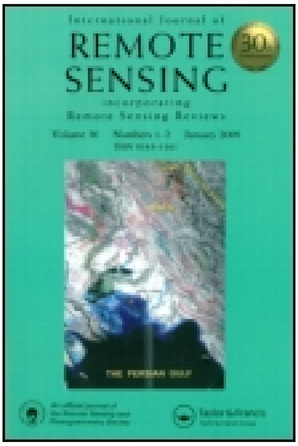

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Mariette Vreugdenhil [a] [b], Richard A.M. de Jeu [b] & Jeffrey P. Walker [c]

[a] Centre for Water Resource Systems, Vienna University of Technology, Karlsplatz 13/222, A-1040, Vienna, Austria

[b] Faculty of Earth and Life Sciences, VU University Amsterdam, 1081 HV, Amsterdam, The Netherlands

[c] Department of Civil Engineering, Monash University, Clayton, VIC, 3800, Australia

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Mariette Vreugdenhil[a,b]*, Richard A.M. de Jeu[b], and Jeffrey P. Walker[c]

[a]*Centre for Water Resource Systems, Vienna University of Technology, Karlsplatz 13/222, A-1040 Vienna, Austria;* [b]*Faculty of Earth and Life Sciences, VU University Amsterdam, 1081 HV, Amsterdam, The Netherlands;* [c]*Department of Civil Engineering, Monash University, Clayton, VIC 3800, Australia*

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A new methodology to derive the spatial distribution of clay pans from satellite microwave data is presented. Soil moisture has a different temporal signature in clay pans compared with other soils, which is directly reflected in the satellite-observed brightness temperatures. Three years of Advanced Microwave Scanning Radiometer Earth Observing System (AMSR-E) 6.9 GHz microwave observations were compiled and analysed over continental Australia to identify clay pans. This led to the development of a brightness temperature variance index (BTVI), which shows a strong spatial correspondence to an existing soil texture map and the ability to map clay pans for semi-arid regions. This simple method emphasizes the potential use of passive microwave remote sensing for soil type mapping.

1. Introduction

Soils are pivotal to the cultural and economic development of humans. As one of the most important natural resources, soils are surveyed on a national basis in many countries (Visschers, Finke, and De Gruijter 2007), to plan land utilization at regional and national scale (Odeh and McBratney 2000). Moreover, soils have a direct impact on (sub-)surface processes related to water, energy, and carbon (Mosier 1998; Seneviratne et al. 2010; Santanello et al. 2007), making soil data a key input in land surface–atmosphere, hydrological, and climate models. The variety and significance of applications that require soil data emphasizes the need for reliable data sets.

Soil maps are traditionally created by interpolating point data from soil surveys. Despite the digital revolution, most soil maps are still based on these conventional soil-mapping methods. In 1990, the FAO/UNESCO completed a global Soil Map at a scale of 1:2,500,000. This map was updated in and adopted by the International Union of Soil Science as the standard for soil correlation and nomenclature in 1998 (FAO 2000). This map is primarily based on traditional soil surveys, and is unreliable for regions with sparse soil cores, especially in more remote areas.

Remote sensing can potentially add value in areas with sparse ground observations. For example, Chabrillat et al. (2002) demonstrated a technique to map expansive clay soils with airborne hyperspectral remote sensing. Furthermore, Barnes and Baker (2000) used

*Corresponding author. Email: mav@ipf.tuwien.ac.at

multispectral airborne and satellite (Landsat TM and SPOT) data to determine different soil texture classes by correlation of image data with laboratory analysis. The accuracy of classifying different soils ranged from 50% up to 100%, hence showing that the use of hyperspectral remote sensing looks very promising. However, these results are specific to the study area and may not apply at other locations. Furthermore, access to such high-resolution data is often limited to dedicated study areas and airborne surveys are expensive.

This study explores the capability of passive microwave remote sensing for soil-mapping applications. Passive microwave remote sensing can be a powerful tool for soil mapping because it provides information on the top few centimetres of the soil at a large spatial scale, eliminating the need for areal averaging of point measurements, it is freely available and provides global coverage every few days.

Previous studies have demonstrated the potential use of passive microwave remote sensing for soil mapping. For example, Mattikalli et al. (1998) showed the relationship between brightness temperature dynamics and soil texture, and Summerell et al. (2009) found a strong spatial correspondence between microwave observations after rainfall and major geological features. However, all these studies were based at catchment scale and were not tested for other regions. Consequently, this study seeks to develop an approach to using passive microwave remote sensing observations for soil mapping, with global application.

