



The potential of multitemporal Aqua and Terra MODIS apparent thermal inertia as a soil moisture indicator

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ABSTRACT

Variations in surface thermal inertia—the resistance to temperature variations—can be indicative for variations in soil moisture. In this paper, we present a flexible multitemporal approach to derive an approximation of thermal inertia, called apparent thermal inertia (*ATI*), from daily Aqua and Terra MODIS observations. In a first step, a varying number of land surface temperature measurements were, together with the time of observation, fit to a sinusoidal function to obtain diurnal surface temperature amplitudes. These were subsequently combined with surface albedo to derive *ATI*. This was done for the southern part of the African continent for the year 2009. Apparent thermal inertia was compared both spatially and temporally to AMSR-E soil moisture, generated by the algorithm developed by the Vrije Universiteit Amsterdam and NASA. The temporal behaviour of apparent thermal inertia, derived using MODIS data only, showed a strong correspondence to that of AMSR-E soil moisture, especially in arid and semi-arid environments. The approach showed some limitations for vegetated terrains. Further post-processing is required to filter meteorologically induced noise and to transform *ATI* to actual soil moisture content.

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1. Introduction

The water held in the top few centimeters of the soil is a key variable in many hydrological, climatological and ecological processes. Models describing these processes often need spatially distributed soil moisture information as input. These data are difficult and costly to acquire through in situ measurements, especially at high temporal frequencies. This justifies the amount of research invested in the derivation of soil moisture related information from remote sensing. Different types of remote sensing systems are currently used to infer soil moisture at different spatial and temporal scales, each with its specific characteristics and limitations. While coarse resolution microwave radiometers and scatterometers are today considered the only satellite systems able to routinely measure soil moisture at global scale (Wagner et al., 2007), their spatial resolution is too low for many local applications. Synthetic aperture radars (SAR) can reach a much higher spatial resolution. This, combined with the sensitivity of the backscatter signal to surface soil moisture and with the atmospheric permeability to microwave radiation, makes approaches using SAR attractive for

applications on watershed and field scale. Strong perturbation of the backscatter signal by surface roughness and vegetation cover, however, strongly hampers the applicability of these approaches when ancillary ground reference data is not available (Verhoest et al., 2008). Optical sensors complemented with thermal infrared channels have, in spite of the strong atmospheric attenuation and the limited penetration depth of the used signal, received much attention as a source of information on soil moisture content and surface evaporation (Kalma et al., 2008; Verstraeten et al., 2008). This is mainly due to the wide range of spatial resolutions covered by this group of sensors and the observed relation between surface temperature and surface soil moisture content. One group of methods combining optical and thermal information is based on the concept of thermal inertia.

The thermal inertia of a material or surface determines its resistance to temperature variations and is function of the material's bulk density, specific heat capacity and thermal conductivity. As these three properties are material-specific, different materials can be distinguished by their thermal inertia, offering numerous applications in terrestrial and planetary geology (Cracknell and Xue, 1996). Furthermore, since the thermal conductivity of soils changes with fluctuating moisture level (Minacapilli et al., 2009), thermal inertia can be used as a soil moisture indicator, given all other soil properties constant over space or time. Unfortunately, bulk density,

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specific heat capacity and thermal conductivity cannot be derived from remote sensing, thus mapping of thermal inertia through remote sensing requires alternative approaches.

For several decades, thermal inertia has been approximated using land surface temperature differences as acquired by infrared thermometers. As materials with higher thermal inertia will experience smaller temperature changes than materials with low thermal inertia, given identical external driving forces, the night/day or pre-sunrise/midday temperature differences in remote sensing images can be used to discriminate between materials or soil moisture levels. The first physically based models to derive thermal inertia for geologic mapping of the Earth's surface including remote sensing data originate from the early and mid 70s (Kahle et al., 1976; Watson, 1973). More formulations for the computation of thermal inertia were suggested in the subsequent years (Idso et al., 1976; Price, 1977, 1980; Pratt et al., 1980; Abdellaoui et al., 1986). However, these all assume the availability of meteorological and/or other ancillary data, and are thus limited in use.

In contrast to these earlier models, Xue and Cracknell (1995) developed a methodology that required only a single ground measurement, being the time of maximum surface temperature in the daytime. For operational use, they suggest to replace this parameter by the time of maximum air temperature. This meteorological information may however not always be available. Furthermore, the time of maximum air temperature can differ from the time of maximum surface temperature. Sobrino and El Kharraz (1999a) therefore adapted this methodology by obtaining the time of maximum surface temperature from the remote sensing data itself. As such, a method to derive thermal inertia requiring only remotely sensed surface temperature and albedo was obtained.

A very basic approximation of thermal inertia, solely requiring surface albedo and a night-day surface temperature pair, was obtained by simplification of the Price (1977) model. This approximation was originally applied on Heat Capacity Mapping Mission (HCMM) data and named apparent thermal inertia (Short and Stuart, 1982). Apparent thermal inertia was initially found to be of limited use in areas with strong evapotranspiration (Price, 1985). Wet surfaces allow considerable evaporation and/or transpiration during the daytime, thus reducing daytime surface temperatures through evaporative cooling and introducing errors in apparent thermal inertia. Nevertheless, apparent thermal inertia recently received renewed interest for mapping of both geology (Mitra and Majumdar, 2004) and soil moisture (Tramutoli et al., 2000; Verstraeten et al., 2006) because of its simple formulation requiring remote sensing data only.

