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Satellite land surface temperature and reflectance related with soil attributes☆

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ABSTRACT

Soil attributes (clay, organic matter and moisture) directly influence land surface temperature (LST). Although there are several studies using soil spectra measured by satellites, soil evaluation through LST is still scarce. The objective of this research was to define the influence of soil attributes on LST and satellite image spectra. The study area (198 ha) is located in São Paulo state, Brazil. Soil samples were collected in a 100 × 100 m (0–0.2 m) regular grid. A Landsat 5 image, with bare soils, was acquired and LST was extracted using the inversion of Planck's function in band 6. Land surface emissivity was estimated using the Normalized Difference Vegetation Index threshold method. Reflectance values were extracted from bands 1 to 5 and 7. Linear regression (LR) models were calibrated for soil attributes prediction. Each model used a different set of covariates: (a) LST; (b) elevation; (c) spectral reflectance; and (d) all predictors. Ordinary kriging was performed and its results were compared to maps obtained from LR. There was significant correlation between soil attributes and reflectance, LST, and elevation. Models using only elevation presented poor performance for prediction of clay, sand, OM, and iron oxides; models using LST, moderate; and Vis-NIR-SWIR bands, good. The use of LST for estimating soil attributes increases the predictive performance when associated with surface reflectance, improving the validation of models. Mapping of clay, sand, OM and iron oxides using Landsat 5 products can strongly enhance agriculture management approaches.

1. Introduction

The study of soil temperature based on remote sensing (RS) focuses on the electromagnetic radiation emitted by the soil surface primarily at a wavelength around 10,000 nm (Hillel, 2004). The interactions determined by the physical properties of the matter and the energy wavelength are registered on RS images, from which it is possible to interpret features. In thermal infrared (TIR) RS, the emittance (or emission) is studied, which represents the energy previously absorbed by an object that is converted to heat and released in longer wavelengths (Sabins, 1996).

Sensors operating in the TIR region capture the emittance energy allowing the derivation of TIR RS products such as the Land Surface Temperature (LST) (Kuenzer and Dech, 2013). LST data obtained from satellite sensors is useful for several environmental studies, including vegetation and fire monitoring, geological, sea and soil studies (Bonn and O'Neill, 1993; Kuenzer and Dech, 2013; Li et al., 2013).

Studies based on TIR RS are mainly related with soil moisture, as LST is highly influenced by its content (Bonn and O'Neill, 1993). However, recent studies reveal that it is possible to relate LST to soil attributes, such as texture (Osińka-Skotak, 2007; Wang et al., 2015; Müller et al., 2016) and organic matter (OM) content (Zhao et al., 2014). There are no works performed on tropical regions, where soil variation is common and its evaluation through RS is crucial given their agriculture and natural resource importance.

The estimation of soil attributes using proximal and satellite RS has been widely reported (Viscarra Rossel et al., 2006; Chen et al., 2008; Ben-Dor et al., 2009). The soil spectral responses in the regions of visible (Vis), near infrared (NIR), and shortwave infrared (SWIR) have a strong relationship with soil attributes, such as clay, OM and iron oxides (Chang et al., 2001). Thus, their prediction through Vis-NIR-SWIR is a consolidated technique, particularly using laboratory sensors

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such as spectroradiometers. Regarding orbital sensors, the use of remotely sensed digital elevation models (DEM) also contributes to the prediction of soil attributes, considering that terrain features influence on the model's performance (McBratney et al., 2003; Moura-Bueno et al., 2016). However, the inclusion of TIR data in the form of LST for topsoil attributes prediction is still scarce and it can help in digital soil mapping (DSM).

Even though soil attributes prediction via laboratory spectroradiometers (LS) has been reported with results usually better than those obtained using satellite surface reflectance data, in the last approach, soil information in the spatial resolution of the used sensor is obtained. For Landsat, we can achieve such information every 30 m (pixel size) and with the inclusion of LST, while for LS, the spatial resolution is the same of the sampling density, and additional analyses are needed to spatialize the data. Moreover, the atmospheric interferences that can hinder the use of satellite data are minimized by image selection (in the case of Landsat, the temporal resolution is 16 days) and also processing techniques, such as atmospheric correction.

LST differentiation can be enhanced in soils with variations in sand, clay, and OM, due to their different thermal properties. Osińka-Skotak (2007) found that topsoil texture has an important impact on LST, and the same type of soil can reach differences of up to 4 °C in brightness temperatures depending on texture variation. These differences are closely related to the water content of soil, because its thermal properties strongly influence LST. Thus, the behavior of LST in response to soil moisture provides information about its texture (Wang et al., 2012; Wang et al., 2015; Müller et al., 2016). Since soil texture is related with surface temperature, the same is expected for mineralogy. Attention has been caught to the study of thermal properties of rocks and their respective minerals (Eppelbaum et al., 2014). Soil clay minerals such as iron oxides may contribute to the LST obtained from clayey soils.