Specifically, this study will make use of the Advanced Microwave Scanning Radiometer (AMSR-E) on board the Aqua satellite. AMSR-E scanned the Earth's surface between 2002 and 2011 with a global coverage every two days (Njoku et al. 2003). Microwave observations are sensitive to the dielectric properties of the soil, and to soil moisture in particular. Soil moisture has a different temporal signature in clay soils compared with other soils, and this is directly reflected in the brightness temperatures (Liu et al. 2010). By looking at spatial and temporal dynamics in the brightness temperatures of clay pans, and comparing these with other soils, clay pans could be detected and the method applied on a global scale, since a global data set is provided at a spatial resolution of 0.25°. This research has a particular focus on the potential use of passive microwave remote sensing for detecting clay pans. Owing to the desirable agricultural and hydraulic characteristics of clay soils, these are disproportionally important for cropping and irrigation in particular (Liu et al. 2010) and accurate identification and characterization of these soils is important. As a case study, an area in Australia is selected where extensive clay pans are present.

2. Study area

The study area is situated in north Queensland, Australia, and covers an area of 475,000 km^2 (Figure 1). The climate is characterized by hot humid summers, average annual rainfall varies from ca. 300 mm to 800 mm, and land cover is dominated by pasture. The study area is characterized by two extensive clay pans (Northcote et al. 1960–1968), orientated from north-northwest to south-southeast (Figure 1). This, in combination with the homogeneous character of the vegetation, precipitation, evaporation, and temperature, makes this area suitable to evaluate the soil-mapping capability of passive microwave observations.

3. Data

3.1. Soil data

In this study, existing soil data are compared with AMSR-E data. Soil data were obtained from the Australian Bureau of Agricultural and Resource Economics and Sciences

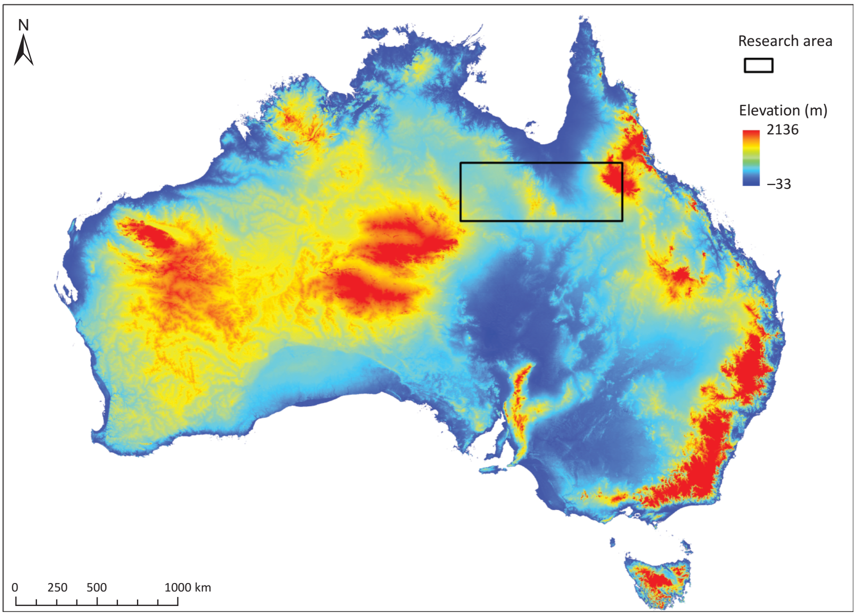

Figure 1. Elevation map for north-eastern Australia, showing clay pans located in the study area.

(ABARES). A raster data set provides an indication of the percentage of clay, silt, and sand present in the topsoil. The data set is created by combining CSIRO soil data (Northcote et al. 1960–1968) and national- and state-level digitized land system maps and soil surveys. This raster data set has a grid resolution of 0.001° (approximately equivalent to 1.1 km). To coincide with the AMSR-E data, the soil map is resampled into a spatial resolution of 0.25° using a majority filter, determining the new cell value based on the most popular values within the filter window, and reducing clay content to 28 classes varying from 7% to 64%. For the statistical analysis, only classes containing more than five observations are used, leaving 16 classes. Maps showing percentage clay, silt, and sand present in the topsoil are combined to discriminate between areas where there is more than 40% clay content in the topsoil (hereafter called clay pans) and where there is less than 40% clay content (non-clay pans).

