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The potential of Pathfinder AVHRR data for providing surrogate climatic variables across Africa and Europe for epidemiological applications

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Abstract

Surface climatic conditions are key determinants of arthropod vector distribution and abundance and consequently affect transmission rates of any diseases they may carry. Remotely sensed observations by satellite sensors are the only feasible means of obtaining regional and continental scale measurements of climate at regular intervals for real-time epidemiological applications such as disease early warning systems. The potential of Pathfinder AVHRR Land (PAL) data to provide surrogate variables for near-surface air temperature and vapour pressure deficit (VPD) over Africa and Europe were assessed in this context. For the years 1988-1990 and 1992, correlations were examined between meteorological ground measurements (monthly mean air temperature and VPD_{grd}) and variables derived from Advanced Very High Resolution Radiometer (AVHRR) data (LST and VPD_{sat}). The AVHRR indices were derived from both daily and composite PAL data so that their relative performance could be determined. Furthermore, the ground observations were divided into African and European subsets, so that the relative performance of the satellite data at tropical/sub-tropical and temperate latitudes could be assessed.

Significant correlations were shown between air temperature and LST in all months. Temporal variability existed in the strength of correlations throughout any twelve-month period, with the pattern of variability consistent between years. The adjusted r^2 values increased when elevation and the Normalised Difference Vegetation Index (NDVI) were included, in addition to LST, as predictor variables of air temperature. Attempts to derive monthly estimates of atmospheric moisture availability resulted in an over-estimation of VPD_{sat} compared to ground observations, VPD_{grd}. The use of daily PAL data to derive monthly mean climatic indices was shown to be more accurate than those obtained using monthly maximum values from 10-day composite data. A subset of the 1992 data was then used to build linear regression models for the direct retrieval of monthly mean air temperature from PAL data. The accuracy of retrieved estimates was greatest when NDVI was included with LST as predictor variables, with root mean square errors varying from 1.83°C to 3.18 °C with a mean of 2.38 °C over the twelve months.

Keywords

AVHRR; land surface temperature; vapour pressure deficit; epidemiology; Africa; Europe

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INTRODUCTION

Abiotic climatic conditions are critical factors in determining the geographical distribution of arthropod vectors and the incidence of infections they can transmit (Hay *et al.*, 1997). For example, environmental variables derived from meteorological satellite sensors have been used to explain the distribution and seasonal abundance of economically and medically important tick species (Randolph, 1993) or tick-borne diseases at both temperate and tropical latitudes (Randolph, 2000), as well as the distribution and abundance of a range of tsetse fly species in West Africa (Rogers *et al.*, 1996; Rogers, 2000). Spatial and temporal fluctuations in climatic conditions also influence disease risk, such as the seasonality of malaria in human populations (Hay *et al.*, 1998a; 1998b), as well as providing the information to drive proposed epidemic early warning systems for malaria (Connor *et al.*, 1999; Hay *et al.*, 2000a). Reliable assessments of the changing risk to human populations requires accurate, timely and extensive (geographically and temporally) information on climate (Hay, 1997) and is therefore of considerable interest to epidemiologists and public health workers alike (Hay, 2000; Hay *et al.* 2000b).

Studies that require meteorological data for large geographical areas depend on the regional infrastructure for meteorological data collection. These data are typically collected as point samples from weather stations, whose distribution is rarely designed to capture the range of climate within a region. Dissemination periods of these climatic data are also variable, limiting their use for real-time predictions. The paucity in spatial resolution of meteorological records may be compensated for by various methods of interpolation between known sites. This has proved very successful in predicting temperatures distant from meteorological stations, but measurements need to be of relatively high density and uniformly distributed (Lennon and Turner, 1995). Remotely sensed observations by satellite sensors, by contrast, allow quantitative measurements of key climatic variables at regular intervals over regional and global scales (Hay *et al.*, 1996; Goetz *et al.*, 2000).

