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Evaluation of MODIS surrogates for meteorological humidity data in east Africa

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Abstract

Satellite remote sensing technology has shown promising results in characterizing the environment in which plants and animals thrive. Remote sensing scientists, biologists, and epidemiologists are adopting remotely sensed imagery to compensate for the paucity of weather information measured by weather stations. With measured humidity from three stations as baselines, our study reveals that Normalised Difference Vegetation Index (NDVI) and atmosphere saturation deficits at the 780 hPa pressure level (D_{MODIS}), both of which were derived from the MODerate-resolution Imaging Spectroradiometer (MODIS) sensor, were significantly correlated with station saturation deficits (D_{stn}) ($r = 0.42–0.63$, $p < 0.001$). These metrics have the potential to estimate saturation deficits over east Africa. Four to nine days of lags were found in the NDVI responding to D_{stn} . For the daily estimations of D_{stn} , D_{MODIS} had a better performance than the NDVI. However, both of them poorly explained the variances in daily D_{stn} using simple regression models (adj. $R^2 = 0.17–0.39$). When the estimation temporal scale was changed to 16-day, their performances were similar, and both were better than daily estimations. For D_{stn} estimations at coarser geographic scales, given that many factors such as soil, vegetation, slope, aspect, and wind speed might complicate the NDVI response lags and model construction, D_{MODIS} is more favourable as a proxy of the saturation deficit over ground due to its simple relationship with D_{stn} .

1. Introduction

Humidity is one of the fundamental abiotic factors that determine which animals and plants can survive and thrive (Marion et al., 2003). Therefore, humidity is important in bionomics (Aldasoro et al., 2004, Markow and O’Grady, 2008), habitat protection and restoration (Dabrowska-Zielinska et al., 2009), and epidemic forecasting (Shope, 1991, Kiang et al., 2006, Bhunia et al., 2010), etc. Humidity is usually measured at weather stations 2 m above the ground. However, infrastructure such as weather stations is often limited in underdeveloped areas of Africa (Fall et al., 2006). In these areas, remote sensing data are often used as proxies for actual station data driven by the need for high spatial and temporal resolution, low cost, and easy access to data (Kalluri et al., 2007, Goward et al., 1994, Gleiser and Gorla, 2007). Recent work in east Africa on tsetse fly (*Glossina spp.*, a vector for trypanosomiasis) distributions has led to the development of an ecological model (DeVisser et al., 2010) that has motivated an interest in developing more spatially and temporally accurate input temperature, humidity and land-use type data for predicting tsetse prevalence. This study evolved from an investigation of humidity input to the Tsetse Ecological Distribution model (DeVisser et al., 2010). We also hope our findings provide useful information for other disease epidemiology or biogeography studies.

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Vegetation is influenced by, and affects, local climate, especially moisture. Rogers and Randolph (1991) found that the annual Normalized Difference Vegetation Index (NDVI) is strongly correlated with the mean annual saturation deficit over Africa ($r = 0.700$, $p < 0.001$). Remotely-sensed NDVI therefore seems to be an acceptable substitute for yearly mean meteorological humidity (Hay et al., 1996). For finer temporal scales such as daily, few studies are reported on relationships between NDVI and saturation deficits. This study aims to address this shortcoming.

The recent introduction of the Atmospheric Profiles Product, derived from MODIS (MODerate-resolution Imaging Spectroradiometer) sensors on board EOS-Terra and EOS-Aqua satellites, provides new opportunities to explore a new estimation methodology for air humidity. In particular, the MODIS Atmospheric Profile product (MOD07_L2) provides atmospheric profiles including dew point temperature and air temperature on a daily basis at 20 vertical atmospheric pressure levels and at 5×5 km spatial resolution (Seemann et al., 2006). Using Aqua MODIS, profiles may be produced at 1 km pixel resolution when cloud-free. Thus, for this study, we used Aqua MODIS imagery when possible.

Station data are sparse in remote areas of Africa. This scarcity makes remote sensing of environmental conditions crucial for models and predictions. The main objective of our study is to evaluate two meteorological humidity proxies, specifically, MODIS NDVI and MODIS saturation deficit, by comparing them with ground-measured humidity from three weather stations in east Africa site by site.