3.2. AMSR-E data

Between June 2002 and October 2011, the AMSR-E sensor on board NASA's Aqua satellite observed the Earth surface at different frequencies, providing a global coverage every two days. The AMSR-E observations at C-band (6.9 GHz) frequency have the highest soil penetration depth (approximately 1 cm) (Njoku et al. 2003) and are most suited to monitoring soil moisture dynamics over Australia (Draper et al. 2009). The spatial resolution of the data at C-band is 75 $\times$ 45 km and they were resampled into a 0.25° grid. Therefore, three years (2004–2006) of resampled AMSR-E brightness temperatures retrieved at C-band (Ashcroft and Wentz 2003) were used in this study. To account for outliers, a moving average filter is applied to the time series using a span of 10 data points.

The drawback of using AMSR-E data in this case is the spatial resolution of the data. Since AMSR-E data have a spatial resolution of 75 $\times$ 45 km and are resampled into a 0.25° grid, brightness temperature (T_b) values provided for each 0.25° are actually related to a wider area. Therefore, measured T_b might disagree with the expected values, especially if the measured area is characterized by extremely different emissions (Santi 2010). Consequently, the outskirts of the clay pans and small sand patches in clay pans may possibly not be reflected, or else distorted, in the AMSR-E data. To overcome this effect, AMSR-E data with sand patches in a clay pan with size smaller than 50 km were excluded from this analysis.

4. Background and methods

4.1. Soil texture, soil moisture, and passive microwave remote sensing

The soil properties affecting soil water movement are hydraulic conductivity and water-retention characteristics. These soil water properties are closely related to soil physical properties. Clay soils have a larger water-retention capacity than sand soils and lower hydraulic conductivity (Gupta and Larson 1979; Rawls, Brakensiek, and Saxton 1982). Soil water properties are directly responsible for the temporal signature of soil moisture, meaning that a clay soil would show a different temporal soil moisture response than a non-clay soil.

The sensitivity of passive microwave remote sensing to soil moisture is well known, especially for sparsely to moderately vegetated regions (Dorigo et al. 2010; Liu et al. 2011). Several studies have shown the acquisition of reliable soil moisture values from observed brightness temperature over such regions (Wagner et al. 2007; Draper et al. 2009; Gruhier et al. 2010; Wanders et al. 2012).

Previous studies have demonstrated that remotely sensed soil moisture contents and their temporal changes could be used to identify soil types (Mattikalli and Engman 1997; Mattikalli et al. 1998). Their research was based on the dry-down dynamics of soils with varying soil texture after a rainfall event, showing that sandy soils drain more quickly than loamy soils due to their higher hydraulic conductivity. During the dry-down period, loamy soils register a higher total soil moisture change than sandy soils (Figure 2). Since clay has a lower hydraulic conductivity than loam, it is assumed that this theory also holds for clay soils. Furthermore, clay is prone to cracking during dry periods, and this process can affect the measured soil moisture, resulting in higher brightness temperatures than surrounding areas. This is due to increased drying caused by cracking of the clay (Liu et al. 2010). Consequently, the effect of cracking clays is a larger variation of the T_b values in clay soils. These studies imply that soils containing more clay show a higher variance in soil moisture than sandy soils, and infer that clay pans should be characterized by a higher variance in soil moisture values, thus showing a higher variance in brightness temperatures. Taking this into account, remote sensing of soil moisture dynamics is a potential tool to derive clay pans.

4.2. Approach

Identification of clay pans requires a methodology having a strong response to changes in soil moisture while being relatively unaffected by other parameters like physical temperature and vegetation. Using AMSR-E data, several models are developed to determine the most suitable approach to clay pan detection in the studied area: the mean over the horizontally polarized brightness temperatures ($T_{b,H}$) and vertically polarized brightness temperatures ($T_{b,V}$), the variance over $T_{b,H}$ ($\sigma^2_{T_{b,H}}$) and $T_{b,V}$ ($\sigma^2_{T_{b,V}}$), the Microwave Polarization Difference Index (MPDI), the standard deviation over the MPDI (σ_{MPDI}), and the Brightness Temperature Variance Index (BTVI). The MPDI is given according to Owe, de Jeu, and Walker (2001) as