This paper reports on the potential of Pathfinder AVHRR Land (PAL) data to provide continental-scale surrogate variables of near-surface air temperature and vapour pressure deficit, two climatic variables important in understanding arthropod vector ecology and disease distribution. The PAL data (James and Kalluri, 1994) are used to calculate monthly indices of land surface temperature (LST) and vapour pressure deficit (VPD_{sat}), which are then compared with monthly ground observations of mean air temperature (T_a) and (VPD_{grd}), respectively, in Africa and Europe. In addition, the AVHRR observations are composited into monthly values using different methods, and their relative performances as surrogates of climatic conditions are assessed using an independent data set (1992 daily data for Europe). Finally, estimates of monthly mean air temperature are retrieved from empirical regression models and compared to surface observations.

This study recognises that the relationship between surface temperature and air temperature is rarely 1:1 and that other studies have concentrated on estimating air temperature directly from AVHRR data by utilising the negative relationship between LST and the Normalised Difference Vegetation Index (NDVI) (e.g. Prince *et al.*, 1998; Czajkowski *et al.*, 1997; Prihodko and Goward, 1997; Prince and Goward, 1995). This has become known as the TVX (temperature/vegetation index) method (Goward *et al.* 1994; Prince and Goward, 1995). Epidemiological applications often need extended temporal climatic data sets, spanning years rather than days or months. The TVX method is computationally demanding so that the simplicity of calculating LST using the Price (1984) using Pathfinder AVHRR data was favoured. The suitability of the TVX method in epidemiological mapping will be assessed at a future date.

This investigation is an extension of previous work (Hay and Lennon, 1999), which assessed the accuracy of both spatial interpolation and remote sensing methods for providing land surface temperature, vapour pressure deficit and rainfall surfaces for Africa during 1990. The present study uses a longer period of observations (1988-1990 inclusive) to compare the accuracy of remotely sensed data for providing LST and VPD_{sat} surfaces in tropical Africa and temperate Europe.

MATERIALS AND METHODS

The analyses consisted of comparisons between meteorological variables derived from ground observations (monthly mean T_a and VPD_{grd}) and variables calculated using thermal channels 4 and 5 from PAL data (LST and VPD_{sat}). Monthly meteorological observations are published by the NOAA National Climatic Data Center (NCDC) for selected meteorological stations that adhere to World Meteorological Organisation (WMO) instrumentation and data collection standards (NOAA, 1990). Monthly mean air temperature, T_a (°C), and monthly mean vapour pressure, V_p (mb), observations were collated from 250 and 178 meteorological stations in Africa (1988-1990 inclusive) and Europe (1992 only) respectively (Figure 1).

VPD_{grd} (mb) was calculated from T_a in Kelvin, and V_p from formulae provided by Unwin (1980)

$$VPD_{grd} = Svp - V_p \quad (1)$$

where the saturation vapour pressure, Svp (mb) was given by:

$$\log_{10} Svp = 9.24349 - (230/T_a) - (500/T_a^2) - (100000/T_a^3) \quad (2)$$

The VPD is a measure of the lack of moisture equilibrium between an object and the surrounding atmosphere; the higher the VPD the more rapid the potential rate of desiccation.

PAL data (Agbu and James, 1994) were obtained from the Goddard Space Flight Center Distributed Active Archive Center (GSFC-DAAC) for the same duration as the meteorological data. PAL data are distributed with 12 data layers per observation, including five bands of spectral AVHRR data, the NDVI, and six bands of ancillary information, including date, sun/sensor geometry and data quality flags. Channel 4 (Ch4) and channel 5 (Ch5) brightness temperatures were used to calculate LST using the equation of Price (1984),

$$LST = Ch4 + 3.33 (Ch4 - Ch5) \quad (3)$$

and total precipitable water content in the atmospheric column, U , (kgm^{-2}) (Eck and Holben, 1994) where;

$$U = A + B (Ch4 - Ch5) \quad (4)$$

and, A and B are constants, 1.337 and 0.837 respectively.

The estimated precipitable water content, U (in cm), was then converted to a near surface dew point temperature, T_d (°F), the temperature to which a sample of air must be cooled for it to become saturated and condense, using the following relationship (Smith, 1966);

$$T_d = \frac{\ln U - ((0.113 - \ln(\lambda + 1))}{0.0393} \quad (5)$$

where I is a variable that is a function of the latitude and the time of the year. In this analysis, mean values of $I = 2.99$ and 2.74 were calculated from the annual mean I presented by Smith (1966) for latitudes representing Africa and Europe, respectively.

