Evaluating Land–Atmosphere Coupling Using a Resistance Pathway Framework

A. L. HIRSCH AND A. J. PITMAN

ARC Centre of Excellence for Climate System Science and Climate Change Research Centre, University of New South Wales, Sydney, New South Wales, Australia

V. HAVERD

CSIRO Oceans and Atmosphere Flagship, CSIRO, Canberra, Australian Capital Territory, Australia

(Manuscript received 20 October 2015, in final form 28 July 2016)

ABSTRACT

This paper presents a methodology for examining land–atmosphere coupling in a regional climate model by examining how the resistances to moisture transfer from the land to the atmosphere control the surface turbulent energy fluxes. Perturbations were applied individually to the aerodynamic resistance from the soil surface to the displacement height, the aerodynamic resistance from the displacement height to the reference level, the stomatal resistance, and the leaf boundary layer resistance. Only perturbations to the aerodynamic resistance from the soil surface to the displacement height systematically affected 2-m air temperature for the shrub and evergreen boreal forest plant functional types (PFTs). This was associated with this resistance systematically increasing the terrestrial and atmospheric components of the land–atmosphere coupling strength through changes in the partitioning of the surface energy balance. Perturbing the other resistances did contribute to changing the terrestrial and atmospheric components of the land–atmosphere coupling strength through changes in the partitioning of the surface energy balance but did not lead to systematic changes in the 2-m air temperature. The results suggest that land–atmosphere coupling in the modeling system presented here acts mostly through the aerodynamic resistance from the soil surface to the displacement height, which is a function of both the friction velocity and vegetation height and cover. The results show that a resistance pathway framework can be used to examine how changes in the resistances affect the partitioning of the surface energy balance and how this subsequently influences surface climate through land–atmosphere coupling. Limitations in the present analysis include grid-scale rather than PFT-scale analysis, the exclusion of resistance dependencies, and the linearity assumption of how temperature responds to a resistance perturbation.

1. Introduction

Land–atmosphere coupling can be considered a two-legged process split into terrestrial and atmospheric components (Guo et al. 2006). The terrestrial component is associated with the covariability between soil moisture and the surface turbulent energy fluxes (e.g., Dirmeyer 2011a). The atmospheric component is associated with the covariability between these fluxes and surface heating, entrainment, or boundary layer growth (e.g., Santanello et al. 2011). Research on land–atmosphere coupling has included investigating the convective triggering of precipitation in response to antecedent soil moisture conditions (e.g., Findell and Eltahir 2003a,b; Tawfik and Dirmeyer 2014), the thermal and hydrological pathways of land–atmosphere coupling (e.g., Dirmeyer 2011a; Dirmeyer et al. 2013a,b, 2014), anticipated changes in land–atmosphere coupling in response to climate change (e.g., Seneviratne et al. 2013; Lorenz et al. 2015), and the sensitivity of land–atmosphere coupling to model physics (e.g., Santanello et al. 2011; Hirsch et al. 2014b).

Research on land–atmosphere interactions commonly focuses on the influence of soil moisture variability on surface temperature. One of the most well-known methods of quantifying how the land surface affects the atmosphere in a climate model is the “coupling strength” approach introduced by Koster et al. (2004).
The first Global Land–Atmosphere Coupling Experiment (GLACE-1; Koster et al. 2006) used a methodology for evaluating the strength of land–atmosphere coupling in climate models. Regions of strong coupling, where precipitation and temperature are sensitive to soil moisture variability, were located in the transition zones between humid and arid climates. GLACE-1 results focused on the Northern Hemisphere with simulations run over a single boreal summer [June–August (JJA)]. Since these results were not applicable for the Southern Hemisphere summer, Hirsch et al. (2014b) undertook the first assessment of coupling strength for the austral summer [December–February (DJF)] over Australia. By implementing the GLACE-1 methodology in the Weather Research and Forecasting (WRF) Model (Skamarock et al. 2008), simulations were conducted to understand the uncertainty associated with different model physics and soil moisture states. Hirsch et al. (2014b) showed parts of northern and central Australia to be strongly coupled and therefore another land–atmosphere “hotspot” region, although the strength of the coupling was strongly influenced by the large-scale modes of variability.

Comer and Best (2012) revisited GLACE-1 in one climate model and demonstrated that the land–atmosphere coupling strength was sensitive to soil moisture availability, which in turn was controlled by the soil hydraulic conductivity and suction parameters in their land surface model (LSM). However land–atmosphere interactions are not only characterized by the soil properties (e.g., Qu and Hall 2006; Chen and Zhang 2009; Dutra et al. 2011; Puma et al. 2013; Colman 2013; Crook and Forster 2014) but also by the characteristics of the overlying vegetation (e.g., Ferguson et al. 2012; Lorenz and Pitman 2014). Vegetation is therefore important, particularly via the albedo, leaf area index, and roughness length, which vary with vegetation type (e.g., Boisier et al. 2012). The role of vegetation in land–atmosphere coupling is complicated by the dynamic behavior of vegetation (e.g., growth, defoliation, etc.) and land-use change (e.g., Hirsch et al. 2014). Hirsch et al. (2014a) demonstrated that there was a consistent weakening of the soil moisture–maximum temperature coupling strength for regions that experienced a change from forest to crops, irrespective of the choice of model physics used (e.g., planetary boundary layer and cumulus schemes). Chen and Zhang (2009) also found that land–atmosphere coupling demonstrated vegetation dependence when expressed as a function of the surface exchange coefficients that control the amount of energy returned to the atmosphere.

External to the GLACE studies that evaluated land–atmosphere coupling, other coordinated experiments such as the Project for the Intercomparison of Land-Surface Parameterization Schemes (PILPS; Henderson-Sellers et al. 1995) or the Global Soil Wetness Project (GSWP; Dirmeyer 2011b) evaluated the sensitivities of the surface turbulent energy fluxes to parameters and parameterizations within LSMs. Complementing PILPS, Desborough (1999) attempted to replicate the spread of the PILPS multimodel results using different modes for characterizing the surface energy balance (SEB) within a single LSM. This involved increasing the complexity of the SEB by a stepwise addition of algorithms for stability correction, canopy interception, bare ground evaporation, canopy resistance, and surface resistance. Desborough (1999) calibrated the resistance terms within the LSM to produce the same total annual evaporation between the different experimental modes and then examined how the fluxes varied at shorter time scales. The results showed that the explicit treatment of resistances was important for the simulation of evaporation at daily time scales. This may have implications for how land–atmosphere coupling evolves in response to evapotranspiration variability and the partitioning of the SEB.