The coupling between apparent thermal inertia and soil moisture is not straightforward. True thermal inertia can be converted to soil moisture when soil properties are known (Lu et al., 2009; Minacapilli et al., 2009). Apparent thermal inertia might be directly related to soil moisture for areas with limited extent so that only a single soil and land cover type are present (e.g. individual fields). Over areas with varying geology or land use, however, soil moisture can only be extracted using a multitemporal approach (Tramutoli et al., 2000; Verstraeten et al., 2006). Since geology and soil composition in general change only over very long time scales, short-term changes in (apparent) thermal inertia can be linked to changes in soil moisture.

Sensors on sun-synchronous polar orbiting satellites such as NOAA/AVHRR or Aqua and Terra MODIS provide day- and night-time land surface temperature measurements on a near-daily basis at approximately 1 km resolution, which allows for the derivation of time series of daily apparent thermal inertia. However, these sensors suffer from the disadvantage, compared to lower resolution geostationary sensors, that the time of observation of a position on the ground may differ between two consecutive days. Aqua's equatorial crossing time, for example, is approximately 1:30 pm

in ascending mode and 1:30 am in descending mode. Due to the wide swath width of the MODIS instrument (2330 km), however, the local solar time of observation at a particular point at the Earth's surface can be considerably earlier or later than the time at nadir, resulting in possibly large differences in time of observation for two consecutive days. Additional heating or cooling will occur during this time span, hampering meaningful comparison of apparent thermal inertia images of different dates. A second limitation of most (apparent) thermal inertia methods up to present is that they use only two surface temperature observations as (approximations of) the diurnal temperature range, except for the method of Sobrino and El Kharraz (1999a) which requires four daily measurements. When one of these observations is lacking—due to cloud cover or because the area of interest lies between sensor swaths, which is common in regions near the equator—the (apparent) thermal inertia for that day can obviously not be derived.

Here we propose a methodology to derive apparent thermal inertia by a multitemporal approach, using Aqua and Terra MODIS data of a full year. The method is based on a sinusoidal approximation of the diurnal surface temperature curve, where a sinusoid is fitted to either four, three or two MODIS land surface temperature observations, depending on the number of available observations. The methodology allows for a certain flexibility and exploits the full amount of information gathered by the MODIS instrument. The method is applied on a sub-continental scale for the year 2009, the derived apparent thermal inertia is validated using coarse resolution passive microwave data.

2. Methodology

In this study, the diurnal temperature cycle is approximated as a sinusoid defined by:

$$T(t_i) = \bar{T} + \frac{A}{2} \cos(\omega t_i - \psi). \quad (1)$$

In Eq. (1): $T(t_i)$ is the surface temperature at time t_i [K]; $\bar{T}$ the diurnal average surface temperature [K]; A the amplitude of diurnal temperature cycle [K]; ω the angular velocity of rotation of Earth [rad s^{-1}]; t_i the time of day [s]; ψ is the phase angle [rad].

Considering the phase ψ known, e.g. from in situ measurements, then Eq. (1) contains two unknowns: $\bar{T}$ and A . The amplitude and average temperature can thus be derived for each pixel for each day with two observations ($t_i, T(t_i)$) or with more (n) observations using a least squares approach. The solutions for A and $\bar{T}$ then become, denoting $T_i \equiv T(t_i)$:

$$\frac{A}{2} = \frac{n \sum_{i=1}^n \cos(\omega t_i - \psi) T_i - \sum_{i=1}^n \cos(\omega t_i - \psi) \sum_{i=1}^n T_i}{n \sum_{i=1}^n \cos^2(\omega t_i - \psi) - \left(\sum_{i=1}^n \cos(\omega t_i - \psi) \right)^2} \quad (2)$$

and

$$\bar{T} = \frac{\sum_{i=1}^n T_i - (A/2) \sum_{i=1}^n \cos(\omega t_i - \psi)}{n}. \quad (3)$$

With $n=2$, the exact solution for the diurnal amplitude is:

$$\frac{A}{2} = \frac{T_1 - T_2}{\cos(\omega t_1 - \psi) - \cos(\omega t_2 - \psi)}. \quad (4)$$

The MODIS sensor onboard Aqua and Terra can provide up to four land surface temperature observations each day. A maximum number of observations can be used to derive the diurnal temperature amplitude from Eqs. (2) or (4). In the case of only two

temperature measurements, it is advisable to derive the diurnal amplitude using day–night pairs only, since two daytime or two nighttime observations would result in small differences in both numerator and denominator of Eq. (4).