2. Data

2.1 Meteorological saturation deficit

RH (relative humidity) and saturation deficit are two common measurements for humidity. However, using saturation deficit rather than RH to measure the effect of atmospheric moisture conditions upon living organisms is more desirable (Anderson, 1936). Saturation deficit, characterized by the difference between the saturation vapour pressure and the vapour pressure of a volume of air, gives a very direct indication of the atmospheric moisture conditions independently of the temperature. The fact that two different areas have the same RH does not imply a similarity in the amount of water vapour in the atmosphere unless temperatures are also identical. Areas having the same saturation deficits, on the other hand, do influence evaporation rates in the same way and represents a better basis for comparison. Therefore, we used saturation deficit as the measurement of meteorological humidity. Saturation deficits were not measured directly at our weather stations, but they can be calculated from RH and temperature data using a formula given by the World Meteorological Organization (WMO, 2008):

$$D_{\text{stn}} = e_s - e \quad (1)$$

$$e = (\text{RH}) e_s \quad (2)$$

$$e_s = 6.112 \exp [17.67 T / (T + 243.5)] \quad (3)$$

where D_{stn} (hPa) is the saturation deficit derived from weather stations; e_s (hPa) is the saturation vapour pressure at temperature T (°C); e (hPa) is the actual amount of water vapour.

Air temperature and RH observations were obtained from three HOBO Weather Stations (MicroDAQ.com Ltd., NH, USA) located in south Kenya (Figure 1). Elevations of the three

stations were 644 m for Station 1, 661 m for Station 2, and 766 m for Station 3. Surrounding areas of the three stations were all grasslands with low dense shrubs. These stations span a mild ecotone from sparse vegetation to open savanna in the Lake Natron valley.

Data were recorded every three hours in 2010. To understand the intraday variation of the humidity, we recorded rainfall, temperature, and RH every 10 min in one week (26 October to 2 November 2010) (Figure 2). Based on our 10 min interval observations, without rain effects, D_{stn} in all stations had similar daily variation patterns that varied periodically (Figure 2). D_{stn} reached the daily minimum and maximum values at around 6 a.m. and 3 p.m. local time, respectively, which also were the coldest and hottest times of the day. The Aqua satellite passing time is approximately 2:30 a.m. and 2:30 p.m. local time, indicating that the daytime moisture level detected by Aqua MODIS is close to the daily maximum saturation deficit while the nighttime level is about 77% of the daily minimum saturation deficit if we assume the increase of moisture is linear from 3 p.m. to 6 a.m. the next day. As maximum dryness is a key factor for tsetse survival (Knight, 1971, Rogers and Randolph, 1985), the daytime Aqua MODIS products were compared with the synchronous D_{stn} for potential suitability as a proxy for moisture.

As we can see from Figure 2, the periodical pattern of the daily saturation deficit variations were interrupted by rainfall events that made D_{stn} decrease immediately. But in the next day after the rainfall, the pattern returned to normal. Therefore, during rainy days, the saturation deficit detected by Aqua MODIS might not approximate the maximum values.

2.2 MODIS data

The satellite data used in this study included:

1. Temperature of 780 hPa pressure level ("Retrieved_Temperature_Profile_16", MYD07_L2, 1 km resolution, 2010);
2. Dew point temperature of 780 hPa pressure level ("Retrieved_Moisture_Profile_16", MYD07_L2, 1 km resolution, 2010);
3. Vegetation Indices 16-Day L3 Global 1 km (MYD13A2, 1 km resolution, 2010)

The MODIS atmospheric profile retrievals algorithm is based on the Fast Transmittance Model where the atmospheric layers are numbered from space to the surface with 101 levels (Hannon et al., 1996). These layers vary smoothly in thickness from several tenths of a km near the surface to several km at the highest altitudes. Atmospheric profile retrievals are saved at only 20 levels from 5 hPa to 1000 hPa in the MOD07_L2 data (Seemann et al., 2006). An atmospheric profile level that was higher than the surface and as close to the surface as far as possible was chosen to obtain a best estimation of surface moisture. Based on the surface pressure parameter from MYD07_L2, the surface pressures over the stations during 2010 varied between 830 hPa to 875 hPa. The retrieval profile pressure level of numbers 16 and 17 is 780 hPa and 850 hPa, respectively. To make sure no empty data for low surface pressure days, the temperature ("Retrieved_Temperature_Profile_16", MYD07_L2) and the dew point temperature ("Retrieved_Moisture_Profile_16", MYD07_L2) of level 16 rather than level 17 were used to derive e_s and e , respectively, based on equation (3). The MODIS saturation deficits (D_{MODIS} , hPa) were the differences of the saturation and actual vapour pressures (i.e. e_s and e) (Equation 1).