The dew point temperature values were then converted to Kelvin and used to calculate VPD_{sat} (KPa), using the equation provided in Prince and Goward (1995):

$$VPD_{sat} = 0.611 \left[\exp \left(17.27 \times \frac{T_{air} - 273}{T_{air} - 36} \right) - \exp \left(17.27 \times \frac{T_d - 273}{T_d - 36} \right) \right] \quad (6)$$

in which T_{air} represents air temperature. VPD_{sat} was converted to units of mb for direct comparison with VPD_{grd} . In equation 6, remotely sensed estimates of LST were substituted for the T_{air} variable assuming that LST is an adequate surrogate. The validity of this assumption is assessed in the following analyses.

The relationship between LST and ambient air temperature is influenced, among other things, by the amount of vegetation cover at the Earth's surface. In this analysis vegetation cover is represented by the NDVI:

$$NDVI = \frac{Ch2 - Ch1}{Ch2 + Ch1} \quad (7)$$

where $Ch2$ and $Ch1$ are, respectively, reflectance measured by the infrared and red bands of the AVHRR. The NDVI is positively related to both green vegetation amount and its level of photosynthetic activity (Myneni, *et al.*, 1995).

PAL data are supplied as daily images or decade composites (two 10-day and one variable compositing period per month). Each pixel in a ten-day composite stores data from a single date within a consecutive 10-day period when atmospheric contamination is considered to be at a minimum *i.e.* the date of maximum NDVI (Holben, 1986). For the period 1988-90 inclusive, daily images were used to calculate climatic indices for Africa, but the composite data were used for Europe, since the two continental data sets were originally derived separately. To assess the influence of the different PAL data types on the accuracy of the climatic surrogates, indices were calculated for Europe in 1992 using both daily and composite data.

All images were subjected to a quality control process whereby cloudy pixels as determined by the Clouds from AVHRR (CLAVR) algorithm (Stowe *et al.* 1991), were masked, as were pixels with extreme sun/sensor viewing geometry (see methodology in Hay and Lennon, 1999). The daily and 10-day LST images were condensed into single monthly images by taking the maximum value of LST over the monthly period, thereby reducing the occurrence of cloud-contaminated pixels still further. The rationale is that clouds are generally colder than the land so that the highest thermal value in the series will probably be the least cloud contaminated, especially at tropical latitudes (Lambin and Ehrlich, 1995). The VPD data were composited into monthly images by using the VPD from the date in the month or decade when the NDVI was highest. Very high latitude stations in Europe tended to return negative values of VPD in the winter months. These were excluded from the subsequent analyses.

LST and VPD_{sat} were extracted from each monthly image for those pixels corresponding to the latitude and longitude of each meteorological station. Regression analyses were performed on the meteorological and satellite variables for each month, and for each year of data (1988–1990) to assess inter-annual consistency. It was hypothesised that T_a would be strongly correlated with LST at monthly temporal resolution. Since T_a can deviate from LST significantly depending on surface conditions (Goetz 1997), such as vegetation cover and topography, NDVI and elevation are added to the multiple regressions as dependent variables to test how they affected the amount of explained variance. Another hypothesis was that some of the unexplained variance may be related to the method used to composite the AVHRR data. More regression analyses are performed using an independent dataset (daily PAL data for Europe in 1992). Climatic indices extracted from the maximum monthly AVHRR value are termed MMAX variables and those using the satellite observation from the date of the maximum NDVI are termed MVC (Maximum Value Composite). In addition, the daily observations were used to derive a mean value from all the cloud-free observations recorded for the month and are termed MMEAN variables. The optimum combination of predictor variables was then used to build regression models to retrieve estimates of monthly mean near-surface temperature directly, and to assess their accuracy using root mean square errors (RMSEs). For this, the 1992 meteorological station data set for Europe are divided randomly in two; one half was used to build the regression models and the other to test the accuracy of retrieved estimates.