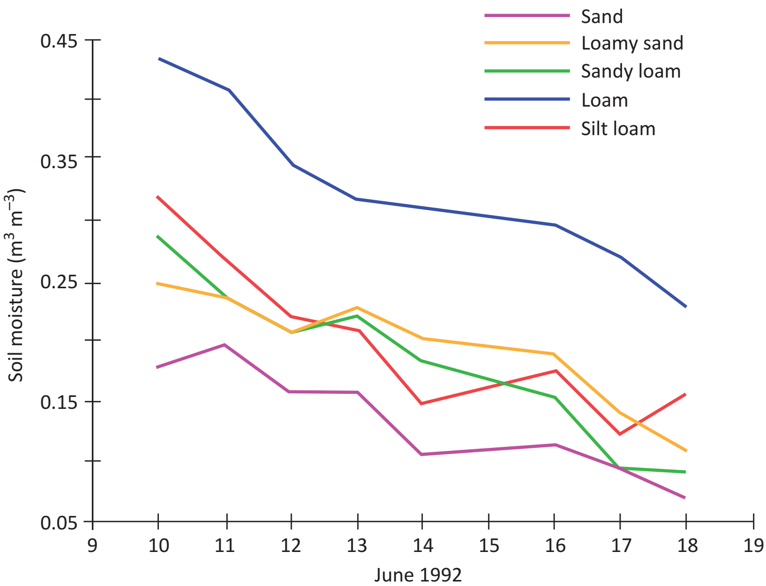

Figure 2. Temporal variation in surface soil moisture during the Washita 1992 experiment for various soil texture types typically found in the little Washita basin. The study area experienced a clear dry-down from very wet to dry over a period of nine days. Different soils types exhibited distinct characteristics of soil moisture contents and associated temporal changes, which could thus be used as indicators of soil texture (after Mattikalli and Engman 1997).

$$\mathrm{MPDI} = \frac{T_{\mathrm{b,V}} - T_{\mathrm{b,H}}}{T_{\mathrm{b,V}} + T_{\mathrm{b,H}}}. \tag{1}$$

The BTVI is a model developed for this research and defined as

$$\mathrm{BTVI} = \frac{\sigma^2_{T_{\mathrm{b,V}}} - \sigma^2_{T_{\mathrm{b,H}}}}{\sigma^2_{T_{\mathrm{b,V}}} + \sigma^2_{T_{\mathrm{b,H}}}}. \tag{2}$$

Images were created to produce spatial patterns according to these models, and compared with existing soil data. The average values of the different models are extracted for clay and non-clay pans, and the capability of each model to discern between clay and non-clay pans is analysed using an unpaired Welch's *t*-test (Welch 1947). The Welch *t*-test accounts for unequal variance in the two samples. Differences in the two sample means were considered statistically significant at $p > 0.05$. Consequently, the model having the highest *t*-test determines which method differentiates best between clay and non-clay pans.

5. Results

Table 1 shows the mean values and variance over the modelled results found in clay pans as compared with the surrounding soils, with t giving the results of Welch's t-test. The statistical analysis demonstrates that models based on the temporal dynamics of soil moisture, such as $\sigma^2_{T_{\mathrm{b,H}}}$,$\sigma^2_{T_{\mathrm{b,V}}}$, σ^2_{MPDI}, and BTVI, give a higher value for t and thus discriminate better between clay pans and other soils.

Table 1. Welch's t-test (T), mean (μ), and variance (σ^2) of observed and calculated variables over clay pans and all other soils. The rows $\mu_{\text{non-clay pans}}$ and $\sigma^2{}_{\text{non-clay pans}}$ give the mean and variance for all values measured in non-clay pans for each product. The rows $\mu_{\text{clay pans}}$ and $\sigma^2{}_{\text{clay pans}}$ give the mean and variance for all values measured in clay pans for each product. The column T gives the result of the Welch's t-test, indicating the capability of each model to discern between clay and non-clay pans.

	$T_{\text{b,H}}$	$T_{\text{b,V}}$	MPDI	$\sigma^2\ T_{\text{b,H}}$	$\sigma^2\ T_{\text{b,V}}$	σ^2 MPDI	BTVI
$\mu_{\text{non-clay pans}}$	260.93	285.67	0.05	33.30	40.85	0.01	−0.09
$\mu_{\text{clay pans}}$	254.24	284.37	0.06	79.11	66.40	0.01	−0.33
$\sigma^2{}_{\text{non-clay pans}}$	41.70	4.63	0.00	285.13	252.22	0.00	0.01
$\sigma^2{}_{\text{clay pans}}$	22.64	1.85	0.00	1141.26	331.63	0.00	0.01
T	12.78	7.89	−9.89	−17.46	−15.71	−19.75	23.50

Figure 3 shows the spatial distribution of $\sigma^2_{T_{\text{b,H}}}$, $\sigma^2_{T_{\text{b,V}}}$,$\sigma^2_{\text{MPDI}}$, and BTVI, overlain with the distribution of the clay pans. On a large scale, these four models closely resemble the spatial distribution of clay pans. Qualitatively, BTVI shows the best spatial correspondence to the soil data, especially in the more western areas.

