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Mapping spatial and temporal variation in tree water use with an elevation model and gridded temperature data

Mana Gharun*, Tarryn L. Turnbull, Joseph Henry, Mark A. Adams

Faculty of Agriculture and Environment, University of Sydney, 1 Central Ave, Eveleigh, Sydney 2015, NSW, Australia

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ABSTRACT

Tree water use is a major component of the water balance in forested catchments of semi-arid areas, as more than 80% of the incoming rainfall may be used by overstory trees. Managers are unable to easily predict water use and thus water yield, for the majority of eucalypt-dominated catchments in south-east Australia, owing to the variety of dominant and co-dominant species, their distributions with respect to landform, and the lack of species- and landform-specific knowledge of the regulation of water use. Moreover, the costs incurred to quantify input variables for available complex, process-based models, generally encourage finding alternative approaches. This study tested the adequacy of using just two easily measured variables for estimating rates of tree water use, using a model derived from data-learning techniques. The inputs are (1) measured daily atmospheric demand for water and (2) potential incoming radiation derived from surface topography and solar declination. Artificial neural networks (ANNs) and genetic programming (GP) models were trained and validated using in situ observations of vapour pressure deficit (VPD) and estimates of potential solar radiation (Q_{pot}), for a period of two years, at each of 10 forest stands across the high country of the states of New South Wales and Victoria. The models were tested using a random 50% of the collected data that was independent, i.e. not used in model development.

Atmospheric demand was selected because it strongly affects tree water use irrespective of site and species. Potential solar radiation was selected as a proxy for radiation, because it is relatively easy to estimate for any location for which elevation data are available in digital format, and since radiation strongly controls photosynthesis (through stomatal behaviour) and thermal balance.

Genetic programming resulted in models better able to predict rates of sap flux. A selected GP model was able to describe the relationship between tree sap flux, VPD, and potential radiation with good accuracy, and was used to map tree water use across the catchment.

1. Introduction

A significant portion of south-east Australia's montane catchments are dominated by eucalypt forests. Water yield from these headwaters to the Murray Darling Basin is highly dependent on the influence of forest functional type on energy and water exchange across the catchment. Transpiration alone explains a significant proportion of the changes in the stream flow (Mitchell et al., 2012), while the sensitivity of catchment water balance to vegetation water use increases as the ratio of potential evapotranspiration to rainfall increases (Zhang, 2004).

Rates of tree water use are now routinely measured using sap flow sensors. Physically-based models that subsequently draw on such sap flow data are used internationally to predict vegetation water use (Chuang et al., 2006; Granier and Loustau, 1994; Williams et al., 2001). Determinants of tree water use are complex. While physical processes are reasonably straightforward to represent mathematically, the biological processes are problematic. A general response within the literature is to greatly simplify these processes; albeit that the resulting models are then somewhat limited in their application. Consequently, there is a large number of experimental formulae for estimating tree water use. These include: (1) physically-based equations that describe the functions of the system and the physical laws that govern these processes (Chuang et al., 2006; Diaz-Espejo et al., 2012)—these equations require extensive input data which is seldom readily available at

* Corresponding author at: Faculty of Agriculture and Environment, University of Sydney, Level 4, Biomedical Building, 1 Central Avenue, Australian Technology Park, Eveleigh, Sydney 2015, NSW, Australia. Tel.: +61 2 8627 1037; fax: +61 2 8627 1099.
E-mail addresses: mana.gharun@sydney.edu.au (M. Gharun), tarryn.turnbull@sydney.edu.au (T.L. Turnbull), joseph.henry@cleanenergyregulator.gov.au (J. Henry), mark.adams@sydney.edu.au (M.A. Adams).

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each location within a landscape; (2) empirically-based models that do not require extensive inputs, but which need local parameterization and are not usable for species other than those studied (Buckley et al., 2012; Dierick and Hölscher, 2009; Langensiepen et al., 2006). Researchers have also built simpler forms of empirical models that are based on VPD and photosynthetically active radiation (Q, specific to waveband ca. 400–700 nm of solar radiation). Even so, application of these simpler models across the landscape is still limited by the difficulty of parameter estimation (Dierick and Hölscher, 2009; Dye and Olbrich, 1993). Alternatively sap velocity is often predicted using statistical models (e.g. linear or non-linear regression models), based on vapour pressure deficit and solar radiation that correlate well with sap velocity (Zeppel et al., 2004).

In general, limitations of available process-based models across a range of fields, has led to application of data-driven, machine learning techniques that solve optimization problems and find structure among potential relationships. Some of the most applied methods of such 'soft computing' in the field of hydrology and water resources, include artificial neural networks (ANNs) and genetic programming (GP). Their application has been encouraged by promising results for many prediction problems in hydrology (ASCE, 2000).

For example, these methods have been successful in accurately estimating processes such as pan evaporation (Kişi et al., 2012; Terzi, 2013), evapotranspiration (Aytek, 2009; Cobaner, 2011; Parasurman et al., 2007), reference evapotranspiration (Shiri et al., 2012), soil moisture (Makkeasorn et al., 2006), precipitation (Kisi and Shiri, 2011), ground water table depth fluctuations (Shiri and Kisi, 2011), rainfall-runoff relationship (Minns and Hall, 1996; Savic et al., 1999; Whigham and Crapper, 2001), suspended sediments in streams (Aytek and Kişi, 2008), and risks in water supply (Babovic et al., 2001).