In the derivation of Eqs. (2)–(4) we have assumed the phase ψ , corresponding to the time of maximum surface temperature, to be known. We suggest a variation on the method of [Sobrino and El Kharraz \(1999a\)](#) to derive this value. Starting from Eq. (1) and taking the difference between $T(t_i)$ at two satellite overpass times and dividing this by the difference at two other overpass times, we obtain:

$$\psi = \arctan(\xi) + \pi \quad (5)$$

with

$$\xi = \frac{(T_1 - T_3)(\cos(\omega t_2) - \cos(\omega t_4)) - (T_2 - T_4)(\cos(\omega t_1) - \cos(\omega t_3))}{(T_2 - T_4)(\sin(\omega t_1) - \sin(\omega t_3)) - (T_1 - T_3)(\sin(\omega t_2) - \sin(\omega t_4))}. \quad (6)$$

While [Sobrino and El Kharraz \(1999b\)](#) used only three temperature observations with NOAA/AVHRR data, we use Eq. (6) with four MODIS observations in order to optimally approximate the sinusoidal fit on four data points and to minimize the probability that a phase angle is derived on days with cloud cover. ψ can thus be derived for a time series of MODIS images for all days with four surface temperature measurements. On the resulting time series of phase angle values we performed additional interpolation and smoothening. The reasons for this are twofold. The first is to eliminate day-to-day meteorological influences and influences of measurement errors. Second, the number of days with four daily MODIS ($t_i, T(t_i)$) observations will be low on certain places on Earth. Interpolating ψ values allows for pixels on days with fewer than four observations to be further processed. The smoothening and interpolation are done by a harmonic analysis of time series ([Verhoef, 1996](#)). This algorithm basically calculates a Fourier series based on time series of ψ for each pixel in a scene. After selecting a limited number of frequencies, outliers in the original dataset relative to the modeled harmonic are discarded and a new Fourier series is calculated based on the remaining data points. This process is repeated iteratively until a predefined fit to the data is reached or until a predefined minimum number of ψ values remain. Given the potential seasonal variation of the time of maximum daytime temperature with solar declination or vegetation phenology, a single harmonic with a frequency of one year is likely to be sufficient. The interpolated value of ψ can then be retrieved for every pixel for every day of the year.

The derivation of the diurnal surface temperature amplitude, using the interpolated values of ψ and at least one daytime and one nighttime observation, assumes a sinusoidal behaviour of the surface temperature. To validate this assumption, the fit of the modeled temperature curve to the observations can be checked for pixels for the days where four observations are available. This results for each of these days in a root mean square error (RMSE). For a longer period of time, e.g. a full year, the average RMSE for each pixel in an image can thus be derived. The performance of the sinusoidal model is compared to the advanced thermal inertia model of [Xue and Cracknell \(1995\)](#), further developed by [Sobrino and El Kharraz \(1999a\)](#), who used a second order approximation of the surface temperature, and which can easily be rewritten in a way very similar to Eq. (1):

$$T(t_i) = a_0 + a_1[C_1 \cos(\omega t_i - \psi) + C_2 \cos(2\omega t_i - f(\psi))] \quad (7)$$

with

$$C_1 = f_1(\delta, \varphi, \psi) \quad \text{and} \quad C_2 = f_2(\delta, \varphi, \psi). \quad (8)$$

The coefficients a_0 and a_1 in Eq. (7) can be found similarly as in Eqs. (2)–(3), after which an average RMSE can be derived for days with four ($t_i, T(t_i)$) observations in a similar way.

With the diurnal surface temperature amplitude derived from Eq. (2), apparent thermal inertia images are derived as ([Short and Stuart, 1982](#)):

$$ATI = C \frac{1 - \alpha_0}{A} \quad (9)$$

with

$$C = \sin \varphi \sin \delta (1 - \tan^2 \varphi \tan^2 \delta)^{1/2} + \cos \varphi \cos \delta \arccos(-\tan \varphi \tan \delta). \quad (10)$$

In Eqs. (9)–(10): ATI is the apparent thermal inertia [K^{-1}]; α_0 the surface albedo [-]; C the solar correction factor [-]; φ the latitude [rad]; δ is the solar declination [rad].

ATI thus is a measure of the temperature increase caused by the proportion of radiant energy that is absorbed by the Earth's surface. The solar correction factor C changes over space and time to normalize for solar flux variations with latitude and solar declination. The solar declination δ , required for the calculation of C , is found using the method of [Iqbal \(1983\)](#):

$$\begin{aligned} \delta = & 0.006918 - 0.399912 \cos(\Gamma) + 0.070257 \sin(\Gamma) \\ & - 0.006758 \cos(2\Gamma) + 0.000907 \sin(2\Gamma) \\ & - 0.002697 \cos(3\Gamma) + 0.00148 \sin(3\Gamma) \end{aligned} \quad (11)$$

with

$$\Gamma = \frac{2\pi(n_d - 1)}{365.25}. \quad (12)$$

In Eqs. (11)–(12): Γ is the day angle [rad] and n_d is the day number [-].

3. Study area and data sets

3.1. Study area

The study area is the part of continental Africa south of the parallel of 15° South. This area comprises the countries of South Africa, Namibia, Botswana, Zimbabwe and parts of Mozambique. Climate varies significantly within the region, from extremely arid along the Atlantic coast of Namibia to a Mediterranean climate around the Cape and humid at the eastern coast of Mozambique. A strong seasonality is present due to the proximity to the Tropic of Capricorn.

3.2. Terra/Aqua MODIS

Standard preprocessed MODIS products are distributed through the Land Processes Distributed Active Archive Center (LP DAAC), located at the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center (<http://lpdaac.usgs.gov>). Albedo and land surface temperature products are offered at a 1 km or a 0.05° resolution. For reasons of data volume, the global 0.05° level 5 products MCD43B3 (Terra + Aqua 16-day albedo), MOD11C1 (Terra daily land surface temperature) and MYD11C1 (Aqua daily land surface temperature) were used in this study for the period January–December 2009. This way, the study area is covered by images of 600 by 400 pixels.