The mean values for σ^2_{MPDI}, $\sigma^2_{T_{\text{b,H}}}$, $\sigma^2_{T_{\text{b,V}}}$, and BTVI for 16 clay classes are shown in Figure 4(a) for the standard data, while data with small sand patches removed are shown in Figure 4(b). Increase in t was 1.6, 0.6, 1.1, and 2.8 for σ_{MPDI}, $\sigma^2_{T_{\text{b,V}}}$, $\sigma^2_{T_{\text{b,H}}}$, and BTVI, respectively, resulting in a range of t from 16.31 to 26.27. Again, BTVI gives the highest t and discriminates better between clay pans and other soils.

6. Discussion

According to the statistical analyses, the newly developed BTVI is considered the best of the models tested for clay pan detection with passive microwave satellite data, having t-values of 23.50 when using the standard data and 26.27 when excluding small patches of sand and clay. A high t-value implies that mean BTVI for clay pans and non-clay pans differs significantly and that the method discriminates between clay pans and other soils.

Figure 3(d) clearly shows that clay pans are characterized by low BTVI values. The t-value (Table 1 and Figure 4) demonstrates that BTVI bears the strongest relation to soil texture and hence clay soils. This also implies that the temporal signature of the microwave response in clay soils differs significantly from that in non-clay soils and can thus be used to detect clay pans. However if this is so, variation in soil moisture or the effect of cracking clay as described by Liu et al. (2010) needs to be further explored, for example using *in situ* soil moisture measurements.

BTVI is calculated using $\sigma^2_{T_{\text{b,H}}}$ and $\sigma^2_{T_{\text{b,V}}}$, and is developed to minimize the impact of temperature variations that affect both the $\sigma^2_{T_{\text{b,H}}}$ and $\sigma^2_{T_{\text{b,V}}}$, resulting in an index that is predominantly a function of the temporal dynamics in vegetation and soil moisture. To verify the effects of vegetation dynamics on BTVI, the variance in the vegetation optical depth (τ) over three years was derived using the VUA-NASA algorithm (Owe, de Jeu, and Holmes 2008), as shown in Figure 3(e). Vegetation optical depth is a dimensionless parameter that is largely a function of vegetation water content and biomass (de Jeu 2003). The spatial distribution of the variance in τ alone is insufficient to discriminate between clay pans and other soils, which suggests that there is no significant relationship between vegetation dynamics and BTVI. In addition, the impact of vegetation, measured as AMSR-E optical depth and NDVI, has a minimal effect on the AMSR-E soil moisture data in this region (Liu et al. 2010). Therefore, we can assume that vegetation has a minimal effect on BTVI in this region and that in sparsely vegetated areas BTVI is mainly controlled by temporal dynamics in soil moisture.