RESULTS AND DISCUSSION

Relationships between Remotely Sensed LST and Monthly Mean T_a Observations

There are consistent significant correlations between remotely sensed LST estimates and monthly mean T_a observations for both the African and European continents. Linear regressions show positive and significant relationships in all months ($P \ll 0.01$, minimum $n = 105$, maximum $n = 164$ observations). RMSEs ranged from 2.8 to 7.5 K with a mean of 4.8 K for Europe, and 3.2 to 4.7 K with a mean of 3.9 K for Africa. The adjusted r^2 of the monthly data are plotted as a temporal profile (Figure 2a). The proportion of explained variance accounted for by LST suggests that this variable can be used with confidence as a reliable surrogate indicator of T_a over wide geographical areas with certain caveats.

The important observations in figure 2a are the seasonal trends in the strength of the relationships and their consistency for all three years of data. If LST is to be used as a predictor of T_a , knowledge of the annual variability in the strength of the correlation and its cause is essential. Spatial and temporal variations in surface conditions, e.g. vegetation cover and elevation, are likely to be responsible for a large degree of residual variance in the regressions and the observed temporal variability in correlations. When NDVI and elevation, in addition to LST, are used as predictor variables of T_a in multiple regressions, r^2 values are higher than those obtained using LST alone (Figure 2b and Table 1). The inclusion of NDVI as a predictor variable helps reduce temporal fluctuations in r^2 , probably because the vegetation phenology and its effects on surface thermal properties are represented. Elevation has not been explicitly parameterised in any equations to estimate LST from satellite data, but should be considered where application is required at the broad spatial scale or where the range in local elevation is large. At an altitude of 2000 m, for example, atmospheric attenuation of thermal IR radiation will be significantly less than for a site at sea level, since the radiation must travel through 2 km less atmosphere before reaching the satellite sensor. Such inaccuracies in the original remotely sensed signal will obviously reduce the accuracy of the LST estimate derived from Price (1984). Topographic variability also has a strong influence on ambient air temperature and, as with vegetation, can determine the difference between surface and air temperatures. The inclusion of elevation in the multiple regressions therefore improves r^2 values in a similar fashion to the inclusion of NDVI. Fortunately,

global elevation data, such as the United States Geological Survey Global Land Information System (USGS GLIS) exist at sufficient resolution to be included in continental scale analyses.

Although there is little difference in the yearly mean of the monthly r^2 values between the continental data sets (Table 1), the pattern of monthly variability in the LST/ T_a relationship is not consistent between Africa and Europe (Figure 2a or 2b). Differences between the two continents exist in the timing of the maximum and minimum r^2 . For Africa, the maximum r^2 values occurred around the months of May and June, whereas for Europe maximum r^2 occurred from August to October. Within any given month, there is a broad latitudinal range of meteorological stations covering a wide diversity of climatic regions and biomes. Future analyses will stratify the meteorological stations with respect to latitude, to determine the significance of the differences in temporal patterns of r^2 between Europe and Africa. The temporal consistency of regression slope coefficients and intercepts also needs to be examined.

This study has assumed that the empirical relationship between LST and T_a is sufficiently strong for practical applications within epidemiological mapping and the results support this to some extent. It is recognised, however, that the relationship between LST and T_a is not 1:1, as exemplified in the scatterplots (Figure 3), and that LST can deviate significantly from air temperature over areas varying in surface characteristics such as vegetation density, surface albedo and wetness. The influence of vegetation helps explain the increase in r^2 when NDVI is introduced into the multiple regressions. As mentioned previously, other studies have concentrated on retrieving air temperature estimates directly from remotely sensed data by exploiting the negative relationship between T_s and NDVI (Prince *et al.*, 1998; Czajkowski *et al.*, 1997; Prihodko and Goward, 1997; Prince and Goward, 1995). Due to the low thermal inertia properties of vegetation canopies, ambient air temperature does not deviate greatly from canopy temperature, even when the vegetation is actively transpiring. The observed NDVI/LST relation is extrapolated to an NDVI of an infinitely thick vegetation canopy to provide an estimate of air temperature. In site-specific tests Goward *et al.*, 1994 report accuracy of predicted air temperature typically within $\pm 2^\circ\text{C}$ of actual air temperature. More recent studies report an accuracy of 3.9°C over a range of 36°C (Prince *et al.*, 1998), 5 K (Czajkowski *et al.*, 1997) and 2.92°C (Prihodko and Goward, 1997). The aim of this study, however, was not to estimate air temperature directly, but to test whether T_s can be useful as a surrogate variable of T_a across continental scales and over extended periods of time.