Times of land surface temperature observations in the M**D11C1* products are given in Coordinated Universal Time. Local solar time is given by:

$$t_i = UTC + \frac{\lambda}{\omega}. \quad (13)$$

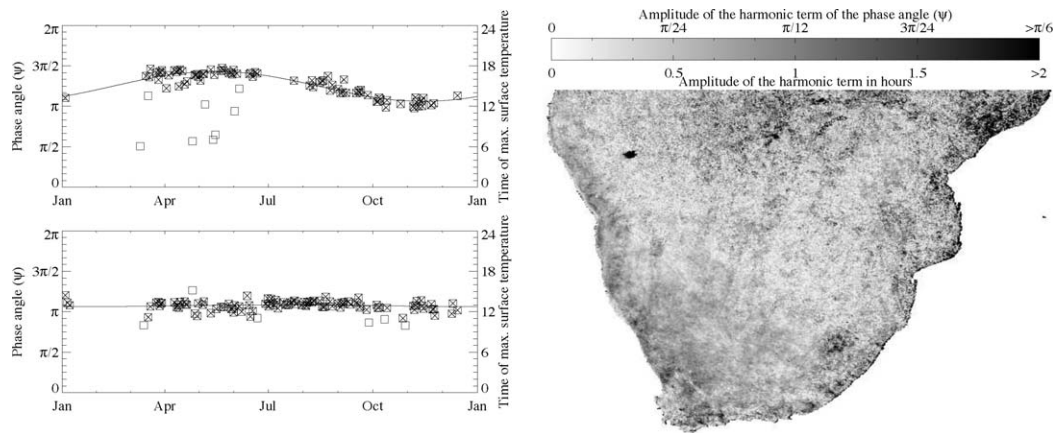


Fig. 1. Left: Two examples of harmonic analysis of phase angle (ψ) time series, one with a strong seasonality (top) and one with a weak seasonality (bottom) of ψ . Boxes are estimates of ψ derived for days with four surface temperature observations. The resulting interpolation (full line) is calculated on the checked boxes only. Right: Map of the amplitude of the harmonic term.

In Eq. (13): UTC is the Coordinated Universal Time [s] and λ is the local longitude [rad].

3.3. AMSR-E soil moisture

Soil moisture derived from Advanced Microwave Scanning Radiometer - Earth Observing System (AMSR-E) data was used as a reference product. The AMSR-E instrument onboard the Aqua satellite provides passive microwave measurements at high temporal and low spatial resolution. Different daily global soil moisture products for both the ascending and descending pass are created using different algorithms (Jackson, 1993; Njoku et al., 2003). We selected the (descending node) soil moisture product at 0.25° resolution developed at the Vrije Universiteit Amsterdam (VUA) in collaboration with NASA (Owe et al., 2008). From comparative studies, this algorithm was found to result in stronger correlations to in situ soil moisture measurements than others (Draper et al., 2009; Gruhier et al., 2010; Wagner et al., 2007). The region of southern Africa is only weakly influenced by radio frequency interference (Njoku et al., 2005), which makes the AMSR-E soil moisture product for this region a reliable reference dataset. A 7-day running temporal average filter was applied on the soil moisture images of 2009 in order to fill data gaps and to reduce temporal noise.

4. Results and discussion

4.1. Diurnal surface temperature amplitude

For each pixel in the study site, the phase angle ψ was computed according to Eqs. (5)–(6) for all calendar days of the year 2009 where four observations—i.e. a sequence of Aqua night, Terra day, Aqua day and Terra night images—were available. This was the case for on average 130 days, with a standard deviation of 30 days. These phase angle values were smoothed and interpolated for days with fewer than four observations by the harmonic analysis of time series using a single harmonic with a frequency of one year (Fig. 1). In general, the amplitude of the harmonic was found to be low, with an average of 0.81, indicating a difference in time of maximum surface temperature of 37 min over a full year. It should be noted that large gaps can occur in the original time series of ψ , which reduces the reliability of the constant and harmonic term estimates and causes a speckled effect on the maps of these terms (Fig. 1). This could possibly be mitigated by applying the harmonic analysis to a time series covering multiple years. In areas with multiple rainfall or growing seasons, e.g. in regions closer to the equator, the harmonic analysis using a single harmonic is likely

to break down. This can be solved by adding harmonic terms with higher frequencies.

The validation of the sinusoidal approximation of the diurnal surface temperature behaviour (Eq. (1)) is displayed in Fig. 2, which shows the spatial distribution of the average RMSE for the year 2009. This lies between 1 K and 2 K for most pixels in the study site (spatial average of 1.51 K and standard deviation of 0.22 K). Inland water bodies and wetlands show up clearly in Fig. 2 because of their low root mean square errors. These can be explained by the flat diurnal temperature behaviour of water, which makes them well described by a constant term only. Regions with high temperature amplitudes on the other hand will in general be characterized by larger errors on the temperature estimates. To eliminate these amplitude effects, a relative root mean square error (rRMSE) was derived by dividing the RMSE of each day by the amplitude of that day. The resulting map of the average rRMSE (Fig. 2), with most values between 5 percent and 15 percent of the diurnal temperature amplitude, indicates that the surface temperature behaviour of the more arid western part of the study site is relatively well described by the sinusoidal function. Large rRMSEs at the more vegetated eastern coast however show that the sinusoidal approximation is not valid for these pixels, and that the apparent thermal inertia will there likely be of limited utility.

