Land surface response to precipitation events using MODIS and NEXRAD data

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We have developed a wavelet-based information theoretic approach to examine the interaction between precipitation (PPT) forcing events and the land surface response. Combining Next Generation Weather Radar (NEXRAD) PPT with Moderate Resolution Imaging Spectroradiometer (MODIS) vegetation (NDVI) and surface temperature ($T_s$) data over the Missouri Basin in the north-central USA, we are able to address the spatial and temporal fluctuations surrounding the hydrometeorology of grassland ecosystems. Information theory metrics of entropy and mutual information content are combined with a wavelet multi-resolution analysis to examine to what extent the observed PPT signal directly determines the spatial distribution of the land surface temperature and vegetation and how this relationship varies with spatial scale. Results indicate that (1) there is a reduction in the temporal variance of the wavelet coefficients as the signal is transferred from the PPT into the surface temperature and finally the vegetation signal, (2) there are significant correlations as a function of spatial resolution between PPT–NDVI and PPT–$T_s$ signals which generally increase with spatial resolution, while there is little correlation between the NDVI and $T_s$ signals as a function of resolution, and (3) the scale-wise entropy and the mutual information content of the signals increase for all fields as the spatial resolution increases. This provides a methodology for determining the relative impact of regional climatology and local land–atmosphere interactions as a function of spatial scale.

1. Introduction

The spatial and temporal variability of water and energy cycling directly impacts the lives of people in many ways, ranging from flash floods to agricultural production to the effects of global climate change. Precipitation (PPT) is one of the primary factors which determines the observed variability of water, carbon and energy cycling between the land surface and atmosphere. The input of PPT impacts land–atmosphere interactions at both short and long timescales. The short-term response is governed by changes in soil moisture and the associated impacts on surface albedo and surface temperature ($T_s$). The longer term impacts are associated with changes in both the amount and structure of vegetation.

A number of studies have related the land surface response to atmospheric forcing factors such as PPT. The surface, through the role of soil moisture, acts as a

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low-pass filter to the high frequency variability commonly observed from atmospheric data (Entekhabi et al. 1996). Increases in soil moisture due to PPT has an immediate impact on the surface net radiation by decreasing the albedo and surface temperature (Eltahir 1998). Both of these effects act to increase the total net radiation and form the basis for a soil moisture–PPT feedback mechanism. Due to the large heat capacity of water, the diurnal range in surface temperature increases as the soil begins to dry, generally resulting in a negative correlation between soil moisture and surface temperature (Lakshmi et al. 2003). This negative correlation can be extended to PPT–surface temperature correlations, which vary in both time and space and can be used to assess the local land–atmosphere interactions (Brunsell 2006).

Remote sensing of soil moisture has largely focused on the use of the microwave brightness temperature, which can be related to soil moisture in areas of low vegetation (Jackson 1997, De Ridder 2000). The negative correlation between soil moisture and surface temperature provides an opportunity for assessing the impact of PPT events on the surface radiative budget through the application of infrared remote sensing. In the infrared portion of the spectrum, surface temperature can be used to quantify the near-surface soil moisture when used in conjunction with a combination of a vegetation index and a methodology such as the ‘triangle method’ (Gillies and Carlson 1995, Capehart and Carlson 1997, Vicente-Serrano et al. 2004).

Satellite remote sensing also provides an excellent opportunity to assess the response of vegetation to PPT events via the use of various products such as the Normalized Difference Vegetation Index (NDVI). Vegetation indices provide insight into spatial and temporal vegetation dynamics via multi-temporal observations of surface reflectance. Satellite observations of vegetation have shown the annual and long-term transient nature of vegetation (Goward and Prince 1995, Lambin and Ehrlich 1997). The focus of many remote sensing studies has been on relating the magnitude of these past changes in vegetation indices to changes in biomass and inferring the changes in dynamics necessary to produce the observed change.

Of course, the spatial and temporal evolution of land surface properties is not solely determined by the distribution of PPT, however it should be a major determinate for grassland ecosystems, which are often water limited (Ham et al. 1995, Ham and Knapp 1998). To some extent it seems relatively intuitive that the observed spatial variability in vegetation and soil moisture should be determined by PPT climatology. However, we wish to quantify the extent to which this is true. More specifically, we wish to address how the influence of spatial variability in PPT determines the spatial variability in the land surface and how does that influence vary with spatial scale.

