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Australian mean land-surface temperature

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ABSTRACT

The mean land-surface temperature represents an important boundary condition for many geothermal studies. This boundary is particularly important to help constrain the models made to analyse resource systems, many of which are shallow in nature and observe relatively small thermal gradients. Consequently, a mean land-surface temperature map of the Australian continent has been produced from 13 years of MODIS satellite imagery, for the period 2003–2015. The map shows good agreement with independent methods of estimating mean land-surface temperature, including borehole surface-temperature extrapolation and long-term, near-surface ground measurements. In comparison to previously used methods of estimating mean land-surface temperature, our new estimates are up to 12 °C warmer. The MODIS-based method presented in this study provides spatially continuous estimates of land-surface temperature that can be incorporated as the surface thermal boundary condition in geothermal studies. The method is also able to provide a quantification of the uncertainties expected in the application of these estimates for the purposes of thermal modelling.

1. Introduction

The thermal budget of the crust forms an important element in our overall understanding of geological systems. Indeed, while the embedded thermal energy of the crust represents an energy resource of itself, crustal temperature is also an important constraint on geodynamic modelling, hydrogeochemical modelling, the accurate interpretation and inversion of geophysical data sets, and the formation and preservation of both petroleum and mineral systems (*e.g.* Beardsmore and Cull, 2001; Clauser, 2003; Davies, 1999; Magoon and Dow, 1994; Sandiford et al., 2002; Wyborn et al., 1994). In particular, the shallow thermal models used for the analysis of resource systems may only be interested in subsurface temperatures of up to 100–200 °C. Errors of a few degrees can have significant impacts on the interpretations drawn from such models (Peters and Nelson, 2012).

Conductive thermal models of the crust are subject to many sources of uncertainty. These include uncertainty in the geological structure, rock properties (thermal conductivity and heat production), and in the model boundary conditions (typically fixed basal heat flow and fixed surface temperature). The focus of this paper is on the specific choice of a fixed temperature to apply as the surface boundary condition. Previous studies have already highlighted the importance of this parameter, particularly on the sensitivity of results from shallow thermal models (*c.f.* Kohl et al., 2001). However, in the absence of detailed ground-temperature sampling, studies to-date have generally had to rely on the use of proxy data.

In the past, many researchers have simply adopted the average annual air temperature as the surface boundary constraint (*e.g.* Middleton, 1979; Chapman et al., 1984; Goutorbe et al., 2008; Danis et al., 2010). Others have leveraged the adiabatic lapse rate of air to estimate topography-dependent empirical corrections for known ground-surface temperatures (*e.g.* Kohl et al., 2001, 2003). However, air temperature is only one of the variables influencing ground temperature, and its use has a proxy has long been recognised to introduce error. Howard and Sass (1964) compared ground surface temperature values, derived from borehole thermal gradient extrapolations, with mean annual air temperature values for 11 boreholes across the Australian continent, mostly from Western Australia. Results suggested an increase of 3 °C of mean ground surface temperature over mean annual air temperature. Since then, several Australian studies have adopted this +3 °C offset as a standard correction to apply to the mean annual air temperature as a method to estimate ground surface temperature (*c.f.* Beardsmore and Cull, 2001; Cull and Conley, 1983; Meixner et al., 2012). Similar corrections have also been applied internationally (*e.g.* Bartlett et al., 2006; Blackwell et al., 1980; Deming and Chapman, 1988; Majorowicz and Jessop, 1981).

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Several previous studies have estimated the land-surface temperature at specific points across the Australian continent. In a local study of the Carnarvon Basin in Western Australia, Beardsmore (2005) extrapolated observed borehole thermal gradients to show that the estimated mean land-surface temperature was 6 °C warmer than mean annual air temperature; twice the average suggested by Howard and Sass (1964). Gerner and Budd (2015) analysed data from 108 continuous borehole temperature logs and 81 Bureau of Meteorology ground temperature sensors from across the continent and demonstrated that the difference compared to average annual air temperature was 3.38 °C averaged across the entire dataset. This result was not substantially different from that of Howard and Sass (1964), however, with individual sites recording differences of 1–8 °C, a fixed correction factor of 3 °C can result in errors of up to 5 °C in some areas. Unfortunately, Gerner and Budd (2015) lacked the spatial detail required to draw rigorous quantitative conclusions and estimates of uncertainty.

Remote sensing provides an opportunity to achieve the spatial resolution required for detailed mapping of land-surface temperature at regional and continental scales. Preliminary studies have previously demonstrated the potential for such an approach to be applied within a geothermal context (Horowitz and Regenauer-Lieb, 2009; Horowitz, 2015). In particular, Horowitz and Regenauer-Lieb (2009) presented a map of mean Australian land-surface temperature. Their study however, was limited by the six year record of satellite data available. The general approach developed in these earlier studies is adopted here with modification. The method is applied to the whole Australian continent, using a much longer record of observations, and with comparison to other independent measurements of mean land-surface temperature. The validity of an empirical +3 °C correction to the mean annual air temperature will also be briefly examined.