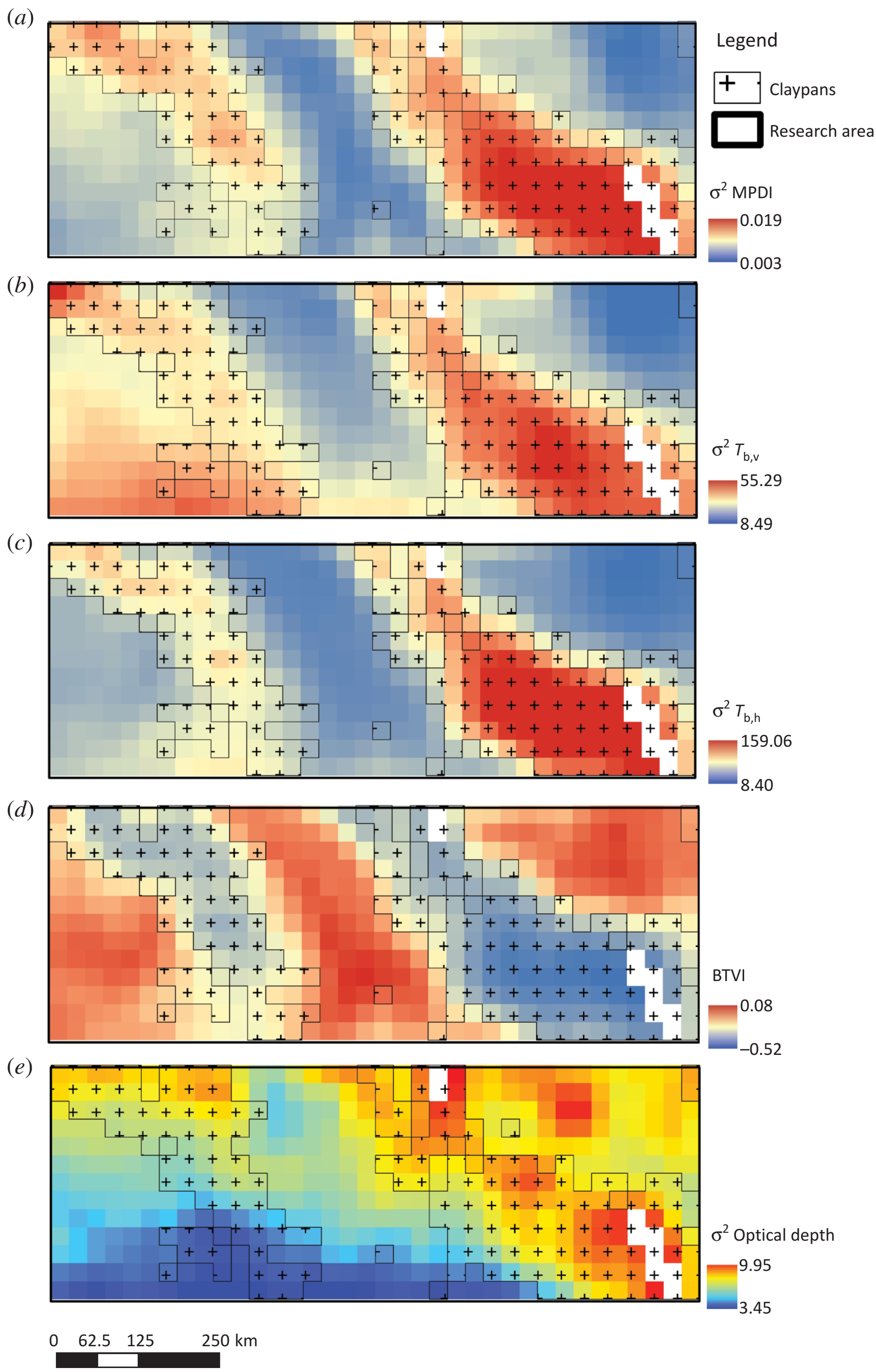

Figure 3. Plots of clay pans shown by cross-hatched areas in relation to (*a*) variance in MPDI, (*b*) variance in $T_{b,V}$, (*c*) variance in $T_{b,H}$, (*d*) BTVI, and (*e*) optical depth.

