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Detecting geothermal anomalies and evaluating LST geothermal component by combining thermal remote sensing time series and land surface model data

Romaguera M.[a,*], Vaughan R.G.[b], Ettema J.[a], Izquierdo-Verdiguier E.[a], Hecker C.A.[a], van der Meer F.D.[a]

[a] Faculty of Geo-Information Science and Earth Observation (ITC), University of Twente, Hengelosestraat 99, P.O. Box 217, Enschede 7500AE, The Netherlands
[b] US Geological Survey, Astrogeology Science Center, Flagstaff, AZ, USA

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ABSTRACT

This paper explores for the first time the possibilities to use two land surface temperature (LST) time series of different origins (geostationary Meteosat Second Generation satellite data and Noah land surface modelling, LSM), to detect geothermal anomalies and extract the geothermal component of LST, the LST_{gt}. We hypothesize that in geothermal areas the LSM time series will underestimate the LST as compared to the remote sensing data, since the former does not account for the geothermal component in its model.

In order to extract LST_{gt}, two approaches of different nature (physical based and data mining) were developed and tested in an area of about $560 \times 560\ km^2$ centered at the Kenyan Rift. Pre-dawn data in the study area during the first 45 days of 2012 were analyzed.

The results show consistent spatial and temporal LST_{gt} patterns between the two approaches, and systematic differences of about 2 K. A geothermal area map from surface studies was used to assess LST_{gt} inside and outside the geothermal boundaries. Spatial means were found to be higher inside the geothermal limits, as well as the relative frequency of occurrence of high LST_{gt}. Results further show that areas with strong topography can result in anomalously high LST_{gt} values (false positives), which suggests the need for a slope and aspect correction in the inputs to achieve realistic results in those areas. The uncertainty analysis indicates that large uncertainties of the input parameters may limit detection of LST_{gt} anomalies. To validate the approaches, higher spatial resolution images from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data over the Olkaria geothermal field were used. An established method to estimate radiant geothermal flux was applied providing values between 9 and 24 W/m^2 in the geothermal area, which coincides with the LST_{gt} flux rates obtained with the proposed approaches.

The proposed approaches are a first step in estimating LST_{gt} at large spatial coverage from remote sensing and LSM data series, and provide an innovative framework for future improvements.

1. Introduction

Thermal infrared remote sensing (RS) and the derived land surface temperature (LST) can be used for geothermal applications to map thermal anomalies and calculate the geothermal heat flux (Haselwimmer and Prakash, 2013; Ramsey and Harris, 2013; van der Meer et al., 2014). Although most of the published literature has focused on the use of airborne thermal imagery with high spatial resolution (i.e. < 5 m) during the last decade several authors have worked on the use of medium resolution thermal imagery from Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS) (90 m, 120 m, and 1 km spatial resolution respectively).

Coolbaugh et al. (2007) used ASTER thermal imagery to map geothermal anomalies at Bradys Hot Springs (US). The method aimed to minimize temperature variations caused by the diurnal heating effects of the sun in order to highlight subsurface contributions of geothermal heat. A pseudo-temperature image was created after the correction of albedo, terrain slope, and thermal inertia effects.

Eneva and Coolbaugh (2009) used ASTER imagery and elaborated on the importance of incorporating nighttime temperature inversions, along with the effects of elevation when using thermal remote sensing

* Corresponding author.
E-mail address: mireia.romaguera@uv.es (M. Romaguera).

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for geothermal activity detection. Gutierrez et al. (2012) implemented this improvement by including altitude in thermal anomaly detection in the geothermal complexes of the Andes (Central Chile).

Watson et al. (2008) used a simplified surface energy balance equation and Landsat data to calculate a 'residual terrestrial emittance anomaly' throughout Yellowstone National Park that clearly discriminated geothermal from non-geothermal areas. The resulting values provided a lower bound on geothermal heat flux for that system, with values between 0 and 94 W/m^2.

Vaughan et al. (2012) analyzed ASTER and MODIS thermal data at the Yellowstone National Park acquired in the 2000–2010 period. The method identified normal background changes, so that significant or abnormal changes due to geothermal activity could be recognized. The radiant geothermal heat for the whole area resulted in an estimate of about 2 GW of thermal energy.

Other examples and applications to other areas can be found in some recent literature like Qin et al. (2011) and Eskandari et al. (2015) amongst others.

Most of the aforementioned works used data acquired on specific dates and times, based on their availability. Regarding time series, the use of Landsat and ASTER limited the studies to a temporal frequency of 16 days or more (due to clouds or lack of acquisitions), which might not be sufficient to monitor changing surface conditions. In this context, Vaughan et al. (2012) increased the temporal frequency by using MODIS 1 km radiances. These are typically taken four times daily (twice at day and twice at night).

Night time acquisitions were preferred in all these studies to analyze geothermal anomalies so that sun heating effects were minimized. In particular, at the coldest time of the day (pre-dawn), the relative contribution of the geothermal component to LST is higher. However, with the aforementioned datasets, it was not always possible to choose a specific analysis time and date because of the limitation in acquisition time over a specific area.