In order to determine to what extent the PPT signal is observed within the surface temperature and vegetation signals, we adopt an information theory approach. This allows us to examine how the atmospheric forcing of PPT is transferred into a quickly responding soil moisture effect and then into a longer term vegetation response.

One of the primary limitations for assessing the impact of PPT events on the land surface has been the lack of high resolution PPT data. Next Generation Weather Radar (NEXRAD) estimates of PPT are produced hourly on an approximate $4 \times 4 \text{ km}^2$ grid, providing far greater spatial resolution than the available gauge
networks. Of course, NEXRAD estimates are a remote sensing product and are thus subject to error. Studies have indicated that NEXRAD tends to underestimate PPT over the long term with considerable gauge–radar variability at hourly accumulations (Smith et al. 1996, Young et al. 2000). However, this study is dependent on high spatial resolution data at temporal scales equal to 8 days or longer (to correspond to Moderate Resolution Imaging Spectroradiometer (MODIS) data), and temporal aggregation of the NEXRAD product tends to decrease random error in the estimates. Using the NEXRAD operational estimates of PPT allows us to investigate land surface dynamics across a broad area at the highest possible spatial resolution.

Understanding the mechanisms involved in the transfer of information from high frequency atmospheric forcing to the lower frequency land surface response has implications for the predictability of land–atmosphere interactions. These include the ability to use proxy observations of the atmosphere and vegetation structure to predict the surface energy fluxes and biomass response at short timescales. Several issues must be addressed before it is possible to address how different spatial and temporal scales influence the predictability of functional and structural responses of the land surface. Therefore the objectives of this work are to: (1) Assess the spatial and temporal scales of NEXRAD PPT and MODIS surface temperature and NDVI in the Missouri Basin and (2) quantify the extent to which the spatial distribution in surface temperature and NDVI are directly related to the spatial variability of PPT and how this influence varies with spatial scale.

This is a new application of information theory within the framework of earth system science. We are proposing to assess the ability of the land surface to filter high frequency atmospheric properties into lower frequency soil moisture and vegetation responses. These issues are of prime importance to the research community as the ability to forecast future land cover changes and the coupled global climate change are among the most pressing issues facing the scientific community for the benefit of humankind.

2. Study area and data sources

The grasslands of the north-central USA provide a relatively simple ecosystem in which to assess the applicability of information theory metrics to the study of land–atmosphere interactions. There has been extensive work within the remote sensing community attempting to quantify the extent to which remotely sensed variables (e.g. NDVI) respond to PPT events in grassland ecosystems. While there is an obvious intuitive correlation between PPT and biomass (Wang et al. 2003), little work has gone beyond simple correlation analysis. Grasslands also comprise a large portion of the Earth’s surface and account for a majority of the agricultural and grazing lands.

We focus on the Missouri Basin of the north-central USA. The Missouri Basin encompasses over 1.3 million km² south of the US–Canadian border. Figure 1 shows the numerous NEXRAD sites in the region which provide high resolution PPT estimates, as well as the number of (mostly) independent daily rain gauges to validate the NEXRAD PPT. The maximum effective range (230 km) for the NEXRAD radar units is shown for reference.

NEXRAD Stage III rainfall estimates from the National Weather Service (NWS) Missouri Basin River Forecast Center (MBRFC) are used for this study. The Stage III product combines radar and rain gauge observations to develop gridded,
multisensor PPT estimates. The rainfall estimates are produced hourly and are georeferenced using the Hydrologic Rainfall Analysis Project (HRAP) grid. The HRAP grid has a cell size of approximately $4 \times 4$ km$^2$, but the actual resolution varies with latitude. In areas where there is no radar coverage (e.g. Montana, Wyoming and a small part of South Dakota) the Stage III product is based solely on interpolation of the gauges. The NEXRAD rainfall estimates were aggregated to 8-day totals and then resampled using a nearest-neighbour approach to a 0.05° (approximately 5 km) grid to match the resolution of the MODIS surface temperature data. This resampling was accomplished using the ArcGIS 9.1 software package.