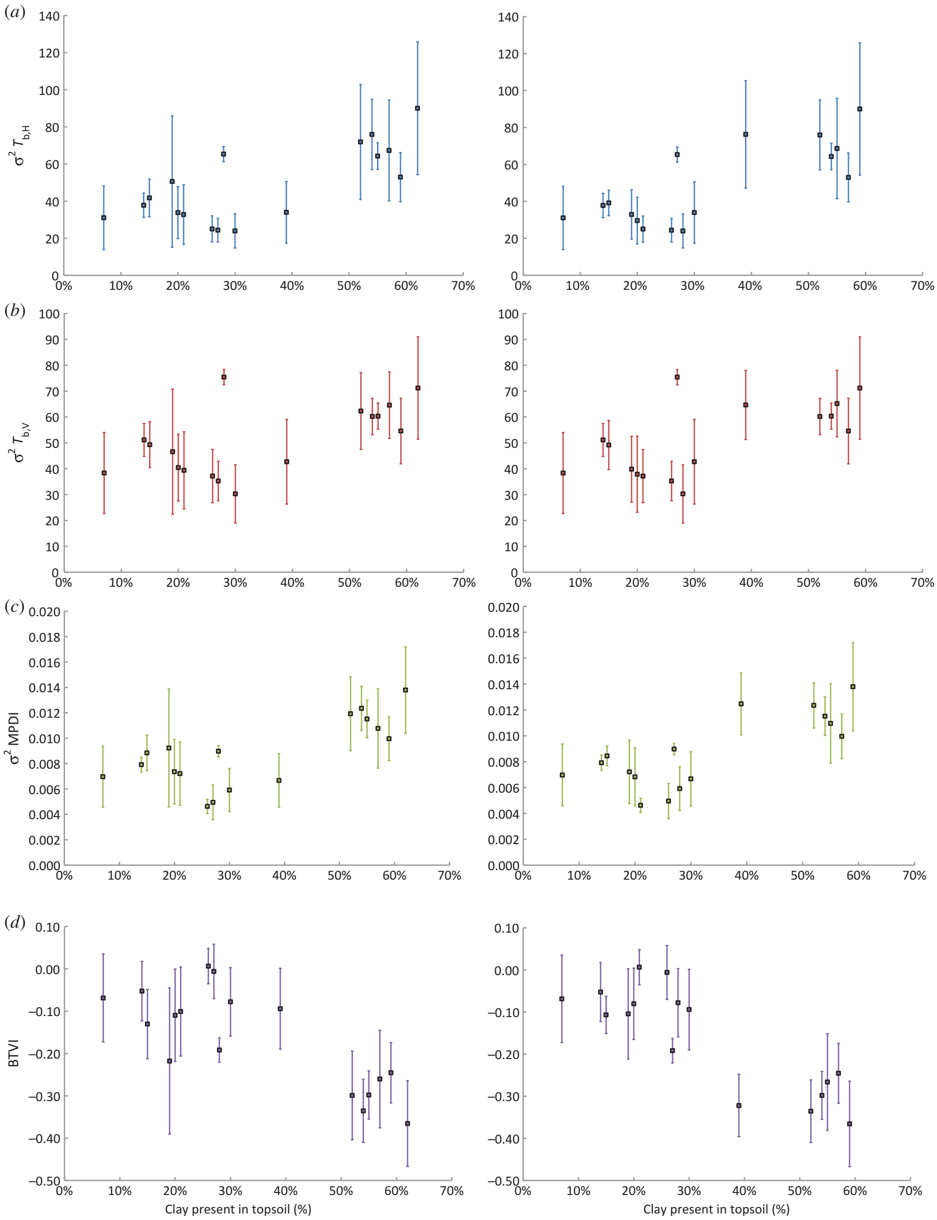

Figure 4. Mean values for (*a*) variance in $T_{b,H}$, (*b*) variance in $T_{b,V}$, (*c*) variance in MPDI, and (*d*) BTVI plotted against clay content using all data (left) and adjusted data, with small sand patches excluded (right). Error bars show the standard deviation and the dashed vertical line the boundary between clay pans and other soils.

There are, however, a few drawbacks to the technique presented in this study. Owing to the spatial resolution of AMSR-E, BTVI shows no response to small clay pans or other soils extending less than 50 km. However, since these small fields are represented in the soil data, the correspondence of BTVI to clay pans is distorted if not removed. Consequently, application of BTVI to microwave data at a higher spatial resolution could be useful to further explore its potential. Downscaling techniques to increase the spatial resolution of passive microwave observations are slowly becoming available (e.g. Santi 2010), and with the recent launch of AMSR 2 in 2012, it is expected that a resolution of 5 × 8 km can be obtained (Parinussa et al. 2012). However, the potential value of these techniques to extract clay pans at such a resolution is a topic that still needs to be explored.

The spatial resolution of the data used in studies to detect and map soil texture and/or clay pans using visible, near infrared, and hyperspectral imaging (Barnes and Baker 2000; Odeh and McBratney 2000; Chabrillat et al. 2002) is much higher than that for AMSR-E data. However, measurements at these spectral bands are often affected by atmospheric interference, soil colour, presence of a soil crust, and vegetation cover, increasing the need for extensive data processing (Kariuki, Woldai, and Van Der Meer 2004; Kaleita and Dilawari 2006; Mulder et al. 2011). The advantage of passive microwave remote sensing is that it can penetrate clouds and has a reduced sensitivity to land surface roughness and vegetation.

A few studies (Mattikalli and Engman 1997; Mattikalli et al. 1998; Santanello et al. 2007; Summerell et al. 2009) investigated the derivation of soil properties using passive and active microwave data assembled at a higher spatial resolution. These studies, used the different temporal dynamics of soils during dry-down events. They demonstrated that remote sensing of soil moisture can be a promising tool to derive soil properties or soil texture. However, the drawback of the technique used in these studies is its dependence on single rainfall events, which makes it difficult to apply on a larger scale (i.e. a continental scale). Although BTVI is not dependent on individual rainfall events, it is still based on the hydraulic conductivity, water-retention capacity, and temporal response of soil moisture. It is expected that in areas of extreme (continuous) precipitation (e.g. tropical regions and deserts), this technique will be less reliable.

Looking at BTVI over continental Australia (Figure 5(*a*)), it is clear that there are a few regions where it shows no clear correspondence. There are two areas where BTVI indicates the presence of clay pans, but the soil map does not confirm this. However in these areas, the soil map shows low reliability (Figure 5(*b*)) and thus it is unclear whether the soil map is sufficiently accurate in these areas. BTVI also responds to ephemeral lakes and salt pans, as shows in Western Australia and South Australia (Figure 5(*a*)). Areas with snow cover, dense vegetation, and high surface roughness (i.e. mountainous areas) are excluded, since brightness temperatures are markedly affected by these properties and sensitivity to soil moisture variations is reduced (Wang 1983; de Jeu 2003).