In the case of OM, its presence is related to clay content. Mechanisms of physical and chemical protection of OM from microbial mineralization take place in the soil due to clay particles (Konen et al., 2003). Therefore, soils with high clay content are also associated with high OM, and LST tends to follow a similar relationship with both (Zhao et al., 2014). Through soil texture, it is possible to infer soil hydraulic properties (Müller et al., 2016), such as water holding capacity, and its susceptibility to erosion. The OM also has an important role, as it is linked with soil fertility, water-stable aggregation, and carbon sequestration (Six et al., 2004). The use of RS techniques including TIR products has the potential to improve soil attributes mapping at the farm scale, providing up-to-date thematic maps of texture and OM. In the last case, as its content in the topsoil is very dynamic and changeable in short periods of time due to soil management, the availability of maps is essential for soil quality assessment.

Given this context, the hypotheses of this research are that (1) bare soil surface temperature differs due to soil texture, OM, and clay mineralogy; and (2) LST estimated by RS allows the prediction of some soil attributes. Thus, we expect that both soil attributes and class will help to explain surface temperature variation. The objectives of this research were to (1) differentiate soil textural classes assessing LST values; (2) generate soil attributes prediction models based on different RS variables such as LST, Vis-NIR-SWIR reflectance and elevation; (3) verify to what extent the LST can improve soil attributes mapping; and (4) generate soil attribute maps using geostatistics and compare them with the maps produced using RS variables.

2. Materials and methods

2.1. Study area, soil sampling and wet chemistry analyses

The study area (Fig. 1a) is located in the municipality of Rafard, in the southeast of São Paulo State, in a Paleozoic depression. Previous studies were performed by Nanni and Demattê (2006) and Bazaglia Filho et al. (2013) in this same location. The site is a 198 ha sugarcane field, located in the Tietê watershed, with subtropical mesotermic climate (Cwa) according to Köppen classification (dry winters and wet summers). The average temperature in the coldest month, July, is 18 °C and 22 °C in the warmest one, February. Annual rainfall varies between 1100 and 1700 mm (Nanni and Demattê, 2006).

The Itararé Formation (Tubarão group) represents the geology of the area (Fig. 2a), with siltstone as the predominant lithology. In addition, there are also eruptive diabase dike elements of the Serra Geral Formation (São Bento group) and fluvial old terrace sediments are found near the Capivari river. Altitude varies from 478 to 570 m and the relief is rolling to gently rolling, with slope varying between 0 and 35%. Given the geology complexity and diversity, soils that occur in the study site are very diverse. Sixteen soil profiles were obtained for classification, comprising five groups from the nomenclature of World Reference Base for Soil Resources (IUSS Working Group WRB, 2015). Soils found in the area are classified as Lixisols, Nitisols, Cambisols, Leptosols, Gleysols, and Chernozem (Fig. 2b) (Nanni and Demattê, 2006; Bazaglia Filho et al., 2013).

A regular sampling grid of 100 × 100 m was delineated in the study site (covering 182 ha), with a sampling density of one sample per hectare, comprising 182 auger points in the superficial layer (0–0.2 m). During the field campaign, the area was plowed for following planting. The soil samples were oven-dried for 48 h at 50 °C, ground and sieved (2 mm mesh). Analysis of soil particle size distribution was performed using the densimeter method, in which sodium hydroxide (0.1 mol L^{-1}) and sodium hexametaphosphate (0.1 mol L^{-1}) were employed as dispersing agents (Camargo et al., 1986). For chemical analysis, soil OM content was determined based on the Walkley-Black method (Walkley and Black, 1934). This method determines the organic C and the calculation of soil OM was made using a conversion factor of 1.724. Total clay iron oxides (Fe_2O_3) were determined with a sulfuric acid based methodology (Camargo et al., 1986).

Percentages of sand, silt and clay were used to obtain the soil texture class, using the system proposed by the United States Department of Agriculture (USDA), based on the soil texture triangle. Soil textures were calculated using the *soiltexture* package (Moeys, 2016), in R environment (R Core Team, 2015).

2.2. Remote sensing data and atmospheric correction

A TM/Landsat 5 image was obtained in the Earth Explorer Platform (https://earthexplorer.usgs.gov), from 08/27/1997. This date was chosen due to the availability of bare soil in almost all the study area, as reported by Nanni and Demattê (2006). Besides, August corresponds to the dry season. The SRTM (Shuttle Radar Topography Mission) DEM was also acquired (30 m). From this product we derived information regarding land surface, such as slope, aspect (slope orientation) and solar radiation. These terrain attributes were obtained in ArcMap 10.3 (ESRI, 2011). Solar radiation was calculated for the same date and time of the selected image, according to the algorithm developed by Fu and Rich (2000).

Atmospheric correction and the creation of a bare soil mask were performed in ENVI 5.1 software (Exelis Visual Information Solutions, Boulder, Colorado). For this, we used the FLAASH algorithm (Line-of-sight Atmospheric Analysis of Spectral Hypercubes). It integrates the MODTRAN (Moderate Resolution Atmospheric Transmission) radiation transfer code and accounts for water vapor and aerosol retrieval (Cooley et al., 2002).

The bare soil mask was created to eliminate targets in the image that do not correspond to bare soils, such as vegetation and residues from agriculture (straw). After the mask application, all targets that do not represent soils have a null value. The methodology was adapted from Demattê et al. (2016); Fongaro (2015); and Demattê et al. (2009). This mask was performed just to spectrally confirm that the study area had bare soil during the satellite scene date, because during the field campaign, it was reported that the area was completely bare. Despite this,