Global MYD13A2 data is provided every 16 days at 1 km spatial resolution as a gridded level-3 product in the Sinusoidal projection. Blue, red, and near-infrared reflectance, centred on 469 nm, 645 nm, and 858 nm, respectively, were used to determine the MODIS daily vegetation indices (Huete et al., 1999). For a daily comparison, the 16 day vegetation indices were interpolated into daily vegetation indices using a cubic spline interpolation algorithm

(Boor, 1978). Except for NDVI, the MODIS products also include a new Enhanced Vegetation Index (EVI) that minimizes canopy background variations and maintains sensitivity over dense vegetation conditions. As seen in Figure 3, for the same pixel, the daily variation trends of NDVI and EVI during the year were similar. Correlations with saturation deficits should be similar too. Hence, we only picked one of them, NDVI, as the proxy for humidity. This selection took into account that NDVI was used as a moisture proxy in previous studies (Rogers and Randolph, 1991, Hay et al., 1996) and for the sake of better comparison.

Atmosphere profile data were downloaded through the Level 1 and Atmosphere Archive and Distribution System (LAADS Web) (<http://ladsweb.nascom.nasa.gov/>). Vegetation index data were downloaded from the Land Processes Distributed Active Archive Center (<https://lpdaac.usgs.gov/>).

3. Results

In the same location, D_{stn} was linearly (and inversely) correlated with NDVI ($r = -0.57$ for Station 1, -0.42 for Station 2, and -0.50 for Station 3, respectively; $p < 0.01$), but the maximum correlation value lagged some days (nine days for both Station 1 and Station 2, and four days for Station 3)(Figure 4). The correlations decreased before or after the lagged days.

D_{MODIS} was also significantly correlated with D_{stn} ($r = 0.61$ for Station 1, 0.63 for Station 2, and 0.61 for Station 3, respectively, $p < 0.01$) and the correlations were stronger than the NDVI's. The lagged NDVI and D_{MODIS} were used as predictors, respectively, for D_{stn} . The adjusted coefficients of determination (adj. R^2) of the prediction models were low for both D_{MODIS} (adj. $R^2 = 0.36$ for Station 1, 0.39 for Station 2, and 0.36 for Station 3, respectively) and NDVI (adj. $R^2 = 0.32$ for Station 1, 0.17 for Station 2, and 0.25 for Station 3, respectively) (Figure 5). Based on the values of adjusted R^2 , D_{MODIS} explained the variances of the station saturation deficits better than NDVI. D_{MODIS} were lower than the station saturation deficits, and increased on D_{stn} with linear slopes equal or close to 1.00 (Figure 5). The slopes of NDVI curves varied substantially (-79.8 for Station 1, -37.4 for Station 2, and -47.88 for Station 3), indicating a spatially heterogeneous “NDVI- D_{stn} ” relationship (Figure 5) As expected, the slopes for NDVI regression models were negative, indicating that D_{stn} values were low where NDVI values were high (Figure 5).

NDVI were interpolated from MODIS Aqua 16-day product (MYD13A2), so the daily variation curves were smooth (Figure 6). As shown in Figure 6, saturation deficits predicted by D_{MODIS} fitted D_{stn} better than the ones predicted by NDVI. The variation ranges of saturation deficits in stations were wider than the ones predicted by D_{MODIS} . The saturation deficits predicted by NDVI were only able to describe the trends of D_{stn} generally.

However, when D_{stn} and the saturation deficits predicted by D_{MODIS} and NDVI were averaged within each 16-day period, which was as long as the MODIS NDVI product composition time, saturation deficits predicted by D_{MODIS} and NDVI had comparable performances in D_{stn} prediction (Figure 7, Table 1). Compared with the daily predictions, the 16-day prediction performances of both models were improved; moreover, the improvements in the NDVI models were more obvious than those in D_{MODIS} models (Figure 7, Table 1). Specifically, the Mean Absolute Error (MAE) of the NDVI models vs. the D_{stn} models decreased by 2.33 hPa, 2.45 hPa, and 1.79 hPa vs. 0.90 hPa, 0.58 hPa, and 0.98 hPa for Station 1, Station 2, and Station 3, respectively (Table 1).