We use the 8-day composite of the NEXRAD and MODIS $T_s$ data with 16-day composites of NDVI. The period of 17 January to 15 October 2002 was chosen for the analysis due to this being a continuous period with all of the data sources reporting values over the Missouri Basin. This was deemed an important criterion, as it avoids interpolation issues and their impacts on the results of the temporal analysis. Of course it would be preferable to have a longer time series, but the overall purpose of this paper is to illustrate the methodology and while we are unable to quantify temporal dynamics at the annual and longer timescales, this illustrates the application of the methodology to distinguishing monthly dynamics.
The MODIS NDVI data are from the 250 m 16-day composite assembled by the Global Land Cover Facility at the University of Maryland (Carroll et al. 2002). The surface temperature data are from the 8-day composite available from the Land Processes Distributed Active Archive Center at 0.05° (approximately 5 km) resolution. In order to work with a common projection and spatial resolution, all data were reprojected using nearest-neighbour resampling into a geographic projection (latitude–longitude) with 0.05° spatial resolution and subsampled to the Missouri Basin. The 8-day composites for NEXRAD and \( T_s \) begin and end on the same days, and two 8-day periods comprise the 16-day NDVI composite. Thus, there is no overlap between individual 8-day fields.

3. Methods

3.1 Information theory metrics

The application of information theory to remote sensing data is not new (Price 1984); however, the focus has been primarily on assessing the accuracy of classification algorithms (Narayanan et al. 2002) or quantifying the redundancy between spectral bands of remotely sensed data (Hegarat-Mascle et al. 1997, Mascarilla 1997).

To determine how much of the observed land surface signal is directly due to the PPT signal, it is necessary to determine the information content of each of the data fields. This is determined by the Shannon entropy (Shannon 1948a,b):

\[
H = - \sum_i p_i \log_2 p_i
\]

where \( p_i \) is the probability of the data being in bin \( i \). This is a measure of the total statistical order of the system: lower entropy is more ordered. As a signal moves away from a uniform random variable, the order increases, and the amount of information needed to encode the signal decreases.

The entropy is calculated for the data in both the spatial and temporal domains using kernel density estimations (Moon et al. 1995). This analysis was conducted for the NDVI, \( T_s \) and PPT datasets.

The mutual information content (MIC) is a measure of how dependent two signals (\( X \) and \( Y \)) are on one another. To state this another way, the MIC quantifies how uncertain we are in \( X \) after we measure \( Y \):

\[
I(X, Y) = H(X) + H(Y) - H(X, Y)
\]

where \( H(X,Y) \) is the joint entropy, given as:

\[
H(X, Y) = - \sum_{x,y} p(x, y) \log_2 p(x, y)
\]

If \( X \) and \( Y \) are uncorrelated, then we gain no further information about \( X \) after a measurement of \( Y \), and \( I(X,Y) = H(X) + H(Y) \). The MIC can also be used to assess the mutual information within the same signal as a function of time lag; e.g. \( Y \) is the same as \( X \) with an embedded lag.

The MIC can also be interpreted as the level of redundancy or statistical dependence that is exhibited between different signals, which is very applicable to the remote sensing community (Palus 1995). This is due to the fact that two channels (e.g. \( X \) and \( Y \)) with some level of noise will be correlated, although not perfectly, and
therefore there is some level of redundancy (or information) gained about $X$ after we have knowledge of $Y$. Therefore, the (linear) correlation describes the degree to which two variables are statistically dependent, the MIC quantifies how much information we gain about one variable based on a measurement of the second.

### 3.2 Wavelet analysis

Due to the fact that there are a limited number of images used in this analysis, we approximate the temporal variability by analysing the changes in the spatial domain with time. We calculated the spatial wavelet spectra for a subset of the Missouri Basin for each time period. The subset was a square extent chosen to maximize the number of pixels ($128 \times 128$ pixels) located completely within the basin corresponding to an area of approximately $6.4 \times 6.4^\circ$ (outlined on figure 1). The number of rows or columns for this subset must be a power of two in order to conduct a dyadic (two to the power) decomposition required by the wavelet analysis. The wavelet analysis largely follows that of Brunsell and Gillies (2003) where they analysed airborne and satellite NDVI, surface temperature and modelled surface energy fluxes from the Southern Great Plains 1997 Hydrology Experiment data. The purpose of that analysis was to examine how spatial variability in vegetation and surface temperature affected the spatial distribution of the derived surface energy fluxes. Here, we wish to assess the impact of spatially variable PPT input on the land surface properties of vegetation and surface temperature.

Before we begin the discussion of wavelet analysis, it is beneficial to review the terminology of scale. There are three distinct aspects of scale (Bloschl 1999): (1) **extent**, or the total overall time or area covered by measurements, (2) **resolution**, the time or spatial coverage of an individual measurement (e.g. pixel), and (3) **spacing**, the time or area between consecutive measurements.