The validation of the advanced thermal inertia model of Xue and Cracknell (1995) (Eq. (7)) resulted in a spatial average RMSE for the study site of 1.95 K with a standard deviation of 0.31 K. Notwithstanding its simplicity, the sinusoidal method thus seems to result in a better fit to the data than the more complex, physically based model of Xue and Cracknell (1995). This could be due to a number of assumptions in the latter, including flat topography and a temperature range between 280 and 310 K, which are not imposed on the empirical sinusoidal approximation.

4.2. Spatial ATI patterns

Fig. 3 shows the ATI image at 0.05° resolution for March 26th and the corresponding AMSR-E soil moisture image at 0.25° . Comparison of both products shows that the apparent thermal inertia largely reflects the regional soil moisture pattern, with low values along the Atlantic coastline and higher values towards the east and north. Some specific dry or wet features can also be recognized in both images. The scatterplot of AMSR-E soil moisture versus MODIS apparent thermal inertia, downscaled by a 5 by 5 pixel averaging, for this date (Fig. 4) shows a clear, nearly linear, relation at the lower soil moisture ranges (below $0.3 \text{ m}^3/\text{m}^3$). Above this level, a large amount of high-end noise is present with ATI values up to 0.6 K^{-1}

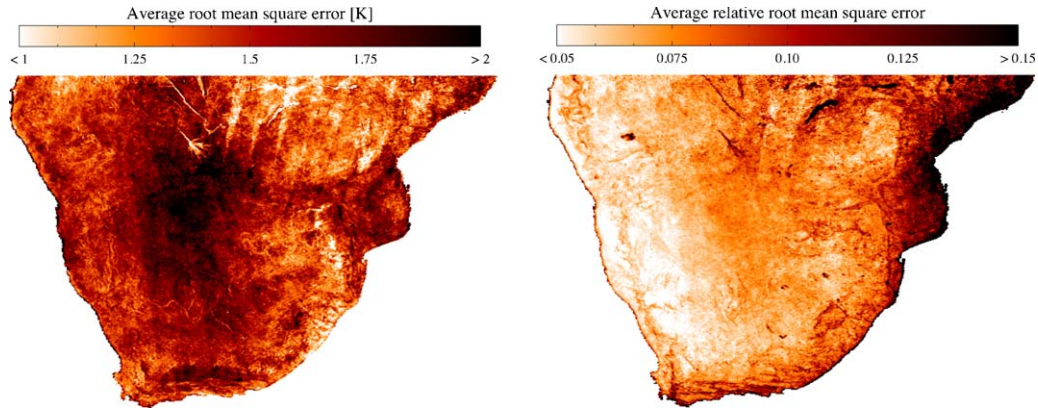


Fig. 2. Left: Average RMSE for the year 2009, derived from days with four surface temperature observations. Right: Average rRMSE, derived for the same period.

(the ordinate in Fig. 4 has been limited to 0.25 K^{−1} for clarity), which limits the overall R² for this date to 0.32.

Two possible reasons for this high end noise are unmasked water bodies and cloud cover in between surface temperature observations. These will both result in lower surface temperature amplitudes, hence unrealistically large *ATI* values. A third reason for the deviation of the best fit, especially in the higher soil moisture ranges, is the propagation of errors through the derivation of the apparent thermal inertia. Given a relationship of the type $y=f(x_1, x_2, \dots, x_n)$, the uncertainty on the dependent variable (Δy) is expressed in a first order Taylor approximation as a function of the uncertainties on the independent variables ($\Delta x_1, \Delta x_2, \dots, \Delta x_n$):

$$\Delta y = \left| \frac{\partial y}{\partial x_1} \right| \Delta x_1 + \left| \frac{\partial y}{\partial x_2} \right| \Delta x_2 + \dots + \left| \frac{\partial y}{\partial x_n} \right| \Delta x_n. \tag{14}$$

The propagation of uncertainties on surface albedo and diurnal surface temperature amplitude through Eq. (9) is thus expressed as:

$$\Delta ATI = \left| \frac{C}{A} \right| \Delta \alpha_0 + \left| C \frac{1 - \alpha_0}{A^2} \right| \Delta A. \tag{15}$$

In Eq. (15): ΔATI is the uncertainty on apparent thermal inertia [K^{−1}]; $\Delta \alpha_0$ the uncertainty on surface albedo [−]; ΔA is the uncertainty on amplitude [K].

The (squared) amplitude in the denominator of both terms of Eq. (15) indicates that in wet regions, hence with low temperature

amplitudes, *ATI* will be very sensitive to errors on *A* and, to a lesser extent, on α_0 . This large sensitivity of thermal inertia to measurement errors at low day–night temperature differences was also acknowledged by other authors (Cai et al., 2007; Verstraeten et al., 2006) and is inherent to all formulations using temperature differences in the denominator.