Research on how terrestrial mechanisms act to limit the supply and demand of soil moisture to the atmosphere in the context of land–atmosphere coupling are limited. The surface turbulent energy fluxes are responsible for driving the diurnal evolution of the boundary layer, influencing surface heating, and the formation of clouds and precipitation (Santanello et al. 2011). These fluxes are sensitive to a series of resistances to heat and moisture transfer, and this resistance framework has a long history [for a detailed review, see Shuttleworth (2007)]. Evapotranspiration is a critical process of land–atmosphere interactions and therefore requires adequate representation of the turbulent transfer within the surface layer that has historically been characterized by the aerodynamic resistance (Shuttleworth 2007). Early formulations of the aerodynamic resistance assumed independence from the underlying surface; however, since the 1950s this has expanded to include the development of additional resistance terms to reflect the vegetation controls on evapotranspiration. This includes the leaf boundary layer resistance (e.g., Finnigan and Raupach), the stomatal resistance (e.g., Ball et al. 1987; Leuning 1995; Medlyn et al. 2011), and a soil surface resistance (e.g., Sellers et al. 1986; Blyth et al. 1993; Shuttleworth 2007; Swenson and Lawrence 2014).

The influence of these resistances to heat and moisture transfer is particularly important when considered in the context of extremes. The role of the land in intensifying heat waves, for example, is linked with how the atmospheric boundary layer responds to land surface...
variability to amplify events (Miralles et al. 2014). It is therefore a priority to understand how land–atmosphere feedbacks are communicated through the soil–plant–atmosphere system. We therefore examine whether using a resistance framework improves the understanding of the components of land–atmosphere coupling. Our goal is not to present a complete understanding of land–atmosphere coupling, where the resistances are not the only factors determining land–atmosphere coupling, but rather, we examine whether using a resistance framework facilitates process-level examination of land–atmosphere coupling.

2. Methodology

a. Model description

The WRF Model (Skamarock et al. 2008) is commonly used for regional climate modeling (e.g., Flaounas et al. 2011; Evans et al. 2012; Di Luca et al. 2014). WRF simulations are typically forced with reanalysis at ~6-hourly intervals to define the lateral boundary conditions. In this study WRF is coupled to the Community Atmosphere Biosphere Land Exchange (CABLE) LSM (Wang et al. 2011; Kowalczyk et al. 2013).

CABLE is a sophisticated LSM that simulates the interactions between microclimate, plant physiology, and hydrology (Wang et al. 2011). CABLE includes a coupled model of stomatal conductance, photosynthesis, and partitioning of absorbed net radiation into latent and sensible heat fluxes, with soil and vegetation contributions calculated separately and then linearly combined into the total sensible and latent heat fluxes. These fluxes form the bottom boundary condition of the atmospheric model. A canopy turbulence model is used to calculate within-canopy air temperatures and humidity. CABLE includes a multilayer soil model with six layers, with the thickness of each soil layer from the top layer corresponding to 0.022, 0.058, 0.154, 0.409, 1.085, and 2.872 m. Soil hydraulic and thermal characteristics depend on the soil type as well as frozen and unfrozen soil moisture content. Each soil type in our model is described by its saturation content, with the flow of water parameterized using Darcy’s law and the hydraulic conductivity related to soil moisture via the Clapp and Hornberger (1978) relationship. The land surface in CABLE is represented by plant functional types (PFTs) consisting of the 10 vegetation types; these are based on the vegetation types defined by the International Geosphere–Biosphere Programme (IGBP; Loveland et al. 2000) and three nonvegetated surfaces (Kowalczyk et al. 2013). Each of these PFTs have parameters that describe canopy height, leaf angle, leaf transmittance, leaf reflectance, and root fraction. CABLE has been extensively evaluated (e.g., Abramowitz et al. 2008; Wang et al. 2011) and benchmarked (Abramowitz 2012; Best et al. 2015) for both global and regional domains.

We use the NASA Land Information System (LIS), version 6.0, to couple CABLE, version 2.0, to WRF, version 3.2.1. LIS is a software framework for running high-resolution land data assimilation systems that integrate advanced LSMs with high-resolution satellite and in situ observational data to accurately characterize land surface states and fluxes (Kumar et al. 2006). LIS can run offline LSM simulations to provide soil moisture and temperature initial conditions for the coupled simulations with WRF.

Within WRF, LIS can be considered as another land surface parameterization option that is called during each time step integration. LIS offline simulations require appropriate surface meteorological forcing to solve the governing equations of the soil–vegetation–snow system and to predict the surface turbulent energy fluxes and soil states. For coupled simulations, LIS-CABLE provides the surface turbulent energy fluxes to WRF, and WRF provides the surface temperature, humidity, winds, total precipitation, and shortwave and longwave radiation to LIS-CABLE. LIS-CABLE is treated like other land surface schemes within WRF, with the required forcing fields mapped onto the appropriate model tiles for LIS. LIS is thoroughly documented in Kumar et al. (2006) and Peters-Lidard et al. (2007).

b. Model configuration

The model domain covers the whole of Australia and is centered at 27.5°S, 133.0°E on a Lambert projection with a spatial resolution of 50 km and 30 atmospheric levels. A model time step of 180 s is used, and a maximum of four tiles per grid cell is implemented in CABLE to help resolve the land surface heterogeneity. The model is initialized and updated at the lateral boundary using ERA-Interim (Dee et al. 2011) at 6-hourly intervals, with the land surface initial conditions obtained from prior LIS-CABLE offline simulations. The configuration of WRF used here follows Evans and McCabe (2010) in using the Yonsei University planetary boundary layer (PBL) scheme, the MM5 Monin–Obukhov surface layer scheme, the Kain–Fritsch cumulus scheme, the WRF single-moment 5-class microphysics scheme, the Rapid Radiative Transfer Model longwave scheme, and the Dudhia shortwave scheme. WRF uses a terrain-following vertical coordinate system with the lowest atmospheric level (of 30) at approximately 20 m. The Monin–Obukhov similarity theory is used at run time to calculate diagnostics at 2 and 10 m above the surface.
c. Resistance pathway framework