Wavelet analysis is a technique that allows viewing of a data series as it would be observed at different resolutions. Each different resolution is referred to as the ‘level of decomposition’. This is beneficial in that it provides a mechanism for separating out the relative importance (i.e. variance contributed) of each resolution to the observed signal. In addition, wavelet techniques allow us to not only determine the variance contributed by each resolution, we also determine when (for a time series) or where (spatially) the contribution is coming. Thus, while similar techniques like the Fourier transform can only tell us which scales are observed in the time (spatial) series, wavelet techniques also tell us where the different scales are most active.

This analysis begins with the discrete wavelet transform of a one-dimensional time series $f(t)$ (Kumar and Foufoula-Georgiou 1997):

$$Wf(m, n) = \sum_{t=0}^{\infty} f(t) \psi \left( \frac{t-n2^m}{2^m} \right)$$

with

$$\psi_{m, n}(t) = \frac{1}{\sqrt{2^m}} \psi \left( \frac{t-n2^m}{2^m} \right)$$

which allows the reconstruction from small to large scales as:

$$f(t) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} D_{m, n} \psi_{m, n}(t)$$
where the contribution of $2^m$ scale at $n2^m$ locations within the overall time series are given by wavelet detailed coefficients ($D_{m,n}$) which are the inner-product of the original signal $f(t)$ and the wavelet $\psi_{m,n}$. Here, we use the Daubechies 2 wavelet.

Extending to the spatial domain (two-dimensional), we can take the one-dimensional wavelet transform in both the horizontal and vertical directions of the two-dimensional dataset. We obtain three sets of detailed coefficients at each level of decomposition, corresponding to high frequency variability in either the vertical, horizontal or both directions.

In order to examine the total variance contributed to the overall signal by each level of decomposition, we use the wavelet spectra. The wavelet spectra are given by:

$$E(m) = \frac{1}{N} \sum_{i=0}^{M} |D_{i,n}|^2$$  \hspace{1cm} (7)

which gives the total energy contributed by scale $m$.

In addition to calculating the spectra, we use the pyramid multi-resolution analysis in the spatial domain to calculate the entropy at each scale. This analysis begins by noting that any two-dimensional $(x, y)$ data field can be reconstructed by progressively adding the finer scale details:

$$f(x, y) = \overline{X_m(x, y)} + \sum_{m \geq m_0} X'_m(x, y)$$  \hspace{1cm} (8)

where $f$ is the original data, $X_m$ is the residual at scale $(m)$, and $X'_m$ are the detail coefficients added to scale $m$ from the next coarsest scale $(m-1)$. By adding the detail coefficients from all scales, the original dataset is reconstructed. We use the $R$ wavethresh package and the Daubechies 2 wavelet family for performing the wavelet multi-resolution analysis.

From the multi-resolution analysis, we are able to take band-pass filtered versions of the original fields by calculating the inverse wavelet transform from the detail coefficients at each level of decomposition while setting the detail coefficients from all other levels to zero. This results in spatial distributed images that are what the original data series would look like if only that resolution were observed. Each level is a dyadic transform, therefore as the scale becomes finer, the number of pixels at that scale increases by a factor of 2. The transformation between approximate spatial resolution (degrees) and level of wavelet decomposition is based on the original resolution ($0.05^\circ$).

### 3.3 Combined analysis

In order to examine the scale-wise response of the land surface to PPT forcing, we combine the wavelet and information theory approaches to analyse how the temporally averaged NEXRAD PPT, the MODIS NDVI and $T_s$ fields vary as a function of spatial scale. The combined analysis begins by conducting the multi-resolution analysis and computing the entropy at each level of decomposition. This is done by adding the detail coefficients ($D_{m,n}$) in each of the horizontal, vertical and diagonal directions and using the inverse wavelet transform to create a band-pass filtered version of the original data at each resolution. Then we calculate the entropy value of the band-pass filtered data at each level of decomposition, which we refer to as the scale-wise entropy. By examining the entropy at each level, we can assess the relative structure of each field as the spatial resolution changes.
To assess the impact of the spatial variability in the PPT field on the $T_s$ and NDVI fields we calculate scale-wise correlations between the band-pass filtered data at the different levels of decomposition. Therefore, we calculate the correlation between the PPT–$T_s$, PPT–NDVI and NDVI–$T_s$ at each spatial scale. The correlation between the PPT and the surface fields at each resolution quantifies the relative influence of the different spatial scales on determining the PPT–land surface interactions.