Some sharp delineations appear in the *ATI* image (Fig. 3) which clearly do not correspond to sudden changes in soil moisture or land cover but are artefacts of the followed methodology. It can be observed that some of these (e.g. a triangular wedge running north northeast to south southwest in the western half of the study site) correspond to the different ($t_i, T(t_i)$) combinations used (Fig. 3). This is clearly a trade-off for the flexibility of our method which allows for any number and combination of surface temperature observations to be fitted to the sinusoidal approximation. Forcing the method to use only a fixed set of observations would eliminate these artefacts but would also result in a large amount of missing data in the regions between 30° north and south where consecutive MODIS swaths have no overlap. It can also be seen that some different input combinations result in seamless transitions in the *ATI* map. Other artefacts do not correspond to different ($t_i, T(t_i)$) combinations used but are already introduced in the derivation of ψ (Fig. 1) and can also be clearly discerned in Fig. 2. These originate from the 16-day repeat cycle of the Aqua and Terra spacecrafts and the associated fixed swath delineations at one hand, and the limited thematic resolution of the time field of the M*D11C1 products of 12 min at the other hand.

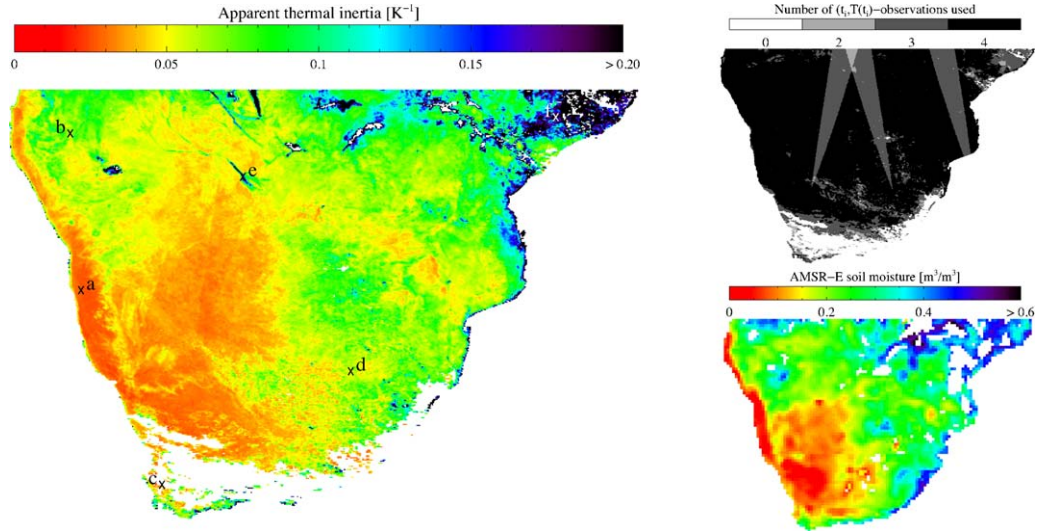


Fig. 3. Left: MODIS apparent thermal inertia for March 26th 2009, with indication of locations of temporal profiles (Fig. 5). Right, top: Number of observations used to derive apparent thermal inertia on March 26th 2009. Right, bottom: VUA-NASA AMSR-E soil moisture for March 26th 2009, interpolated using a 7-day temporal average.

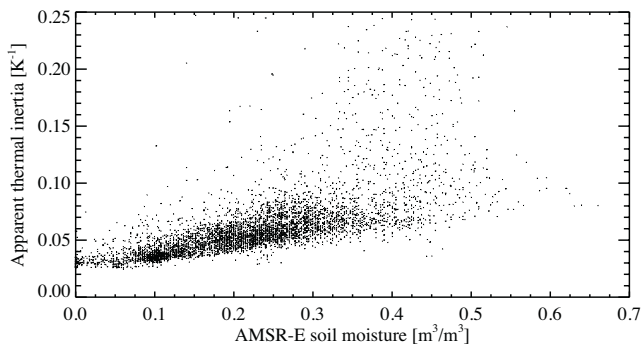


Fig. 4. Scatterplot of AMSR-E soil moisture and apparent thermal inertia for March 26th 2009.

4.3. Temporal ATI patterns

As mentioned before, (apparent) thermal inertia is not only function of surface soil moisture but also of surface geology and land cover. To eliminate these effects of geology it is useful to consider temporal *ATI* profiles on individual locations. By doing so, the signal can be considered to be mainly function of soil moisture, although changes in land cover, in particular vegetation phenology and agricultural practices, should not be ignored. Assuming a linear relationship between AMSR-E soil moisture and apparent thermal inertia, *ATI* can be converted to volumet-

ric soil moisture estimates using the intercept and slope of linear regression between both. This way, the potential of *ATI* as a soil moisture indicator can be quantified in terms of a root mean square error.

Fig. 5 displays a number of temporal *ATI* and AMSR-E soil moisture profiles of 0.25° resolution pixels at different locations in the study site (marked in **Fig. 3**), indicating the capabilities and limitations of the method used. A first time series for a pixel located in the Namib desert (a) shows a permanently low apparent thermal inertia, consistent with the passive microwave estimates (RMSE = 0.018 m³/m³). The lack of a seasonal *ATI* signal indicates that the solar correction factor *C* effectively corrects for differences in surface temperature amplitude induced by day length. Note that apparent thermal inertia will never become zero even at entirely dry soil, since that would require an infinite temperature amplitude. Low day-to-day noise may be caused by measurement uncertainty or different meteorological conditions (e.g. air temperature, wind velocity or air humidity).