The sensible heat flux $Q_s$ and latent heat flux $Q_v$ within an LSM can be represented as a diffusion process analogous to electrical networks (e.g., Fig. 1). The limitations to moisture flow through the soil–vegetation–atmosphere system can be represented as a series of resistances to soil evaporation $Q_s$, transpiration $Q_v$, and wet canopy evaporation. The key resistances within an LSM commonly include an aerodynamic resistance, leaf boundary layer resistance, stomatal resistance, and soil surface resistance (Pitman 2003). The resistance framework used in CABLE is illustrated in Fig. 1. The aerodynamic resistance is a function of the surface wind speed, the surface roughness, leaf area index, and atmospheric stability and is calculated using the localized near-field theory applied to a single canopy layer (Raupach 1989a,b, 1994). In this form, the aerodynamic resistance can be reduced to two terms. The first characterizes the resistance from the soil surface to the zero plane displacement height $d$ denoted here as $r_{0s}$. The second aerodynamic resistance term characterizes the resistance from $d$ to a reference level $z_r$, which is above the roughness sublayer, denoted here as $r_{st}$. In this study, $r_{0s}$ and $r_{st}$ have been perturbed individually to differentiate between the aerodynamic resistance that applies to the soil fluxes alone and the components that apply to both soil and vegetation fluxes. The stomatal resistance $r_{st}$ is calculated using the Ball–Berry–Leuning model (Leuning 1995) for coupled photosynthesis, stomatal conductance, and leaf energy balance. The leaf boundary layer resistance $r_{bl}$ is parameterized using the theory for flow over a flat plate (Finnigan and Raupach 1987).

The equations for all resistance terms are defined in the appendix. Within CABLE we apply perturbations ($-25\%$, $-10\%$, $+10\%$, and $+25\%$) to the four resistance terms ($r_{0s}$, $r_{st}$, $r_{bl}$, and $r_{0s}$), one at a time to examine the influence of each term individually on the surface turbulent fluxes. Each resistance perturbation is applied uniformly across the domain at every model time step. In terms of the physical meaning of changing the resistances, increasing the resistances is indicative of a decrease in moisture availability for evapotranspiration, with the opposite for a decrease in the resistance. Our limited understanding of the actual value of these resistances means that the choice of these perturbations is subjective. We therefore performed offline testing of these perturbations (not shown) to ensure CABLE’s performance remained physically reasonable across the range. By perturbing each resistance individually, we focus on their singular impact on surface climate and therefore do not directly account for dependencies between resistance terms.

We note that all LSMs use an approach analogous to Fig. 1 (e.g., Sellers et al. 1986; Desborough and Pitman 1998; Oleson et al. 2010; Best et al. 2011), but how these are implemented varies widely. We perturb the resistances, rather than the LAI or fractional vegetation coverage, as this enables a direct analysis of the influence of the resistance in partitioning between $Q_s$ and $Q_v$ and between $Q_s$ and $Q_v$. Perturbing LAI, for example, leads to multiple impacts on resistances and prevents the identification of the actual pathways for fluxes through the resistance network.

d. Experimental design

We follow the GLACE-type experiments of Hirsch et al. (2014b) and perform simulations for the austral summer (DJF) for a control (CTL) and each resistance perturbation (EXP), consisting of the four resistances terms ($r_{0s}$, $r_{st}$, $r_{bl}$, and $r_{0s}$) each perturbed by $-25\%$, $-10\%$, $+10\%$, and $+25\%$ (a total of 17 GLACE-type iterations). Each experiment consists of a fully coupled and uncoupled 16-member ensemble, giving a total of 544 simulations. Two-way interactions are enabled for the fully coupled ensemble, with soil moisture values in every soil layer written to file every time step from one of the ensemble members. These values are then used to prescribe soil moisture in all soil layers except the thin surface layer (e.g., Koster et al. 2006) in the uncoupled
ensemble member simulations to effectively decouple the land from atmospheric feedback.

The ensemble initialization and boundary conditions use 16 different austral summers, sampling neutral, El Niño, and La Niña years, starting on 1 December from the ERA-Interim lateral boundary conditions to capture the influence of interannual variability across the region. Two sets of 16-member uncoupled ensemble simulations are run; one with the same dry soil moisture state, corresponding to El Niño conditions from December 1982 to February 1983, prescribed for each ensemble member. The second uncoupled ensemble has the same wet soil moisture state, corresponding to La Niña conditions from December 1999 to February 2000. In this way the influence of a range of soil moisture states on the coupling can be examined, similar to Hirsch et al. (2014a,b). The coupled ensemble simulations differ only by the lateral boundary conditions, whereas for the uncoupled ensemble simulations, the prescribed soil moisture states are selected from one of the coupled ensemble member simulations.

Soil moisture–temperature coupling strength $\Delta \Omega_T$ is calculated following Koster et al. (2006). The calculations are first done for each ensemble, coupled and uncoupled, independently before combining them to calculate $\Delta \Omega_T$.

For each 90-day ensemble member simulation, the first six days are discarded as atmospheric spinup, with the remaining 84 days used to compute 14 six-day average temperature time series for each ensemble member. Using these 14 six-day averaged time series, the ensemble mean time series is calculated. Two variance terms are then calculated from these time series. The first variance $\sigma^2_{T,T}$ is calculated from the ensemble mean time series and represents the temporal variance of temperature for the ensemble (where the angle brackets indicate a time average). The second variance $\sigma^2_T$ is calculated from the time series of all ensemble members ($16 \times 14 = 224$ values) and represents the internal variability of temperature across ensemble members. These two variances are used to calculate $\Omega_T$ to provide a measure of the similarity of the temperature time series across the ensemble members as a result of the boundary forcing:

$$\Omega_T = (16\sigma^2_{T,T} - \sigma^2_T)/(15\sigma^2_T),$$  \hspace{1cm} (1)

where $\Omega_T = 0$ implies that $16\sigma^2_{T,T} = \sigma^2_T$, and therefore the ensemble spread for temperature is due to atmospheric chaos and the boundary conditions have a smaller influence, and $\Omega_T = 1$ implies that $\sigma^2_{T,T} = \sigma^2_T$, and therefore all the temperature time series for the ensemble members are identical where the atmospheric chaos is constrained by the boundary conditions. Evaluating the limit of $\Omega$ as it approaches 1 implies that $\sigma^2_{T,T}$ approaches $\sigma^2_T$ and therefore that the temperature fields between ensemble members become more similar until they converge.