The NDVI changed seasonally, with lowest values at around day 30 and day 260 (Figure 3). During these periods, D_{stn} also varied more substantially than the other time of the year

(Figure 6, Figure 7). As shown in figures 6 and 7, no obvious MAE difference between low and high NDVI seasons was observed.

4. Discussion

Water loss per plant depends on the vapour pressure deficit of the air, leaf structure, and species. Plants in a lower air saturation deficit tend to have higher productivity (Leuschner, 2002). Our study has shown moderate correlations between NDVI and D_{stn} ($r = -0.57$ for Station 1, -0.42 for Station 2, and -0.50 for Station 3; $p < 0.01$). However, we use NDVI as a proxy of air saturation deficit with caution, because there is a lag between plants and the surrounding environment. More specifically, for plants to respond to a saturation deficit, the lag will differ due to different conditions of air temperature, slope aspect, plant species, soil moisture and nutrition. Our study has provided an example on this: Station 3 was near a valley where soil moisture was higher than Station 1 and Station 2, which located in open areas (Figure 1). Better plant growth condition in Station 3 may attributed to the shorter NDVI response lag (four days), compared to Station 1 and Station 2 (nine days).

For a large area, a number of ground measured humidity values with a reasonable geographic distribution over different vegetation and soil are required to define average response lags. These few weather stations are usually not enough, especially in east Africa. On the other hand, if we ignored the response lag, the correlation between NDVI and air saturation deficit would be weaker (in our study, $r = -0.46$ for Station 1, -0.33 for Station 2, and -0.49 for Station 3; $p < 0.01$). This would yield larger uncertainties in humidity estimations. A study in central Africa also showed that incorporating a one-month lag could increase the correlation between rainfall and NDVI from $r = 0.23$ – 0.42 to $r = 0.28$ – 0.68 (Onema and Taigbenu, 2009). A one-month lag is usually applied in other studies such as modelling the arthropod vector systems (Rogers et al., 2002, Rogers and Randolph, 1991). However, our study showed that synchronous NDVI even had stronger correlations with D_{stn} than the 1-month lag NDVI (Figure 4). Obviously, the NDVI responses are different in different locations with distinct environment situations.

Daily NDVI is more stable than temperature and humidity, and a large portion of area is usually covered by clouds and in absence of data, so only 16-day or monthly products are available at the NASA Land Processes Distributed Active Archive Center (LP DAAC). When the 16-day product was interpolated into daily NDVI, it was hardly able to estimate the daily change of station saturation deficit (Figure 5). The weak correlations between NDVI and D_{stn} could be due to the interpolation values, which were not real daily values. Moreover, the Maximum Value Composite (MVC) algorithm for 16-day data composition of the MODIS Vegetation Index could also have a negative effect, because only the maximum values were used during the 16-day period. The real temporal resolution of the NDVI data is 16 days. At this resolution, the performances of NDVI were comparable at the same pixel (Figure 7, Table 1). Therefore, at the plot scale (not at the regional or larger scale), both NDVI and D_{MODIS} can indicate the changes of D_{stn} . Without using the real daily NDVI data, we were not sure that daily NDVI could not explain the variations of D_{stn} , but could conclude that NDVI performed as well as D_{MODIS} well in lower temporal resolution estimations. As for annual resolution, Rogers and Randolph (1991) found mean annual saturation deficit significantly correlated with annual NDVI (derived from the Advanced Very High Resolution Radiometer of the NOAA satellites, 25 km resolution) in Africa ($r = 0.700$, $p < 0.001$), which was higher than the daily correlations in our study ($r = -0.57$ for Station 1, -0.42 for Station 2, and -0.50 for Station 3; $p < 0.01$).