We then compute the MIC between the band-pass filtered data across each level of decomposition, allowing us to examine the extent to which the temporally averaged surface fields are dependent upon the spatial variability in the PPT field. This allows us to address how the spatial distribution of NDVI and $T_s$ are directly due to variability in PPT and how this relationship changes as a function of spatial scale.

It is important to note that we are not addressing temporal dynamics in the sense of the impact of different time lags in the PPT field on the resultant spatial dynamics of the surface temperature and vegetation fields.

4. Results

4.1 Accuracy of 8-day NEXRAD data

If NEXRAD data are to be used to assess the temporal and spatial information content of PPT and the transfer of this information to the land surface, we must have an understanding of the uncertainty inherent to the radar-based rainfall field. Most existing gauge–radar comparisons have used hourly gauge data to evaluate NEXRAD for use in hydrologic modelling (e.g. Young et al. 2000, Grassotti et al. 2003). We have compared gauge and radar estimates of PPT at a wide range of temporal and spatial scales, focusing on those relevant to satellite remote sensing of $T_s$ and NDVI (i.e. temporal aggregation of NEXRAD estimates to 8-day totals).

By focusing on longer timescales for the NEXRAD aggregation, we were able to make extensive use of daily gauge records from the NWS cooperative observer network. Unlike many hourly gauges, the daily gauges are not incorporated in the NEXRAD multi-sensor product and thus present an independent data source for verification. Results indicate that longer time averaging results in better agreement between the radar and gauge data. Figure 2 plots the joint distribution of 8-day NEXRAD and gauge accumulations for the period of study. The correlation between NEXRAD and gauge estimates at this temporal aggregation is 0.85; the average total bias over the study period $-7.3\%$ (underestimation by the NEXRAD product). Estimates on the western edge of the Missouri River Basin exhibit greater bias and overall variability due to the complications of radar-rainfall estimation in complex terrain. In addition, estimates in north-east Wyoming, south-east Montana and a portion of South Dakota are poor due to zero radar coverage, and the product is only based on interpolation of the surface gauges in these regions.

4.2 Information content

To ascertain how the spatial information content varied as a function of time, we calculated the entropy over the Missouri Basin at each time at the original resolution from the original data (PPT, NDVI and $T_s$). Figure 3 shows the temporal variability of the spatial entropy for the NEXRAD and MODIS data. The seasonal cycle is easily identifiable in the NEXRAD and NDVI entropy fields. As the vegetation
senescence, the land surface becomes more spatially homogeneous (less disorder, less entropy). Since a majority of the PPT falls in the summer months, the rise in PPT is followed by a rapid increase to higher values of entropy (around day of year (DOY) 100) after which the active vegetation induces spatial variability and higher entropy values.

Figure 2. Joint distribution of 8-day NEXRAD and gauge estimates, with the 1:1 line shown. The legend shows the value of the probability density function.

Figure 3. Spatial entropy as a function of time for (a) NEXRAD PPT, (b) MODIS $T_s$ and (c) MODIS NDVI.
The temporal variability in the $T_s$ field generally shows the opposite trend of the NDVI and PPT signals. This is expected in that the largest spatial variability occurs earlier in the year when there is less vegetation to moderate the surface temperature signal. As the vegetation and PPT increase, the entropy in $T_s$ generally decreases.

Entropy can also be used to quantify the temporal uncertainty within one pixel. Figure 4 illustrates the temporal entropy for the 2002 season in the Missouri Basin. Given that this is based on a relatively few number of observations, the generality of these results is unknown, but the information theory approach is supportive of the idea of a low-pass filter in that there is decrease in the range of entropy values as the signal progresses through the land–atmosphere system, generally decreasing from the PPT field to the $T_s$ and the NDVI signal.

In addition, there is a general relationship where the higher entropy regions in PPT correspond to lower entropy regions in surface temperature and high regions in the vegetation signal. This can be understood by realizing that a higher entropy value implies greater uncertainty and a more uniform probability density function or histogram. If the PPT events are distributed uniformly in time, there is less variance in the soil moisture leading to lower entropy values in the surface temperature. In addition, these regions exhibit more uniform vegetation cover, which will also act to moderate surface temperature fluctuations.