A second profile (b) was taken over savannah pixels in the north-western part of the study site where seasonal rains result in an increased soil moisture in the first part of the year. This increase is also visible in the *ATI*, although only few estimates are available between February and mid-March due to persistent cloud cover. *ATI* values are furthermore strongly scattered with spurious high outliers, likely caused by cloud cover in between surface temperature observations resulting in erroneous temperature amplitude estimates. An initial drying period in the second half of March is

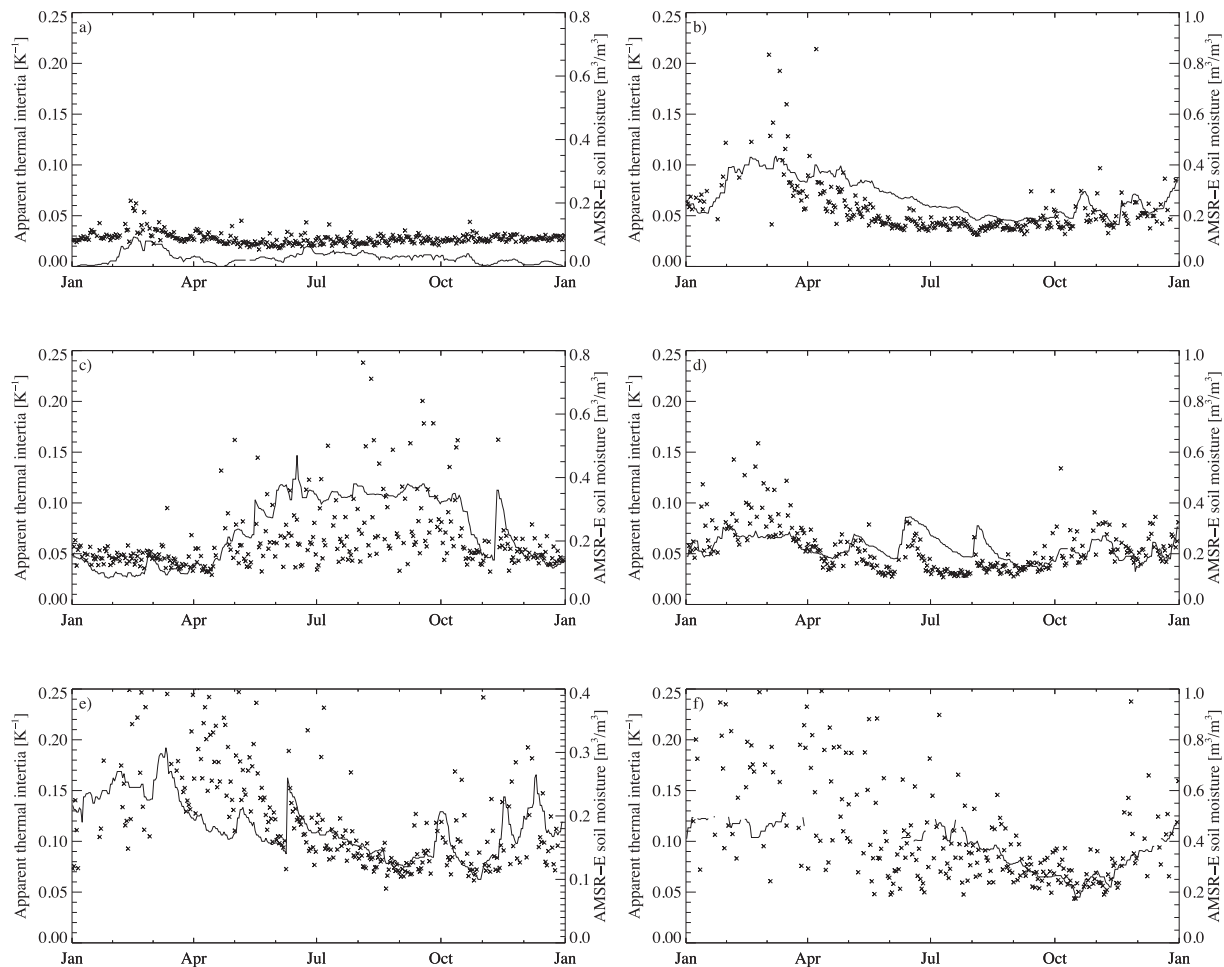


Fig. 5. Temporal profiles of MODIS apparent thermal inertia (crosses) and VUA-NASA AMSR-E soil moisture (full line) for 2009. Right axis (AMSR-E soil moisture) has been scaled for each sub-figure separately for clarity. Sub-figures represent desert (a), savannah (b), cropland (c, d), wetland (e) and closed shrubland (f).

reflected in the *ATI*, as well as the gradual drying from May to October, including a dip in early August. For the remainder of the year the behaviour of *ATI* weakly reflects that of AMSR-E soil moisture, resulting in a RMSE of $0.059 \text{ m}^3/\text{m}^3$.