The coupling strength is inferred by subtracting $\Omega_T$ (coupled) from $\Omega_T$ (uncoupled). Positive values ($\Delta \Omega_T > 0$) indicate that the members of the uncoupled ensemble simulations are more similar than the coupled ensemble. It is anticipated that $\Delta \Omega_T > 0$ is true in most cases as the additional boundary condition imposed by prescribing soil moisture in the uncoupled simulations provides an additional constraint on the internal variability of the uncoupled ensemble.

d. Additional land–atmosphere coupling metrics

We also use metrics of Dirmeyer (2011a) and Dirmeyer et al. (2013a,b, 2014) to evaluate land–atmosphere coupling. We follow the thermal pathway of land–atmosphere coupling that evaluates the covariance of soil moisture $w$, $Q_H$, and surface air temperature $T$ of the lowest layer in WRF using daily averaged values from the coupled simulations. This includes the terrestrial leg

$$I_L = \sigma_w \times \frac{dQ_H}{dw} = \frac{\text{cov}(w, Q_H)}{\sigma_w} = \frac{\sum(w - \bar{w})(Q_H - \bar{Q_H})}{\sqrt{\frac{1}{N}\sum (w - \bar{w})^2}},$$  \hspace{1cm} (2)

the atmospheric leg

$$I_A = \sigma_{Q_H} \times \frac{dT}{dQ_H} = \frac{\text{cov}(Q_H, T)}{\sigma_{Q_H}} = \frac{\sum(Q_H - \bar{Q_H})(T - \bar{T})}{\sqrt{\frac{1}{N}\sum (Q_H - \bar{Q_H})^2}},$$  \hspace{1cm} (3)

and the whole coupling pathway

$$I_{LA} = \sigma_w \times \frac{dT}{dw} = \frac{\text{cov}(w, T)}{\sigma_w} = \frac{\sum(w - \bar{w})(T - \bar{T})}{\sqrt{\frac{1}{N}\sum (w - \bar{w})^2}},$$  \hspace{1cm} (4)

where $\sigma_X$ denotes the standard deviation of variable $X$, $dY/dX$ is the slope of the linear regression of $Y$ on $X$, cov($X$, $Y$) is the covariance between $X$ and $Y$, $N$ is the number of values, and $\bar{X}$ is the average of variable $X$. All metrics are calculated using standardized anomalies of the variables following Dirmeyer (2011a).

3. Results

Our analysis focuses on the shrub and the evergreen broadleaf forest PFTs, with the grid cells corresponding to this analysis illustrated in Fig. 2. These PFTs were selected
on the basis that they are strongly contrasting vegetation types and are generally collocated in the same climatic zone close to the coastline. These PFTs showed distinctive responses to the resistance perturbations explored here. Furthermore, we limit our analysis to regions where the estimated partitioning of $Q_E$ between $Q_S$ and $Q_V$ is consistent with Haverd et al. (2013). It is noted here that these grid cells are generally located in regions where the soil moisture–temperature coupling strength was determined to be weak ($\Delta\Omega_T < 0.1$) in Hirsch et al. (2014b), despite stronger values in the interior of Australia. Therefore, any changes in the coupling strength are indicative that the resistance perturbations are important. The version of CABLE used in this manuscript did not have the capability for subgrid-scale PFT output, and therefore we limit our analysis to gridcell values where each PFT, shrub or forest, is the dominant cover exceeding 50% coverage of the 50-km grid cell. Comparisons between grass and shrubs showed similar changes in response to the resistance perturbations, and therefore we limit our analysis to shrubs that are located near grid cells where the forest PFT is dominant. The duration of all simulations corresponds to 90 consecutive days over austral summer, when soil moisture is already limited. Changes in the total column soil moisture were negligible (within $\pm 0.002$ m$^{-3}$) over the analysis region for the duration of these simulations. It is possible, however, that extending the simulations to a longer period may yield larger changes in soil moisture that are anticipated in response to the affect the resistance perturbations have on evapotranspiration.

The analysis focuses on the surface turbulent energy fluxes $Q_H$, $Q_E$, $Q_V$, and $Q_S$ that are directly affected by changes in the resistance terms, and also the 2-m air temperature that changes in response the surface turbulent energy fluxes. Unless noted otherwise, the analysis uses output from the fully coupled simulations. Note that CABLE also calculates a wet canopy evaporation flux, but we have chosen not to include this flux in our analysis because of its limited sensitivity to the resistance perturbations (changes were within $\pm 0.2$ W m$^{-2}$ of the daily average). Although the wet canopy evaporation flux has the same order of magnitude as $Q_V$, it is a function of the wet canopy fraction that is derived from the gridcell precipitation amount of the atmospheric model. The limited sensitivity of the wet canopy evaporation to the resistance perturbation might be because the precipitation amount is more critical for the calculation of this flux and that over our study region, precipitation is largely driven by the orographic convection along the coast rather than land surface processes.

We first examine the impact of the resistance perturbations on the surface turbulent energy fluxes and 2-m air temperature of the coupled simulations. Figure 3 shows the probability density function (PDF) of the change (EXP – CTL) in the daily average $Q_E$ and maximum 2-m air temperature $T_{\text{MAX}}$ for each resistance perturbation, split according to the shrub and forest PFTs. For the $r_{sl}$ perturbations, both PFTs show a decrease in $Q_E$ corresponding with the increase in $r_{sl}$, while conversely, an increase in $Q_E$ corresponds to a decrease in $r_{sl}$ (Figs. 3a,b). Similarly for $r_{st}$ (Figs. 3i,j), there is also a systematic decrease in $Q_E$ with an increase in $r_{st}$. For $r_{sl}$ (Figs. 3e,f) and $r_{st}$ (Figs. 3m,n), the resistance perturbations do affect $Q_E$, but the change is not systematic and there is limited differentiation between the sign and magnitude of the resistance perturbation that may be related to the magnitude of these resistance terms, where a larger perturbation may be necessary to trigger a systematic change in $Q_E$. Similar changes in $Q_H$ were also found in response to all resistance perturbations (not shown).