### 4.3 Wavelet decomposition

Information theory metrics were coupled with the wavelet decompositions in order to develop a more thorough understanding of the interactions between the PPT and the land surface at multiple spatial scales. The information theory metrics calculated for the remotely sensed data can be extended to assess how much of PPT signal is observed within the temperature and vegetation signals (i.e. the redundancy between the signals) as a function of the spatial and temporal scales. This was done by using two-dimensional wavelet decomposition, and applying the information metrics at each level of decomposition.

Wavelet spectra were calculated for the 128 by 128 pixel (6.4°) square area in the centre of the Missouri Basin (figure 1). Each image was analysed to determine the spatial wavelet spectra, which are plotted in figure 5. Figure 5(a) shows the spatial spectra for the NEXRAD data, figure 5(b) shows the surface temperature spectra, and figure 5(c) shows the NDVI spectra.

There is a consistent relationship regardless of the time period as demonstrated by all slopes being approximately equal for each variable (figure 5). More important is the decrease in temporal variability as the signal progresses through the land–atmosphere system from the PPT into the surface temperature and finally into the vegetation signal, which supports the information theoretic approach developed previously.

### 4.4 Combined analysis

The true power of the analysis techniques comes when the wavelet and information theory approaches are combined to assess how the statistical distributions vary with spatial scale. Figure 6 shows an example for the temporally averaged NDVI field with the density plots used to compute the entropy at several levels. These levels are reconstructed NDVI fields based on the first, third and fifth levels of decomposition, corresponding to spatial resolutions of approximately 0.1, 0.4 and 1.6°. In general,
Figure 4. Temporal entropy for the (a) NEXRAD, (b) $T_s$ and (c) NDVI.

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as the resolution increases, the significance of the tails of the distribution becomes larger (i.e. the distribution becomes more uniform) and therefore the entropy increases. Following the analysis for each of the temporally averaged fields, we compute scale-wise entropy for each dataset (figure 7). The entropy increases with the resolution, but in the PPT and the NDVI fields there is a slight levelling off over the spatial resolutions between 0.5 and 1.0.° The largest range of values from the finest to the coarsest resolution is observed in the PPT. The range of entropy values are decreased in both the surface temperature and into the vegetation signal.

Figure 8 shows the scale-wise correlation between the various fields. This was computed by using the scale-wise approximation from the inverse transformed data fields. There is no clear relationship between the NDVI–Ts correlation and the resolution. One may expect to observe a negative correlation between the two fields (which is manifested at scales of approximately 1 and 4°), as increasing vegetation would typically act to moderate the radiometric temperature. The correlation turns positive at the largest scale (5°), possibly due to a change in the relative importance of local land–atmosphere interactions and a shift towards regional climate controls.

However, a clear trend emerges when examining the correlation between PPT and surface temperature, with an increasing negative correlation with increasing spatial scale. This implies that lower surface temperatures are probably due directly to high PPT at large spatial resolutions. While at smaller spatial resolutions, the correlation is probably lower due to local control of surface temperature due to variability in

Figure 5. Spatial wavelet spectra for the (a) NEXRAD, (b) Ts and (c) NDVI. Each line represents a different time period.
land cover, soil type, etc. The NDVI–PPT correlation shows an increasing correlation up to a resolution of about 3.2° with a decrease to approximately zero correlation at the largest scale. The behaviour at the largest scale is questionable, and perhaps can be explained due to the subset of 128 × 128 being too small and therefore the statistical significance of the largest scale reconstructions is
questionable. Given this dataset, we are unable to comment on this issue and further
analysis using a larger dataset should be conducted. However, we are certain of the
dynamics up to that largest scale in the NDVI-$T_s$ and NDVI–PPT correlations, and
in all of the other analysis. Therefore, another plausible explanation may be issues
related to the NDVI product.

Taken together, figures 7 and 8 imply that the spatial distribution in each
individual field becomes more uniform with increasing spatial resolution, but this is
due largely to the spatial variability in the PPT field. This can be seen as the
dominant factor due to the little correlation between the NDVI and $T_s$ fields with
spatial resolution, while both fields are strongly correlated with the PPT signal as
the spatial scale increases. Additionally, the correlations show (as one would expect)
that the PPT influence on surface temperature causes increasingly negative
correlations to be observed due to the soil moisture effect and higher correlations
between temporally averaged PPT and NDVI resulting from a longer term
climatological influence in vegetation distribution.