The type and quality of the data used in this study may have significant influence on the observed relationships. Ideally, satellite data used for environmental applications should originate from a consistent source. A factor which complicates the comparability of the 1988-90 data series for Africa and Europe is that the African monthly composites were derived by processing daily Pathfinder data, whereas the European monthly images were derived from three 10-day composite images per month using the decade with the maximum NDVI value. It would be unwise to derive a monthly mean value from a maximum of only three satellite observations. Hence, comparisons have been made between remotely sensed *maximum* value composites and the monthly *mean* surface observations. This was not an ideal comparison but, as expected, maximum and mean values were significantly correlated.

The results show the benefit of investing more processing time in the PAL daily data to calculate a mean LST value (MMEAN index), using AVHRR channels 4 and 5 data from all the cloud-free dates left after CLAVR cloud-screening (Figure 4). The MMEAN index produces the highest r^2 value in nearly all months of 1992 for Europe. Both indices (MMEAN, MMAX) derived from the PAL daily data out-perform the MVC index, derived

from the Pathfinder composite data set based on the remotely sensed responses from the decade of maximum NDVI. Compositing using the date of maximum NDVI is popular for removing atmospheric contamination from the time-series, but minimum atmospheric attenuation of short-wave (optical bands) and long-wave (thermal bands) radiation do not necessarily coincide (Lambin and Ehrlich, 1996). The results show that to characterise near surface conditions of temperature accurately for a monthly period, it is best to composite a maximum value or calculate the mean value independent of the date of maximum NDVI, and only the daily PAL data set can provide the data for this.

Having identified the significant empirical relationship between LST and T_a , and the remotely sensed index yielding the strongest correlations (MMEAN), the ability to retrieve T_a estimates empirically was assessed. Linear regression models were built using a randomly generated training data set of 1992 Europe meteorological observations. For each month, three separate regression models were derived using as predictor variables LST, LST + NDVI, LST + NDVI + elevation, respectively. Estimates of T_a were derived using the randomly generated testing data set of meteorological observations (independent from the training data set) as input to the regression models. All r^2 values are significant at $P < 0.01$, except December LST + NDVI + elevation (not significant). The r^2 values derived using LST + NDVI are consistently higher than LST alone, except in July and August (Figure 5). When elevation is included as a predictor variable, the range of r^2 values increases. The highest r^2 values are obtained when elevation is included, but relatively low values in January, March, April and especially December ($r^2 = 0.08$) reduce the mean r^2 to 0.58 (Table 3). RMSEs of retrieved estimates of monthly mean air temperatures were at best 1.77°C (Table 3) and, when averaged over 1992, ranged from 2.38 °C to 2.97 °C depending on the combination of predictor variables.

Relationships between Remotely Sensed VPD and Monthly Mean Ground Observations

Significant positive linear relationships ($P < 0.01$) exist between VPD_{grd} and VPD_{sat} for the African data set (Figure 6a), with RMSEs ranging from 4.7 to 7.1 mb with a mean of 5.8 mb. In contrast, r^2 values for the European data set are in most cases lower (Figure 5 and Table 2). RMSE for Europe range from 0.7 to 3.5 mb with a mean of 1.6 mb, which are smaller than for Africa, but reflect the narrower dynamic range and smaller magnitudes of data values for Europe, as well as the problem of these techniques in dealing with low temperature VPD retrieval. The inclusion of elevation, or elevation and NDVI, as additional predictor variables only marginally improved the fit to the ground data (Figure 6b).

Scatterplots (Figure 7) reveal that remotely sensed estimates of VPD are significantly larger than the ground observations. VPD_{sat} can exceed 200 mb which, compared to expected maxima approximating 70 to 80 mb, are unrealistic. The calculation of VPD_{sat} involves a number of stages in which errors can arise and propagate. Atmospheric water vapour (U) can be problematic (Czajkowski *et al.*, this issue) and in this instance is estimated from an empirical algorithm developed using meteorological data from Mali (Eck and Holben, 1994), but its applicability to other geographical regions needs to be assessed. Estimating U from algorithms derived from established physical models may be a preferable alternative to estimates derived from purely empirical observations. For example, Prince and Goward (1995) used an atmospheric radiative transfer model, LOWTRAN-7 (Kneizys *et al.*, 1988), to derive an empirical relationship between U and the function of LST and AVHRR channel 4/channel 5 radiant temperature differences.