The $r_{sl}$ perturbations affect $T_{\text{MAX}}$ for both shrub (Fig. 3c) and forest (Fig. 3d) PFTs consistent with the changes in $Q_E$. An increase in $r_{sl}$ leads to a decrease in $Q_E$ and consequently an increase in $T_{\text{MAX}}$. For the other resistance perturbations, $T_{\text{MAX}}$ is generally less sensitive to the sign and magnitude of the other resistance perturbations (Figs. 3g,h,k,l,o,p). In particular, it is interesting to note that the $r_{sl}$ perturbations do change $Q_E$ systematically but not $T_{\text{MAX}}$ (Figs. 3i–l).

Overall, Fig. 3 illustrates that, irrespective of which resistance is perturbed, a resistance perturbation translates into a response by the surface turbulent energy fluxes (e.g., $Q_E$). This changes the partitioning of the SEB and can subsequently influence the 2-m air temperature.
This is more clear for \( r_{t0} \) (Figs. 3a–d) than the other resistance terms.

To understand the systematic response of \( QE \) and \( T_{MAX} \), we examine how the resistance perturbations influence the partitioning of the SEB of the coupled simulations (Fig. 4). Figure 4 shows the sensitivity of the diurnal cycle of \( QE \), \( QS \), and \( QV \) to the resistance perturbations over DJF for the shrub and forest PFTs. The solid line shows the control mean, and the shaded regions show the interquartile range (IQR) obtained from the resistance perturbations. For both PFTs the resistance perturbations change the partitioning of the SEB between \( QH \) and \( QE \), as implied by the changes in \( QE \) shown in Fig. 3. The resistance perturbations also influence the partitioning of \( QE \) between \( QS \) and \( QV \), specifically, for shrubs (Fig. 4a). Thus, the sensitivity \( QS \) is larger than \( QV \),
with \( Q_S \) more sensitive to the resistance perturbations. For forests (Fig. 4b), both \( Q_S \) and \( Q_V \) are of similar magnitude, with \( Q_V \) slightly more sensitive to the resistance perturbations than \( Q_S \). Thus, the sensitivity of \( Q_S \) for shrubs suggests that this flux is the dominant flux for moisture transfer through the root–leaf system to the atmosphere. For forests, it is not clear from Fig. 4 which is the dominant flux for moisture transfer.

We also examine how the partitioning between \( Q_H \) and \( Q_E \) is affected by the different resistance perturbations. Figure 5 shows the percentage change [(\( \text{EXP} - \text{CTL} \)/\( \text{CTL} \)] in the daily averaged fraction of \( Q_E \) supplied by \( Q_S \) \([f_{Q_E} = Q_E/(Q_S + Q_V)]\), \( Q_S \), \( Q_V \), \( T_{\text{MAX}} \), and \( T_{\text{MEAN}} \) and minimum \( T_{\text{MIN}} \) 2-m air temperatures for each resistance perturbation for the coupled simulations over DJF. The analysis is again split according to the shrub and forest PFTs. All resistance perturbations, except \( r_{11} \), contribute to changing \( f_{Q_E} \) (Figs. 6a–d). More specifically, \( f_{Q_E} \) has a decreasing trend (from +4% to −4%) when \( r_{11} \) is increased from −25% to +25%. However, these decreasing trends in \( \Delta Q_H \) and \( \Delta Q_E \) result in limited changes in \( \Delta EF \) (Fig. 5l), where the median change is zero for all \( r_{11} \) perturbations.

Given these changes in the partitioning of the surface energy balance between \( Q_H \), \( Q_E \), \( Q_S \), and \( Q_V \) shown in Figs. 4 and 5, we next examine this in the context of changes to the 2-m air temperature for each resistance perturbation individually.

Figure 6 shows the percentage change [(\( \text{EXP} - \text{CTL} \)/\( \text{CTL} \)] in the daily averaged fraction of \( Q_E \) supplied by \( Q_S \) \([f_{Q_E} = Q_E/(Q_S + Q_V)]\), \( Q_S \), \( Q_V \), \( T_{\text{MAX}} \), and \( T_{\text{MEAN}} \) and minimum \( T_{\text{MIN}} \) 2-m air temperatures for each resistance perturbation for the coupled simulations over DJF. The analysis is again split according to the shrub and forest PFTs. All resistance perturbations, except \( r_{11} \), contribute to changing \( f_{Q_E} \) (Figs. 6a–d). More specifically, \( f_{Q_E} \) has a decreasing trend (from +4% to −4%) when \( r_{11} \) is increased from −25% to +25% for both vegetation types (Fig. 6a). In contrast, \( f_{Q_E} \) has no trend and a median of zero for all of the \( r_{11} \) perturbations (Fig. 6b). For both vegetation types, \( f_{Q_E} \) has a strong increasing trend (from −6% to +8%) with the \( r_{st} \) perturbations (Fig. 6c) and a slight increasing trend (from −2% to +2%) for the \( r_{11} \) perturbations (Fig. 6d).

To understand the trends in \( \Delta Q_S \) and \( \Delta Q_V \) separately. Increasing \( r_{11} \) from −25% to +25% for both PFTs leads to a decreasing trend in \( \Delta Q_S \) (Fig. 6e, from +6% to −6%) and a slight increasing trend in \( \Delta Q_V \) (Fig. 6i, −2% to +2%). Both \( \Delta Q_S \)
(Fig. 6f) and $\Delta Q_V$ (Fig. 6i) are largely insensitive to changes in $r_{t1}$ (with medians of zero), consistent with $\Delta f_{QE}$ (Fig. 6b). Increasing $r_{st}$ from $-25\%$ to $+25\%$ contributes to an increasing trend for $\Delta Q_S$ (Fig. 6g, from $-4\%$ to $+6\%$) and a strong decreasing trend for $\Delta Q_V$ (Fig. 6k, from $+10\%$ to $-10\%$). Finally, for $r_{bl}$, the trends in $\Delta Q_S$ and $\Delta Q_V$ are smaller than those for $r_{st}$, where $\Delta Q_S$ has a slight increasing trend (Fig. 6h, from $-1\%$ to $+3\%$) and $\Delta Q_V$ has a slight decreasing trend (Fig. 6l, from $+3\%$ to $-4\%$).