Figure 9 shows the scale-wise MIC for the NDVI and surface temperature
(figure 9(a)), the surface temperature and PPT (figure 9(b)) and the NDVI and PPT
(figure 9(c)). The largest values (lightest shades) correspond to the highest levels of
decomposition in both fields. Recall that the MIC is the amount of information
gained in $X$ by knowledge of $Y$. Therefore, the MIC (NDVI, PPT) as a function of
spatial scale tells us how much knowledge we have of the spatial dynamics of the
NDVI field (and thus the vegetation) by knowledge of the total PPT field. This
implies that the coarsest resolutions are the most statistically dependent upon one
another: knowledge of the coarse scale PPT field tells us a significant amount
concerning the spatial dynamics of the vegetation, while the finest resolutions all
have the least statistical dependence on one another. This suggests that the land
surface is most dependent upon the spatial patterns of PPT at larger scales, while at
finer resolutions there is less dependence on the small scale structure of PPT. To
state this in a different manner: the primary control is large-scale climatology which
equally determines PPT, vegetation, soil moisture and surface temperature

Figure 7. Scale-wise entropy for the NEXRAD PPT, $T_s$ and NDVI.
dynamics, which manifests itself in a large degree of statistical dependence between the various fields. The smaller scale variations are determined by local land–atmosphere interactions and individual values can not be determined from knowledge of the other fields, which thus exhibit more statistical independence.

The same general behaviour is observed for different scale pairings (i.e. off-diagonal) in figure 9. If we only examine one scale of one variable (e.g. NDVI) decomposition, and quantify the MIC as a function of scale with the second (PPT), we generally observe higher MIC as the scale of PPT increases. Note, however that the values are not symmetric around the diagonal: knowledge of the coarse scale NDVI does not tell you the same about the coarse scale PPT compared to what the coarse scale PPT tells you about the NDVI field. The generalizations drawn concerning the NDVI–PPT MIC hold for each of the fields examined in figure 9.

5. Conclusions

We have developed a combined wavelet–information theory approach to examine land–atmosphere interactions with the use of remotely sensed data. Using NEXRAD and MODIS data, we applied this methodology to quantify the land surface response to PPT forcing in the Missouri Basin.

Even with the use of a relatively short time series, we have observed a number of important results including (1) a general reduction in the temporal variance of the wavelet coefficients as the signal is transferred from the PPT into the surface temperature and finally the vegetation signal. This holds in figures 3 and 5, while in figure 7 they appear about equal and in figure 4, the temporal entropy decreases in the order of PPT to NDVI to \( T_s \). (2) The scale-wise correlations between the inverse transformed, band-pass filtered PPT–NDVI and PPT–\( T_s \) signals generally increase in magnitude with spatial resolution. (3) There is little correlation between the NDVI and \( T_s \) signals as a function of spatial resolution, which suggests that for some applications the use of NDVI and \( T_s \) may not be sufficient data sources and high spatial resolution PPT data may be a necessary addition in order to address
land–atmosphere interactions, and (4) the scale-wise entropy and the MIC of the band-pass filtered signals increase for all fields as the spatial resolution increases, but we are able to determine the nature of the increase. This provides a methodology for determining the relative impact of regional climate vs the local impacts of land–atmosphere interactions. Additionally, the examination of scale-wise MIC allows us to quantify the degree to which knowledge of one field at one scale (e.g. large scale

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**Figure 9.** Mutual information content between (a) $T_s$ and NDVI, (b) $T_s$ and PPT and (c) NDVI and PPT as a function of the level of wavelet decomposition.
PPT) can be used to inform us about the dynamics of a different field at a different scale (e.g. small scale NDVI).

These results are supportive of the general idea of the land surface filtering the high frequency PPT signal into a near immediate soil moisture effect and then slowly into a vegetative effect. This is observed in both temporal and spatial domains. While the overall result agrees well with previous research, we are able to quantify how the statistical distribution of both the NDVI and \( T_s \) field are directly due to the spatial variability in PPT and how this relationship varies with spatial resolution.

To our knowledge, this represents the first use of a combined NEXRAD and MODIS dataset for assessing land–atmosphere interactions. In addition, the combination of wavelets and entropy measures to quantify the use of scale-wise information transfer is novel and shows promise for being a useful tool in the study of the transfer of mass and energy between the land surface and the lower atmosphere.

References