The major source of error in the VPD_{sat} , however, is likely to arise from the use of LST as a straight substitution for air temperature, in the final stages of the calculation. Future work will concentrate on using inferred air temperature estimates, derived using the multiple regression methods performed on the 1992 Europe data, rather than LST as input to the VPD

equation (eq. 6). Despite the strong correlations, directly retrieving VPD from remotely sensed data using LST as a substitute for T_a will not produce accurate estimates.

SUMMARY AND CONCLUSIONS

Epidemiologists require readily available and/or easily calculated remotely sensed indicators of near-surface climatic variables affecting disease vector biology. In particular, air temperature and atmospheric moisture conditions are key determinants of arthropod vector ecology and consequent parasite/pathogen transmission. This paper has examined the potential to derive proxy measures of these variables from 8×8 km PAL data using a three-year time series of satellite observations covering two continents, Africa and Europe. Techniques to retrieve air temperature directly from AVHRR data, *i.e.* the TVX method, are not yet validated at the spatial (typically continental) and temporal (multi-year) scales required for immediate use by epidemiologists. Hence, this study has not used the TVX method but investigated LST as a surrogate variable. The simplicity of the calculation of LST from Price (1984) will ensure that it continues to be readily used by researchers of many disciplines (not just epidemiologists) eager to incorporate remotely sensed data into their work. This study has assessed the extent, spatially and temporally, to which LST can be used as a proxy measure of air temperature before breaking down as a surrogate variable.

Correlations between remotely sensed monthly LST observations and monthly ground-based air temperature, T_a , data are high in most cases especially for the tropical and sub-tropical latitudes of Africa. There is temporal variability in the monthly correlations indicating a seasonal influence on the relationships. This is probably due, in part, to changing surface characteristics, especially vegetation cover, between different months of the year. The strength of correlations increases significantly when NDVI and elevation data are included in the multiple regression analyses. Importantly, there was consistency in relationships between the years of study (1988 - 1990).

LST indices derived from the daily AVHRR Pathfinder data are more strongly correlated with monthly mean T_a than those derived from the 10-day composite data. Mean values of LST for each month in 1992 were derived from all the cloud-free daily observations for Europe. These indices are more highly correlated with surface observations than monthly maximum values and observations from the date of maximum NDVI. The use of daily data to derive monthly mean LSTs is, however, dependent on accurate cloud-screening and expensive in terms of computer processing time.

NDVI is an important variable for increasing the strength of relationships between LST and T_a and increasing the accuracy of empirically derived T_a estimates. The accuracy of retrieved T_a over Europe (1992) range from 1.83°C to 3.18°C , with a mean over twelve months of 2.38°C when NDVI and LST are used as predictor variables in a multiple regression.

Attempts to derive monthly estimates of atmospheric moisture availability from AVHRR Pathfinder data result in an over-estimation of VPD_{sat} compared to ground observations, VPD_{grd} . This study substituted LST for air temperature in the calculation of VPD_{sat} , which is likely to be the main reason for the over-estimation. Hence, continental-scale mapping of VPD is dependent on accurate estimation of T_a and will be the topic of future investigations.

The relationships obtained using the Africa and Europe data emphasise the potential of NOAA AVHRR data to provide useful surrogates of climatic variables, on a consistent temporal basis at continental scales. Remotely sensed meteorological data present a significant advance in both temporal frequency and spatial coverage over sparsely distributed meteorological station records. This paper has been a first step in showing

significant relationships, with consistency over a relatively long time period (three years), between satellite observations and climatic variables of key importance to epidemiology.

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Figure 1.
Distribution of the NOAA-NCDC meteorological stations used in this study.

Figure 2.

Coefficients of determination, r^2 , from regressions between monthly mean air temperature T_a and (a) monthly maximum LST (b) LST, elevation and monthly maximum NDVI, for each month from January 1988 to December 1990. NDVI values were unavailable for May 1989, Africa.