There are also changes in 2-m air temperature with the resistance perturbations (Figs. 6m–x). In particular, there is an increasing trend in the 2-m air temperature when increasing $r_{t0}$ from $-25\%$ to $+25\%$, with the magnitude of the temperature change largest for $T_{MAX}$ (Fig. 6m, from $-2\%$ to $+2\%$) followed by $T_{MEAN}$ (Fig. 6q, from $-1\%$ to $+1\%$) and $T_{MIN}$ (Fig. 6u, from $-1\%$ to $+0.5\%$). The limited temperature response (medians generally equal to zero) to the $r_{t1}$ perturbations is coincident with the limited sensitivity of $f_{QE}$, $Q_S$, and $Q_V$ to these perturbations (Figs. 6n,r,v), although we note that there is an increase ($\approx 1\%$) in $\Delta T_{MAX}$ when $r_{t1}$ is increased by $+25\%$ for both vegetation types. Despite the trends observed in $\Delta f_{QE}$, $\Delta Q_S$, and $\Delta Q_V$, the temperature trend for $r_{st}$ (Figs. 6o,s,w) is limited with median changes mostly equal to zero, with the exception of $-0.5\%$ for $\Delta T_{MAX}$ with a $+25\%$ increase in $r_{st}$. For $r_{bl}$, temperature changes are also smaller compared to $r_{t0}$ (Figs. 6p,t,x), although there is a very slight increasing trend in $\Delta T_{MAX}$ (Fig. 6p, from $-0.5\%$ to $+0.5\%$). Overall, Fig. 6 shows that most resistance perturbations, except $r_{t1}$, change $f_{QE}$ via $Q_S$ and $Q_V$, with the clearest systematic response of 2-m air temperature associated with the $r_{t0}$ perturbations.

We use a resistance pathway framework to understand how changes in the partitioning of the SEB influence
As in Fig. 5, but for (a)–(d) fraction of the latent heat flux that is soil evaporation \( \frac{f_{QE}}{Q_S + Q_V} \), (e)–(h) soil evaporation (i.e., \( Q_S \)), (i)–(l) transpiration (i.e., \( Q_V \)), (m)–(p) maximum 2-m air temperature (i.e., \( T_{MAX} \)), (q)–(t) mean 2-m air temperature (i.e., \( T_{MEAN} \)), and (u)–(x) 2-m air minimum temperature (i.e., \( T_{MIN} \)).
surface climate through land–atmosphere coupling. Figures 4–6 showed that the partitioning of the SEB changes in response to these resistance perturbations. However, the temperature response does not always correspond to changes in $D_{QE}$ (Fig. 6), particularly for the $rt$ perturbations. This may be explained by examining how the perturbations influence land–atmosphere coupling.

Figure 7 shows the percentage change $\left[\frac{\text{EXP} - \text{CTL}}{\text{CTL}}\right]$ in the coupling metrics described in the methodology section: the GLACE soil moisture–temperature coupling strength (i.e., $DV_T$), the whole coupling pathway (i.e., $ILA$), the terrestrial component (i.e., $IL$), and the atmospheric component (i.e., $IA$).

![Figure 7](image_url)

FIG. 7. As in Fig. 5, but for different coupling metrics in response to the resistance perturbations for (a)–(d) the GLACE coupling strength (i.e., $DV_T$), (e)–(h) the whole coupling pathway (i.e., $ILA$), (i)–(l) the terrestrial component (i.e., $IL$), and (m)–(p) the atmospheric component (i.e., $IA$).
This is critical for $\Delta \Omega_T$ since if the resistance perturbations do not affect the variance, they would not change $\Delta \Omega_T$. However, the resistance perturbations do change the partitioning of the SEB and therefore should affect $I_L$ and $I_A$, which are both functions of $Q_H$ and therefore sensitive to changes in the SEB. Generally, $\Delta I_L$ has an increasing trend when increasing $r_{st}$ from $-25\%$ to $+25\%$ (Fig. 7i, from $-6\%$ to $+6\%$), although the change in $r_{st}$ from $+10\%$ to $+25\%$ for forests does not change $\Delta I_L$. There is also an increasing trend in $\Delta I_L$ when increasing $r_{st}$ from $-10\%$ to $+25\%$ (Fig. 7k, from $-4\%$ to $+5\%)$. The $\Delta I_L$ only increases by $+6\%$ when $r_{st}$ is increased by $+25\%$ (Fig. 7l), but otherwise median values are approximately zero. For $r_{st}$ (Fig. 7j) there is no systematic increase or decrease in $\Delta I_L$ associated with changing this resistance, with median changes often within $\pm 2\%$. The $\Delta I_A$ also shows some sensitivity to the resistance perturbations (Figs. 7m–p). In particular, $\Delta I_A$ has an increasing trend for changes in $r_{so}$ from $-25\%$ to $+10\%$ (Fig. 7m, from $-6\%$ to $+6\%$) and a decreasing trend for changes in $r_{st}$ from $-10\%$ to $+25\%$ (Fig. 7o, from $+4\%$ to $-6\%$). In summary, the response of the coupling to the resistance perturbations is most clearly observed by splitting the entire feedback pathway into its atmospheric and terrestrial components. This shows that both the terrestrial and atmospheric components of the coupling show a systematic response to the $r_{so}$ and $r_{st}$ perturbations for both PFTs, although there are nonzero changes for the $r_{st}$ and $r_{so}$ perturbations.

The changes in $I_L$ and $I_A$ (Figs. 7i–p) share similarities with the temperature changes (Figs. 6m–x) in response to the resistance perturbations. These are summarized in Fig. 8 for the $r_{so}$ and $r_{st}$ perturbations that showed systematic changes in the coupling. An increase in $r_{so}$ (Fig. 8, left) decreases $f_{Q_E}$ (Fig. 6a) by decreasing $Q_S$ (Fig. 6e) and increasing $Q_V$ (Fig. 6i). The change in $f_{Q_E}$ contributes to increasing both $I_L$ and $I_A$ (Figs. 7l,m) and subsequently increases the 2-m air temperature (e.g., Fig. 6m). Increasing $r_{st}$ (Fig. 8, right) increases $f_{Q_E}$ (Fig. 6c) through increasing $Q_S$ (Fig. 6g) and decreasing $Q_V$ (Fig. 6k). The increase in $f_{Q_E}$ corresponds to an increase in $I_L$ (Fig. 7k) and decrease in $I_A$ (Fig. 7o). The opposing changes in $I_L$ and $I_A$ contribute to negligible changes in 2-m air temperature (e.g., Fig. 6o) that are less distinctive than the changes resulting from the $r_{so}$ perturbations. We note here that the changes in temperature and the coupling indices are not necessarily linearly related to the magnitude of the resistance perturbations.