The saturation deficit calculated from the MODIS Atmospheric Profile product (MOD 07) is another option to estimate saturation above ground. The results presented here show that

D_{MODIS} were strongly correlated with D_{stn} ($r > 0.5$), and daily D_{stn} predicting models with D_{MODIS} as predictor had better performances than those with NDVI as predictor (Figure 5). Nonetheless, the D_{stn} predicting models with D_{MODIS} as predictor still poorly explained the variances in D_{stn} (adj. $R^2 < 0.4$). The poor performances of D_{MODIS} in D_{stn} estimations at least could be attributed to four factors:

1. Elevation D_{stn} were measured in weather stations 2 m height above the ground, while D_{MODIS} were the saturation deficits in higher atmosphere layers. Atmosphere level of 780 hPa pressure at Station 1, Station 2, and Station 3 respectively was evenly about 376 m, 415 m, and 705 m height above ground in 2010 (the atmosphere level heights vary by time). Therefore, D_{stn} and D_{MODIS} were measured values at different levels.
2. Temperature Saturation deficit was calculated from air temperature. Correlations between temperatures in 780 hPa level and those in stations were 0.42 for Station 1, 0.36 for Station 2, and 0.37 for Station 3, which were moderate.
3. Water vapour content Water vapour content was another independent to calculate saturation deficit. Correlations between dew point temperatures in 780 hPa level and water vapour pressures in stations were 0.48 for Station 1, 0.57 for Station 2, and 0.56 for Station 3, which were not very strong either.
4. Scale MODIS data resolution is 1 km grid, while weather station measured values only presented realities of specific spots where the weather stations were. Over complex topography, more errors would propagate aggregating over valleys and hilltops.

The elevation differences were the indirect factor, which subsequently caused the differences in temperatures and water vapour contents from where saturation deficits derived. In an area where the horizontal wind speed is fast, the air from neighbour areas could cause a lower correlation between D_{MODIS} and D_{stn} . However, east Africa is not in a monsoon area and we believe it is an area with satisfactory D_{stn} estimation performance.

The weather stations in our study were located in a small area (Figure 1) and generally were over the same land-cover type. Therefore, our study is just a case study revealing potential relationships between D_{MODIS} , NDVI, and D_{stn} . When the area of interest is another one or wider one, extra measured data are required to construct new regression models before using NDVI or D_{MODIS} as the proxies of D_{stn} . Other parameters such as soil, vegetation, slope, aspect, and wind speed might be considered in a uniform model predicting D_{stn} with NDVI over a wide area. For predicting D_{stn} with D_{MODIS} , the relationship is simpler, so more station measured data with better geographic distribution should result in a better uniform regression model over a wide area.

5. Conclusions

Daily maximum saturation deficit is an important factor that limits the distribution of arthropod vectors such as tsetse fly in east Africa. MODIS on board the Aqua satellite provides global information on atmosphere saturation deficit (calculated from temperature and dew point temperature) and NDVI. Both NDVI and D_{MODIS} are significantly correlated with D_{stn} and have great potentials to estimate saturation deficits over east Africa. However, D_{MODIS} is more favourable as a proxy of D_{stn} for its better performance on a daily scale and simple relationship with D_{stn} . The spatially heterogeneous “NDVI- D_{stn} ” relationship and the time lag of NDVI make NDVI less suitable for the D_{stn} surrogate. Combinations of remotely sensed and observed station data, where available, would likely capture temporal variability better while also providing good spatial coverage.

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Figure 1.
Weather station locations

Figure 2. Ten-minute interval observations of station saturation deficit and rainfall during a week (26 October to 2 November 2010). Arrows are pointing to rainfall events.

Figure 3.
Vegetation indices

Figure 4. Pearson correlation coefficient (r) between station saturation deficit and lagged NDVI. Arrows are pointing to the minimums of r .

Figure 5. Relationships between D_{stn} and D_{MODIS} (a)–(c), and relationships between D_{stn} and NDVI (d)–(f). NDVI is of nine days lagged in both Station 1 and Station 2, and four days lagged in Station 3.

Figure 6.
Comparison of the daily saturation deficits predicted by D_{MODIS} and NDVI.

Figure 7.
Comparison of the 16-day saturation deficits predicted by D_{MODIS} and NDVI.

Table 1

Mean Absolute Errors (hPa) of the daily and 16-day saturation deficits predicted by D_{MODIS} and NDVI.

	Station 1		Station 2		Station 3	
	Daily	16-day	Daily	16-day	Daily	16-day
D_{MODIS}	4.64	3.75	4.80	4.22	4.98	4.00
NDVI	5.59	3.26	6.66	4.22	5.96	4.17