Bearing these drawbacks in mind, it seems reasonable to explore the use of geostationary satellites, which provide thermal data at higher temporal frequencies, namely 15, 30 or 60 min. This type of data improves the ability to monitor geothermal areas in a more continuous and consistent manner, as well as facilitates the geothermal research during night acquisition times.

In particular, the present paper aims to explore the use of Meteosat Second Generation (MSG) time series to map geothermal anomalies and calculate the geothermal component of LST (LST_{gt}). The MSG system provides LST products at a temporal resolution of 15 min and a spatial resolution of 3 km at nadir. The satellite is centered at 0° longitude over the equator with a field of view that covers Europe, Africa and the east side of South America. The formulation for LST retrieval is based on a split-window algorithm (Wan and Dozier, 1996) where brightness temperatures and surface spectral emissivity are the inputs.

The spatial resolution of this data is a limitation when aiming to capture geothermal anomalies that are scattered in space and not always detectable with remote sensors. Vaughan et al. (2012) reported that no clear LST anomalies could be observed at the Yellowstone park when using 1 km resolution MODIS LST products, by comparing the central geothermal pixel with the neighboring ones. Bearing this in mind, an alternative strategy was adopted in this research, where instead of using neighboring pixels to analyze the possible thermal anomalies, an additional LST dataset was included and the assessment was carried out comparing both datasets per pixel.

Simulations obtained with the land surface model (LSM) Noah (Niu et al., 2011) implemented in the Weather Research & Forecast (WRF) model were the second dataset. The equivalent to remote sensing LST is skin temperature in the LSM, which is calculated using a single linearized surface energy balance equation. This LSM does not include a source of subsurface geothermal heat in the formulation, and therefore the surface temperature simulated values will be underestimated in geothermal areas. However, remote sensing techniques based on radiation detection are potentially able to detect the whole radiative surface thermal signal. Therefore, the hypothesis here is that the difference between the two datasets is partially related to the geothermal activity.

Different approaches have undertaken a comparative analysis of LST from remote sensing data and modeling approaches with different objectives (Sohrabinia et al., 2012). Some works attempt to improve LST retrievals via modeling complex land cover and terrain features to improve surface emissivity estimation. Others have attempted to use remote sensing thermal and land cover data to improve atmospheric models for simulation of land surface parameters. Others have used remote sensing LST to study the near-surface air temperature or surface soil moisture. Finally, validation of MODIS LST products was carried out using modeling and in situ measurements.

Therefore, bearing in mind that in general the simulated LST could deviate from remote sensing based LST due to differences in inputs (vegetation, elevation, moisture availability, albedo), and model realizations, the objective here was to achieve a major isolation of the geothermal component, in particular for estimating the geothermal contribution to LST (LST_{gt}).

Two approaches of different nature and complexity were developed, adapted and tested to obtain LST_{gt}. In comparison with the aforementioned literature, they take advantage of the high resolution time series and use two LST datasets (a remote sensing based and land surface model outputs). In the first proposed approach, the methodology given by Romaguera et al. (2012, 2014) was adapted for geothermal applications. The aforementioned research was initially conceived as a tool to assess irrigation by comparing remote sensing and model simulations of evapotranspiration. As a human action, irrigation was not included in the simulations whereas its effects were actually observed via remote sensing. A similar concept was adapted in the present paper. The geothermal source of heat was not included in the simulations whereas remote sensing observations were able to capture the radiative part of it. The adapted approach (a bias method, BIASM in the following) was based on the definition of a reference bias, i.e. the difference between the two LST datasets in non-geothermal areas. Clustering of the area was carried out based on hydro-meteorological and surface properties and a spatial mean LST bias was assigned per cluster. LST_{gt} was then calculated in the whole area as the LST difference between remote sensing and simulations corrected by the reference bias.

The second approach (a data mining method, DMM in the following) developed in this paper was based on data mining and used machine learning techniques to train and build a model that predicted remote sensing LST in reference areas (non-geothermal). The inputs for this model were hydro-meteorological and surface properties obtained from the LSM simulations. The hypothesis here was that when applying the model to geothermal areas, remote sensing predicted LST would be underestimated with respect to measured remote sensing LST since model inputs proceed from simulations, which do not account for the geothermal influence. The LST difference between remote sensing measured and predicted LST provided LST_{gt}.

BIASM and DMM were tested in Kenya, in an area of about $560 \times 560\ km^2$ centered at the Kenyan Rift, where numerous geothermal fields are present. This is an area of great geothermal energy potential, where reconnaissance studies have been carried out since 50s and exploitation exists since 80s in specific areas. In particular, the most important power plant is located in the Olkaria field, next to Lake Naivasha. The analysis was carried out in a time span of 45 days in January and February 2012, by using the night time data obtained at 03:00 UTC (pre-dawn in the study area).

The results were tested by comparing the estimates of geothermal area with existing maps of potential geothermal, built based on surface studies. Moreover, the method given by Vaughan et al. (2012) was applied to the Olkaria area and the radiant geothermal flux was compared with the results of this paper.

The general objective of this work is to fill a knowledge gap in the