4. Discussion

Our results show that a resistance pathway framework can be used to examine the effect the partitioning of the SEB has on surface climate through land–atmosphere coupling. We find the aerodynamic resistance from the soil surface to the displacement height has the greatest influence on 2-m air temperature in our modeling system. Although most resistance perturbations produce comparable changes in $Q_S$ and $Q_V$ (Fig. 6), except $r_{st}$ where there is no trend, it is possible that our results are associated with the relative magnitude of the resistances being perturbed. In particular, if we consider the total resistance to moisture transfer $R_{Tot}$, the distinction between $r_{so}$ and the other resistance perturbations becomes clear. For the soil $Q_E$ and $Q_H$ fluxes $R_{Tot} = r_{so} + r_{st}$, and for the vegetation $Q_E$ and $Q_H$ fluxes $R_{Tot} = r_{st} + r_{st} + r_{so}$. Therefore, it is possible that only the $r_{so}$ perturbations will produce a systematic change in 2-m air temperature because this resistance directly perturbs $Q_S$, which was found to be the dominant flux for shrubs in our analysis region. Further, $r_{so}$ is larger in magnitude than the other resistance terms, and therefore any perturbation to this resistance is likely to produce a clearer result than the other resistance terms. We also note that as we only perturb each resistance independently, where the perturbation is applied after the resistances have been calculated, we cannot examine the influence of how the resistances covary in response to the perturbations. The limited $T_{MAX}$ response to the other resistance perturbations (Fig. 3) might be associated with the partitioning of $Q_E$. In particular, Fig. 4 showed that $Q_S$ is greater than $Q_V$ for shrubs and both fluxes are of similar magnitude for

![Fig. 8. Schematic illustrating the effect of the resistance perturbations on 2-m air temperature ($T_{MAX}$, $T_{MEAN}$, and $T_{MIN}$) through land–atmosphere coupling (left) for the aerodynamic resistance from the soil surface to the displacement height (i.e., $r_{so}$) and (right) for the stomatal resistance (i.e., $r_{st}$). Plus sign indicates an increase and minus sign indicates a decrease.](image-url)
forests. Clearly, our results may change if we examined a region where $Q_V$ is significantly larger than $Q_S$, but our methodology for understanding how the resistances are linked with the coupling would still provide useful insight.

There are three important caveats to the results presented in this manuscript. First, because we limit our analyses to grid cells representing shrub and evergreen boreal forest PFTs, there are insufficient data points to appropriately calculate the field significance of our results. Second, it is not certain that the response of surface climate to the resistance perturbations is linear (e.g., coupling response, Figs. 7e–h). For example, increasing $r_st$ from $+10\%$ to $+25\%$ does not result in a comparable step change in the 2-m air temperature (Fig. 6s) despite large changes in $Q_V$ (Fig. 6k). Finally, we cannot exclude the model and domain dependence of the results presented here, which is why we focus on presenting the resistance pathway framework as a methodology for interrogating the sensitivity of land–atmosphere coupling within a climate model.

Previous research has shown land–atmosphere coupling varies greatly between modeling systems (Koster et al. 2006). This implies that an anomaly at the surface, such as soil moisture or vegetation change, will be translated with varying strength to the atmosphere. Given the role of soil moisture anomalies, or land-cover changes in modifying extremes, this diversity of land–atmosphere coupling strengths is worrisome. We suggest that land–atmosphere coupling errors within the LSM can be usefully examined by using the resistance pathway framework in addition to existing methodologies that examine the influence of root-zone soil moisture, vegetation, and land-use change and atmospheric model physics parameterizations. We suspect that if other groups reproduced our experiments, it would be found that different resistance pathways would be dominant in different modeling systems. For example, evapotranspiration biases in the Community Land Model have been improved by the inclusion of a dry-surface-layer soil resistance parameterization (Swenson and Lawrence 2014).

The version of CABLE used in this manuscript does not include this resistance term, and therefore we cannot evaluate the influence of this resistance. However, future experiments could help isolate the reasons for intermodel differences and simultaneously focus attention on the representation of processes on the land–atmosphere system. Over time, this might help resolve why coupling strength varies between modeling systems.

5. Conclusions

Land–atmosphere coupling is important because it controls the impact of a land anomaly on surface climate. We explore land–atmosphere coupling using an experimental design to isolate the different resistances that control the transfer of moisture and heat from the land to the atmosphere. Our goal is to understand how these resistances taken separately influence the partitioning of the SEB and how this affects surface climate through land–atmosphere coupling. This is a first step to understanding the existing uncertainty in land–atmosphere coupling strength and how this contributes to the emergence of extremes such as heat waves (Miralles et al. 2014).

We have used a resistance pathway framework to apply perturbations within the land surface to identify those fluxes that are more influential on land–atmosphere coupling that translate a resistance perturbation into a shift of the 2-m air temperature. All resistance perturbations contributed to changing the partitioning of the SEB and subsequently 2-m air temperature. We have shown that land–atmosphere coupling over Australia for shrub and evergreen boreal forest PFTs in our modeling system acts mostly through $r_{so}$, the resistance from the soil surface to the displacement height. Here perturbations of $r_{so}$ lead to systematic changes in the 2-m air temperature distribution associated with systematic increases in both $I_L$ and $I_A$ that are not necessarily identified by examining the whole coupling pathway (i.e., $I_{LA}$ and $\Delta Q_V$). The variable $r_{so}$ is a function of the boundary layer friction velocity, vegetation height, and vegetation cover. Changes in $r_{st}$ were also important for the separate terrestrial and atmospheric components of land–atmosphere coupling, but in opposing directions such that systematic changes in 2-m air temperature were not observed. This would be a model-dependent result and we do not suggest this is a general result that can be applied to other models or regions. Rather, we suggest the method we employ has proven useful in understanding the drivers of land–atmosphere coupling within our modeling system.

We conclude that using a resistance pathway framework can help diagnose and separate the mechanisms that control land–atmosphere coupling. We suggest that using this framework across multiple modeling systems may lead to an improved understanding of why models show such disparity in land–atmosphere coupling strength. This would be the first step to resolving these differences and ensuring a more consistent influence from the land on important atmospheric phenomena.