Figure 3. Comparison of T_a with LST for the months with highest correlations (a) sites across Europe for October 1989 (b) sites across Africa for December 1990.

Figure 4.

Coefficients of determination r^2 from regressions between T_a and three LST indices derived from AVHRR data (MMAX = maximum per month of daily data; MMEAN = Mean per month of daily data; MVC = maximum value composite using LST from decade of maximum NDVI).

Figure 5. The strength of correlations, r^2 , between observed and predicted T_a at selected meteorological stations in Europe 1992 using predictor variables LST; LST and NDVI; LST, NDVI and elevation.

Figure 6. Coefficients of determination, r^2 , from regressions between VPD_{grd} and (a) VPD_{sat} (b) VPD_{sat} , elevation and monthly maximum NDVI, for each month from January 1988 to December 1990. NDVI values were unavailable for May 1989, Africa.

Figure 7. Comparison of VPD_{grd} and VPD_{sat} for the months with highest correlations (a) sites across Europe - July 1990 (b) sites across Africa - April 1989.

Table 1

The mean of the January to December (1988-90) adjusted coefficients of determination (r^2) obtained from linear regressions between monthly mean air temperature, T_a , and predictor variables (i) monthly maximum LST (ii) LST and elevation (iii) LST, elevation and NDVI. 1.96 standard errors are given in brackets.

Year	LST			LST + Elevation			LST + Elevation + NDVI		
	Africa	Europe	Africa	Europe	Africa	Europe	Africa	Europe	Europe
1988	0.58 (0.07)	0.52 (0.06)	0.69 (0.04)	0.63 (0.08)	0.70 (0.05)	0.71 (0.05)			
1989	0.53 (0.09)	0.53 (0.06)	0.69 (0.05)	0.66 (0.07)	0.72 (0.06)	0.73 (0.07)			
1990	0.52 (0.07)	0.55 (0.06)	0.66 (0.05)	0.70 (0.04)	0.70 (0.05)	0.77 (0.02)			

Table 2

The mean of the January to December (1988-90) adjusted coefficients of determination (r^2) obtained from linear regressions between monthly mean saturation deficit and predictor variables (i) monthly maximum AVHRR derived vapour pressure deficit VPD_{sat} (ii) VPD_{sat} and elevation (iii) VPD_{sat} , elevation and NDVI. 1.96 standard errors are given in brackets.

Year	VPD			VPD + Elevation			VPD + Elevation + NDVI		
	Africa	Europe	Africa	Europe	Africa	Europe	Africa	Europe	Africa
1988	0.63 (0.07)	0.35 (0.11)	0.66 (0.06)	0.37 (0.10)	0.68 (0.05)	0.38 (0.10)			
1989	0.63 (0.07)	0.48 (0.10)	0.67 (0.05)	0.50 (0.10)	0.68 (0.05)	0.50 (0.10)			
1990	0.63 (0.04)	0.49 (0.11)	0.66 (0.03)	0.51 (0.12)	0.68 (0.03)	0.52 (0.10)			

Table 3

The correlations (r^2) between predicted and observed monthly mean air temperatures and the accuracy of retrieved estimates (RMSE) for 1992.

Month	LST		LST + NDVI		LST + NDVI + elevation		n
	r^2	rmse	r^2	rmse	r^2	rmse	
Jan	0.46	2.44	0.50	2.33	0.39	3.46	23
Feb	0.24	2.60	0.34	2.67	0.37	2.91	47
Mar	0.50	2.07	0.60	1.83	0.65	2.27	53
Apr	0.75	2.12	0.78	2.01	0.62	4.00	58
May	0.67	2.04	0.70	1.96	0.77	1.77	64
Jun	0.50	2.23	0.51	2.20	0.52	2.21	65
Jul	0.79	1.99	0.79	2.00	0.86	1.64	65
Aug	0.72	2.78	0.70	2.88	0.45	5.30	78
Sep	0.73	2.72	0.73	2.72	0.87	2.17	75
Oct	0.78	3.35	0.80	3.18	0.80	3.63	67
Nov	0.63	1.99	0.65	1.97	0.61	2.62	53
Dec	0.51	2.87	0.57	2.79	0.08	3.66	15
Mean	0.61	2.43	0.64	2.38	0.58	2.97	