7. Conclusions

In order to identify clay pans using AMSR-E data, several models using these data were compared with existing soil maps. Clay soils have a different temporal signature to non-clay soils, and this signature is visible in the brightness temperature (i.e. soil texture is reflected in the temporal signature of soil moisture). AMSR-E provides the desired soil moisture data, enabling an examination of the temporal dynamics in soil moisture, a proxy for clay soils. For this study, a new index was developed, BTVI, which is based on the variance in AMSR-E brightness temperatures. The newly developed BTVI is predominantly controlled by soil moisture, since vegetation has a minimal impact on AMSR-E data in the study area. BTVI shows a strong spatial correspondence with existing soil maps and is the most suitable product to identify clay pans.

With the ongoing development of soil moisture retrieval through remote sensing, the technique presented in this paper can be further refined. In particular, remote sensing of soil

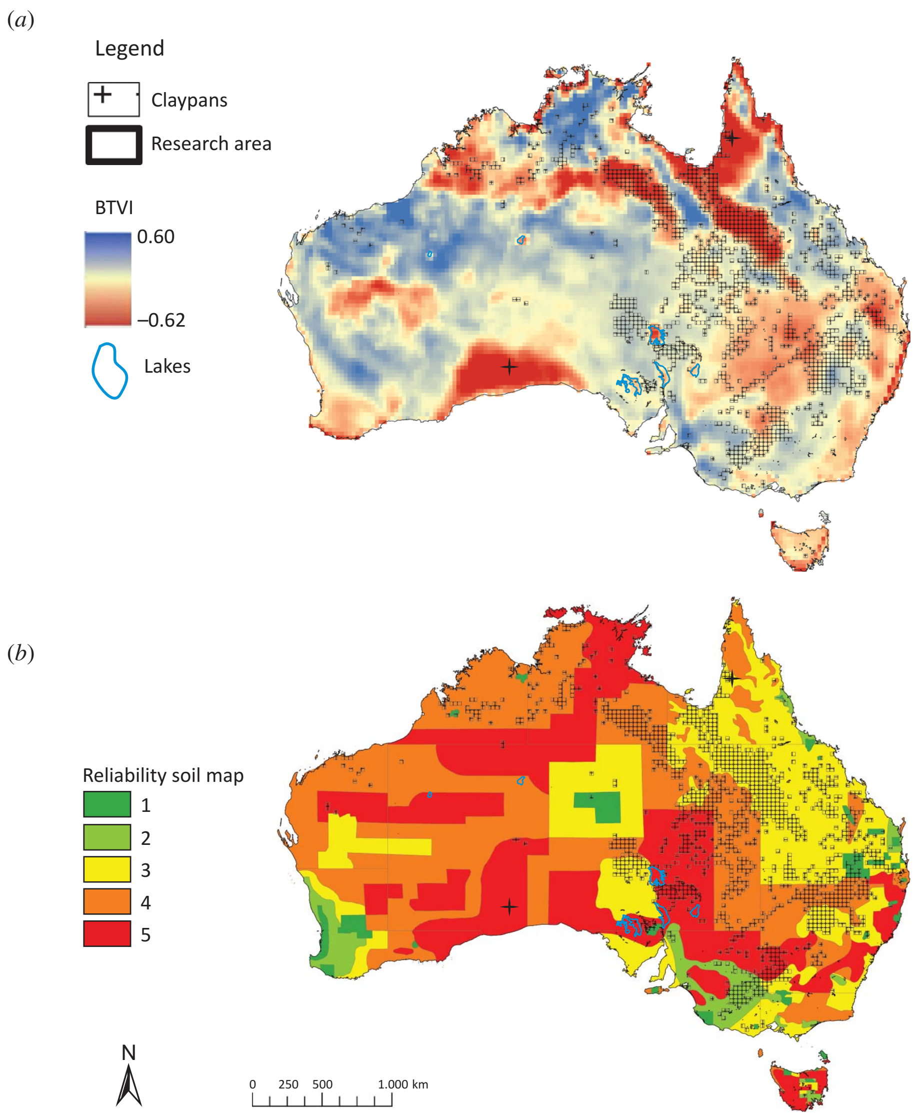

Figure 5. BTVI for Australia (*a*) and reliability map (*b*), where data source classes are listed in order of decreasing reliability. Black stars denote the areas where BTVI indicates the presence of clay pans but the soil map does not.

moisture measurements at a higher spatial resolution could be valuable, and more research is needed to verify whether BTVI is also applicable in other areas (e.g. with different precipitation patterns). It is thus concluded that passive microwave radiometry has the potential to make a valuable contribution to soil mapping and soil data collection.

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