The two following transects are taken over cropland, one in the vicinity of Cape Town (c, $\text{RMSE} = 0.093 \text{ m}^3/\text{m}^3$), the other south-west of Johannesburg (d, $\text{RMSE} = 0.043 \text{ m}^3/\text{m}^3$), with different wet seasons. In both transects, it can be seen that under wet (and vegetated) conditions, *ATI* only poorly reflects soil moisture conditions. During dryer and less clouded periods, however, some short-term wetting and drying events can be clearly discerned, including a drying, sudden wetting and consecutive drying sequence in October–November at site (c) and three wetting-drying events in May, June and August at site (d).

The next profile (e) is over the wetlands of the Okavango delta. Some striking correspondences to AMSR-E data here are a sudden increase in soil moisture early June, followed by a decrease in *ATI* until September. A drying sequence in the second half of March is also clearly reflected. For the remaining part of the year, correspondence is weak, especially between April and June. The overall root mean square error for the year 2009 is $0.033 \text{ m}^3/\text{m}^3$.

A last time series (f) is over a closed shrubland site at the northeastern part of the study site. Here the apparent thermal inertia method fails completely during the largest part of the year ($\text{RMSE} = 0.106 \text{ m}^3/\text{m}^3$). Only during the dryer periods (October–November) a weak relationship between *ATI* and AMSR-E behaviour is visible. It should be noted that the VUA-NASA algorithm produces no soil moisture estimates for a large part of the year for this pixel.

Most striking in the temporal profiles is that for relatively high soil moisture levels a large amount of noise is present in the *ATI* estimates, while this noise is absent at lower moisture levels. Also, *ATI* seems to perform poorly over vegetated surfaces, this in contrast to the findings of Verstraeten et al. (2006) who obtained good soil moisture estimates from apparent thermal inertia from Meteosat over European forests. The poor performance over vegetated terrain was already noticed in the poor fit of the surface temperature observation to the sinusoidal model (Fig. 2). Possibly a higher order model for the approximation of the surface temperature should be used over these areas, although the second order model of Xue and Cracknell (1995) provided a poorer fit to the data than the sinusoidal model. An alternative explanation is that persistent cloud cover or overpassing clouds between observations perturbate the expected temporal behaviour. A decisive answer to this can however not be provided without information with higher temporal resolution, e.g. from meteorological stations or geostationary sensors.

Over arid and semi-arid environments, apparent thermal inertia can clearly detect long-term and short-term soil moisture changes, although *ATI* declines at different rates than AMSR-E soil moisture in drying period. This can, amongst others, be observed in the drying period from May onwards in Fig. 5(b) and after the mid-June wetting event in Fig. 5(d). This is possibly caused by the depth of soil on which *ATI* and AMSR-E soil moisture depend. The C-band observations used to derive the AMSR-E soil moisture product is sensitive to moisture in approximately the top 1 cm of soil (Njoku et al., 2003). The thermal infrared used in the derivation of land surface temperature and *ATI*, on the other hand, is only influenced by the first few millimeters of bare soil, which explains the faster decrease of *ATI*. Over vegetated soils, comparison of *ATI* and AMSR-E soil moisture becomes even more complex, since the algorithm to derive the latter separates influences of soil moisture and vegetation water content in the microwave signal. Apparent thermal inertia on the other hand does not discriminate between canopy cover and soil and will therefore be influenced by vegetation evapotranspiration. It will therefore also be influenced by the vegetation root zone

moisture content, thus causing more discrepancies between *ATI* and AMSR-E soil moisture.

5. Summary and conclusion

A flexible method is presented for deriving apparent thermal inertia (*ATI*), and associated soil moisture related information, from Aqua and Terra MODIS optical and thermal data. In a first step, two, three or four daily temperature observations are used to estimate the diurnal temperature amplitude in a sinusoidal approximation. The sinusoidal approximation provided a fit to the observations of 1.51 K, which approximates the estimated error on the MODIS land surface temperature measurements. The diurnal amplitude is then used in combination with surface albedo to produce daily *ATI* images. Temporal *ATI* profiles showed in general good correspondence with soil moisture derived from coarse resolution AMSR-E data, especially in arid and semi-arid environments. The methodology should be further validated with in situ data and over different environments.

The specific strength of the proposed methodology in comparison to other methods for deriving (apparent) thermal is that there are no strict limitations on the number and time of day of land surface temperature observations. This considerably increases the number of *ATI* estimates that can be computed daily, especially in regions around the equator where swaths of medium spatial resolution sensors have in general no overlap.

An important limitation of the methodology is the vulnerability to noise introduced by meteorological conditions, which is inherent to the use of remote sensing data only. Spatial and/or temporal postprocessing algorithms could largely reduce this noise, e.g. by using the fact that meteorological influences will be strongly correlated spatially but only weakly correlated temporally. A second line of postprocessing is by coupling apparent thermal inertia to data from coarse resolution microwave radiometers (AMSR-E, SMOS) in data fusion models. This way the high spatial resolution information contained in *ATI* time series can be combined with relatively accurate low resolution soil moisture. Disaggregation of coarse resolution soil moisture with optical and thermal data has already been applied successfully (Chauhan et al., 2003; Merlin et al., 2009). The incorporation of thermal inertia into these kind of models seems a promising approach.

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