2. Methods

2.1. Remote sensing

Daily land-surface temperature observations are available as a standard data product of the Moderate Resolution Imaging Spectroradiometer (MODIS). MODIS sensors are installed on two satellite systems; Terra and Aqua. The two satellites are currently operational with Terra commencing observations on 5 March 2000, and Aqua commencing observations on 8 July 2002. The satellites are sun-synchronous, recording both a day-time and night-time pass for a given location in a single 24 h period. The orbit of Terra makes a north-south pass of the equator every 98.8 min at approximately 10:30 am local time, while the orbit of Aqua makes south-north pass of the equator every 98.4 min at approximately 1:30 pm local time. The MODIS land-surface temperature products have $\sim 1\ \text{km}^2$ pixels. The derivation of land-surface temperatures from the observations of these satellites is described extensively in the MODIS land-surface temperature Algorithm Theoretical Basis Document (Wan, 1999), including an accuracy specification of ± 1 °C. Subsequent validation testing suggests that this uncertainty range is generally achieved, but increases with heavy atmospheric aerosol loadings (Wan, 2008).

As water vapour interacts with the wavelengths required for MODIS land-surface temperature observations, cloud cover must be filtered prior to image processing. Where cloud cover has a strong seasonal correlation, such filtering can result in temporal sample biasing. This sampling bias must be taken into consideration when calculating an annual mean land-surface temperature (Fig. 1). Given the nature of annual temperature fluctuations, sinusoidal regression can be used to calculate a temporally-unbiased mean. A standard sinusoidal waveform is given by

$$f(t) = \mu + A\cos(\omega t + \phi) \tag{1}$$

where the temperature, $f(t)$, as a function of time, t (days), is given by the mean, μ (°C), amplitude, A (°C), frequency, ω (radians per day), and

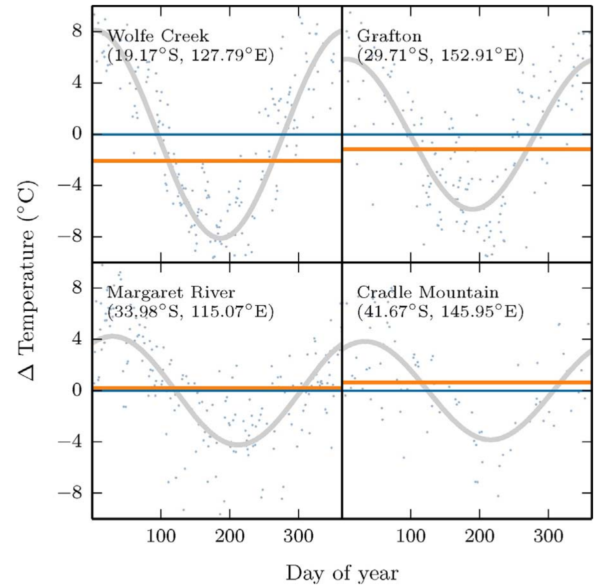

Fig. 1. Cloud-filter induced sample biasing of mean land-surface temperature, as calculated at four locations across the Australian continent using Terra night-pass temperature estimates from 2008. In each case, the magnitude of the sample bias is given by the difference between the arithmetic mean (orange line) and the sinusoidal mean (blue line). The sinusoidal model (grey line) is calculated from the least-squares fit to the observed temperature data (grey dots). The temperature axes are plotted relative to the sinusoidal mean for each location. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

phase shift, ϕ (radians). In the context of modelling the expected annual land-surface temperature in the southern hemisphere, a cosine wave is fitted as the default phase is already closely match to that expected. Furthermore, the wave frequency is known to be annual, and therefore $\omega = \frac{2\pi}{365.24}$. In order to apply a sinusoidal regression to the observed MODIS data, the standard waveform in (1) can be expanded using the angle-sum trigonometric identity to give

$$f(t) = \mu + A\cos(\omega t)\cos(\phi) - A\sin(\omega t)\sin(\phi) \tag{2}$$

Given that A and ϕ are both independent of t, (2) can be simplified to

$$f(t) = \mu + B_1\cos(\omega t) + B_2\sin(\omega t) \tag{3}$$

where $B_1 = A\cos(\phi)$ and $B_2 = -A\sin(\phi)$. It therefore follows that the three unknowns in (3) are given by the least-squares solution of the linear system

$$\begin{bmatrix} 1 & \cos(\omega t_0) & \sin(\omega t_0) \\ \vdots & \vdots & \vdots \\ 1 & \cos(\omega t_n) & \sin(\omega t_n) \end{bmatrix} \begin{bmatrix} \mu \\ B_1 \\ B_2 \end{bmatrix} = \begin{bmatrix} f(t_0) \\ \vdots \\ f(t_n) \end{bmatrix} \tag{4}$$

where $f(t)$ is the observed MODIS data (of n available daily observations). Standard trigonometric relations then allow the amplitude and phase-shift of the annual waveform (1) to be recovered;

$$A = \sqrt{B_1^2 + B_2^2} \tag{5}$$

$$\phi = \arctan\left(-\frac{B_2}{B_1}\right) \tag{6}$$

The MODIS land-surface temperature observations are accompanied by estimates of the uncertainty for each observation. These uncertainties can be propagated through the sinusoidal least-squares regression to provide an indication of the uncertainties in the fitted model parameters, following Aster et al. (2005). This is achieved by first rescaling the linear system in (4) by a weighting matrix, W, such that