Meijun et al. (2007) and Li et al. (2009) used neural networks to predict transpiration from poplar trees and transpiration from fruit trees, however their models requires in-situ measurements of at least three inputs and lack a mathematical framework to describe underlying mechanisms. Numerous studies have compared data-driven techniques with regression models (linear or non-linear) and have underlined the interest in using data-driven methods (see for example Manel et al., 1999; Paruelo and Tomasel, 1997; Shamshiry et al., 2014), however it is unclear how ANNs and GP perform in comparison with regression-based models of tree water use that are provided in the literature.

Evaporative demand and solar radiation have been tested as primary predictors of tree water use because amongst the various influencing climatic factors, humidity and radiation have the greatest effect on transpiration, vegetation function and dynamics (Dye and Olbrich, 1993; Gharun, 2013). VPD and radiation can explain a large proportion (more than 90%) of the variations in sap velocity in eucalypt forests of Australia (Buckley et al., 2012; Gharun et al., 2013a,b; Zeppel et al., 2004) due to relatively sparse canopies that are well-coupled with the atmosphere (Jarvis and McNaughton, 1986) in contrast to for example pine plantations (Teskey and Sheriff, 1996).

VPD can be easily calculated from measurements of air temperature and relative humidity and solar radiation is highly dependent on topography (Hengl and Reuter, 2009), therefore, the apparent solar path can be easily and accurately calculated relative to any location and any surface (Wilson and Gallant, 2000). Topography-driven variables can particularly be promising, since catchment topography is recognized as a critical control of the hydrological response and the resulting spatial organization of the vegetation patterns (e.g. Coblentz and Riiters, 2004; Engelbrecht et al., 2007).

The aim of this study was to test a practical method for mapping tree sap flux across time and space in the high country of south-east Australia.

2. Methods

2.1. Study area

Tree water use and vapour pressure deficit (VPD, kPa) were measured at 10 sites (Table 1) between May 2010 and July 2012 from high country forests that cover the water catchments within Murray Darling Basin in south-east Australia (MDB, between latitudes −35.58° to −36.46° and elevation between 700 and 1700 m above sea level). The high country of south-east Australia, receives an average annual rainfall of between 900 and 1200 mm (based on 30-year standard climatology record 1961–1990, Bureau of Meteorology).

The sites were chosen to capture the full breadth of forests that vegetate the montane headwaters of the MDB: monospecific forest dominated by *Eucalyptus delegatensis* or *Eucalyptus pauciflora*, and mixed species forest dominated by *Eucalyptus radiata*, *Eucalyptus dives*, and *Eucalyptus mannifera*.

2.2. Sap flux and environmental measurements

At each plot, three trees were selected for sap flux measurements. Sap flux (V_s, also called sap velocity, or sap flow per unit sapwood area; $cm^3\,cm^{-2}\,h^{-1}$) was measured using one heat ratio method (HRM, Burgess et al., 2001) probe set on each tree. Each HRM set consists of two needles and a heater probe integrated with a microprocessor. Each needle contains two thermocouples (at different lengths along the needle, corresponding to different depths of sapwood). Raw heat pulse velocities were corrected for wounding using a homogeneous third-order polynomial and assuming a wound diameter of 0.18 cm (Burgess et al., 2001) and zero-flow baseline was determined following the method of Buckley et al. (2011). Air temperature (T, °C) and relative humidity (rH, %) were directly measured 1 m above the forest ground every 30 minutes using electronic sensors. Average daily vapour pressure deficit (VPD, kPa) was calculated from measurements of temperature and relative humidity:

$$\mathrm{VPD} = \left(0.6112\, e^{(17.62\times T)/(243.12+T)}\right) \times \left(1 - \frac{rH}{100}\right) \tag{1}$$

When direct measurements of temperature and relative humidity are not available in the region, these data can be collected from the Bureau of Meteorology of Australia for weather stations, or other climate databases such as SILO (enhanced climate databank hosted by Queensland Climate Change Centre of Excellence), that provide spatially interpolated meteorological variables across Australia (Jeffrey et al., 2001). A full description of the study sites is given in Table 1.

Potential incoming radiation is the energy of solar radiation received by a particular surface point in one day, under clear sky conditions, and it depends on several components including the slope and aspect of the terrain surface (Funk and Hoelzle, 1992). Average potential incoming solar radiation (0.4–1 μm, Q_{pot}, $J\,min^{-1}\,cm^{-2}$) was estimated interactively, by combining a digital elevation model (approximately 30 m resolution, ASTER global DEM), and solar position within a geographic information system, SAGA (System for Automated Geoscientific Analyses, http://www.saga-gis.org). Incoming solar radiation is estimated within the software after calculating the shadowing effect of the surrounding land surface from the DEM, and integrating sun's position on the sky. This approach combines sun's position as the light source, and subsequent inclination angles and shadow effects; the angle at which radiation hits the earth's surface, is corrected for slope and aspect for each point of the landscape (Hengl and Reuter, 2009). Using this approach to describe changes in Q_{pot} across time and space incorporates the interaction between