issues associated with these larger questions. It is anticipated that HyspIRI with its hyperspectral/multispectral capabilities and improved revisit times, will provide the VSWIR and TIR data needed to help answer these questions

In summary, we have presented here a synopsis and description of relevant literature that has been published on thermal infrared remote sensing for analysis of landscape ecological and land surface processes research, since the publication of our article that appeared in *Landscape Ecology* in 1999, and which augments the information presented in our *Thermal Remote Sensing in Land Surfaced Processes* book, published in 2004. To this end, we believe that the review of the literature that is presented here annunciates the overall premise of the importance of TIR data for advancing the science of landscape ecological and land surface processes research. TIR data are now readily available from a number of NASA Earth observing satellite platforms at differing spectral and spatial scales that lend themselves in the overall analyses and modeling of a host of landscape characteristics and processes. In actuality, the volume of TIR data that are now available is somewhat overwhelming, and the specific types of TIR data and the spatial/spectral scales of these data, must be carefully matched with the landscape research in question. Dependent upon the objectives of specific research, it may in fact be prudent to utilize and compare TIR data collected at different spatial and spectral scales from different satellites, to develop a more complete understanding of the thermal characteristics, energy balances, and fluxes, that force or drive the landscape processes of interest. And, there is more TIR data to come in the future with the launch of NASA missions such as HyspIRI as well as Earth observing instruments launched by the European Space Agency (ESA) and other national entities. Through increased use and analyses, the science questions and research associated with developing a more comprehensive visual, qualitative, and quantitative insight into landscape functioning and characteristics that make the land surface, the” ‘landscape”, will be realized.

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