Acknowledgments. This study was supported by the Australian Research Council Centre of Excellence for Climate System Science Grant CE110001028. The computational modeling was supported by the National Computational Infrastructure (NCI) hosted at the Australian National University. Annette L. Hirsch was supported by
an Australian Postgraduate Award and CSIRO Office of
the Chief Executive (OCE) Postgraduate Top-up scholar-
ship. The authors thank three anonymous reviewers who
provided the constructive feedback on this manuscript.

APPENDIX

Definition of Resistances within CABLE

The aerodynamic resistance from the soil surface to the
zero plane displacement height $d$ is given by

$$ r_d = \ln \left( \frac{d}{z_{0\text{soil}}} \right) \exp(2c_{sw}\lambda) - \exp \left[ 2c_{sw}\lambda \left( 1 - \frac{d}{h} \right) \right], $$

where $z_{0\text{soil}}$ is the soil roughness length (m), $\lambda$ is
the canopy leaf area index, and $h$ is the canopy height (m).
The parameters $a_3$, $c_{TL}$, and $c_{sw}$ are the ratio of
the standard deviation of the vertical velocity to the
friction velocity in the inertial sublayer above the canopy ($a_3 = 1.25$), the coefficient of the Lagrangian time scale ($c_{TL} = 0.4$), and the rate of decrease of the standard deviation of the vertical velocity with depth in the canopy ($c_{sw} = 1.0$); $f_{\text{spars}}$ is a sparseness factor and is a function of
$d$ and $h$. The zero plane displacement height is given by

$$ h = 1 - \exp(-\sqrt{c_\theta\lambda})/\sqrt{c_\theta\lambda}, $$

where $c_\theta$ is a model parameter ($c_\theta = 15$).

The aerodynamic resistance from $d$ to a reference
level (i.e., $z_r$) is given by

$$ r_l = r_{l(a)} + r_{l(b)} + r_{l(c)}, $$

which is split into

$$ u_{0}r_{l(a)} = \frac{\exp \left[ 2c_{sw}\lambda \left( 1 - \frac{d}{h} \right) \right] - 1}{(a_3)^{2}f_{\text{spars}}c_{TL}\left( 2c_{sw}\lambda \right)} \quad \text{for} \quad d < z < h, $$

$$ u_{0}r_{l(b)} = \frac{z_{\text{ruff}} - h}{a_3^2f_{\text{spars}}c_{TL}h} \quad \text{for} \quad h < z < z_{\text{ruff}}, \quad \text{and} $$

$$ u_{0}r_{l(c)} = \frac{1}{k} \left[ \ln \left( \frac{z_{r} - d}{z_{\text{ruff}} - d} \right) - \psi_H \left( \frac{z_{r} - d}{L_{MO}} \right) \right] + \psi_H \left( \frac{z_{\text{ruff}} - d}{L_{MO}} \right) \quad \text{for} \quad z_{\text{ruff}} < z < z_r, $$

where $u_0$ is the friction velocity (m s$^{-1}$), $\psi_H$ is a
roughness sublayer influence function [$\psi_H = \ln(c_w) - 1 + c_w^{-1}$ with $c_w = 2$], $L_{MO}$ is the Monin–Obukhov
length (m), $z_{\text{ruff}}$ is the height of the roughness sub-
layer (m), and $k$ is the von Kármán constant ($k = 0.4$).

The stomatal resistance (i.e., $r_s$) is given by

$$ r_s^{-1} = \frac{G_0}{(C_s - 1)(1 - D_f/D_0)}, $$

where $G_0$ is the residual conductance (mol m$^{-2}$ s$^{-1}$),
$A_c$ is the net photosynthesis of the leaf (mol m$^{-2}$ s$^{-1}$),
$C_s$ is the CO$_2$ concentration at the leaf surface (mol mol$^{-1}$),
$\Gamma$ is the CO$_2$ compensation point of photosynthesis
(mol m$^{-1}$), and $D_f$ is the water vapor pressure deficit at
the leaf surface (Pa); $a_1$ and $D_0$ are two model parameters
($a_1 = 4$ for C$_4$ plants and $a_1 = 9$ for C$_3$ plants, $D_0 = 1500$ Pa). The variable $f_{\text{wail}}$ is the soil moisture limitation
on stomatal conductance given by

$$ f_{\text{wail}} = \beta \sum_m w_{m} f_{\text{root,m}} \tau_{gf} - w_{\text{wilt}}, $$

where $w_m$ is the soil moisture content in soil layer $m$, $w_{\text{wilt}}$ is the soil moisture at wilting point, $w_{gc}$ is the soil moisture at field capacity, $f_{\text{root,m}}$ is the fraction of root mass in the soil layer, and $\beta$ is a model parameter between 0 and 1.

The leaf boundary layer resistance (i.e., $r_{l0}$) is given by

$$ r_{l0}^{-1} = \frac{(A_b/k)(U_l/\nu)^{1/2} \sqrt{\nu/k}}{L^{1/3}}, $$

where $\nu$ is the kinematic viscosity of air (m$^2$ s$^{-1}$), $U_l$ is the
ambient wind speed (m s$^{-1}$), $l$ is the leaf or element cross stream
dimension, and $A_b$ is a dimensionless coefficient for
single-sided transfer on a flat plate ($A_b = 0.7$).

REFERENCES

Abramowitz, G., 2012: Towards a public, standardized, diagnostic
benchmarking system for land surface models. Geosci. Model

——, R. Leuning, M. Clark, and A. J. Pitman, 2008: Evaluating the
performance of land surface models. J. Climate, 21, 5468–5481,

Ball, J. T., I. E. Woodrow, and J. A. Berry, 1987: A model pre-
dicting stomatal conductance and its contribution to the control
of photosynthesis under different environmental
conditions. Progress in Photosynthesis Research, Vol. 1, J.

Model Simulator (JULES), model description—Part 1: En-
ergy and water fluxes. Geosci. Model Dev., 4, 677–699,

J. Hydrometeor., 16, 1425–1442, doi:10.1175/
JHM-D-14-0158.1.

resistance to sensible- and latent-heat flux in heterogeneous

Unauthenticated | Downloaded 12/29/22 05:01 AM UTC


