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Key Points:
- Sensitivity of surface temperature to land use and land cover change-induced biophysical change is scale dependent
- Atmospheric feedbacks can either enhance or hinder surface temperature response to biophysical changes
- One-dimensional conceptualization of land-atmosphere interaction is intrinsically linked to certain scales

Supporting Information:
- Supporting Information S1

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Sensitivity of Surface Temperature to Land Use and Land Cover Change-Induced Biophysical Changes: The Scale Issue

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Abstract While the signs of the sensitivities of surface temperature (T_s) to land use and land cover change-induced biophysical changes are relatively well understood, their exact magnitude and how their magnitude depends on the scale characterizing the size of the change remain elusive. In this study, we compare the sensitivities of surface temperature to changes in surface albedo and surface water availability from three analytical/semianalytical models, which are designed for small (<1 km), intermediate (from ~1 to ~10 km), and large (>10–20 km) scales. Results suggest that the sensitivities of surface temperature to biophysical changes are scale dependent due to atmospheric feedbacks. Our results demonstrate that it is important to consider the scale and the associated atmospheric feedbacks when quantifying the sensitivities of surface temperature to biophysical changes.

1. Introduction

Land use and land cover change (LULCC) has a direct impact on the surface temperature (T_s) through altering land surface biophysical properties and thus land-atmosphere exchanges of mass, momentum, and energy. Such impacts are often called the biophysical effects of LULCC (see recent reviews by Pielke et al., 2011 and Mahmood et al., 2014). Given the highly regionalized nature of LULCC, in certain areas the biophysical effects of LULCC can be stronger than the global impact of increasing greenhouse gas emissions in terms of magnitude (Boisier et al., 2012; Davin & de Noblet-Ducoudré, 2010; de Noblet-Ducoudré et al., 2012; Feddema et al., 2005; Lawrence et al., 2016; Pitman et al., 2009). As a result, it is important to understand and quantify these biophysical effects (Alkama & Cescatti, 2016; Bright et al., 2017; Forzieri et al., 2017), which also forms the basis for developing land-based climate mitigation policies (Bonan, 2008; Bright et al., 2015; Naudts et al., 2016; Pielke et al., 2002).

The overarching question to be addressed can be summarized as how much the surface temperature would change when the land surface biophysical factors, including surface albedo, aerodynamic features, as well as conditions that regulate water exchanges between the land and the atmosphere such as soil moisture and vegetation characteristics, are perturbed by a finite amount (Δ). The signs of changes in surface temperature in response to biophysical perturbations are relatively well understood (e.g., an increase in surface albedo tends to cause a decrease in surface temperature). However, whether and how such changes in surface temperature depend on the horizontal scale characterizing changes in biophysical factors remain elusive. Addressing the scale dependence of surface temperature sensitivity to biophysical perturbation frames the scope of this study.

While complex models such as weather, climate, and earth system models have been extensively used to simulate the biophysical (and also biogeochemical) effects of LULCC (Boisier et al., 2012; Davin & de Noblet-Ducoudré, 2010; de Noblet-Ducoudré et al., 2012), simple models that can quantify the sensitivities of surface temperature to changes in individual biophysical factors are still needed for at least two reasons. First, improving our physical understanding of the coupled land-atmosphere system and how it is altered by different types of perturbations continues to be an important goal of our research, which requires simple models that capture the essential physics but are not obscured by the complexity of equations. Second, simple models can be used as diagnostic tools to analyze simulation results from complex models. In particular, simple models have unique values in helping disentangle the interactions and feedbacks encoded in complex models. With this in mind, we will focus on simple models in this study.

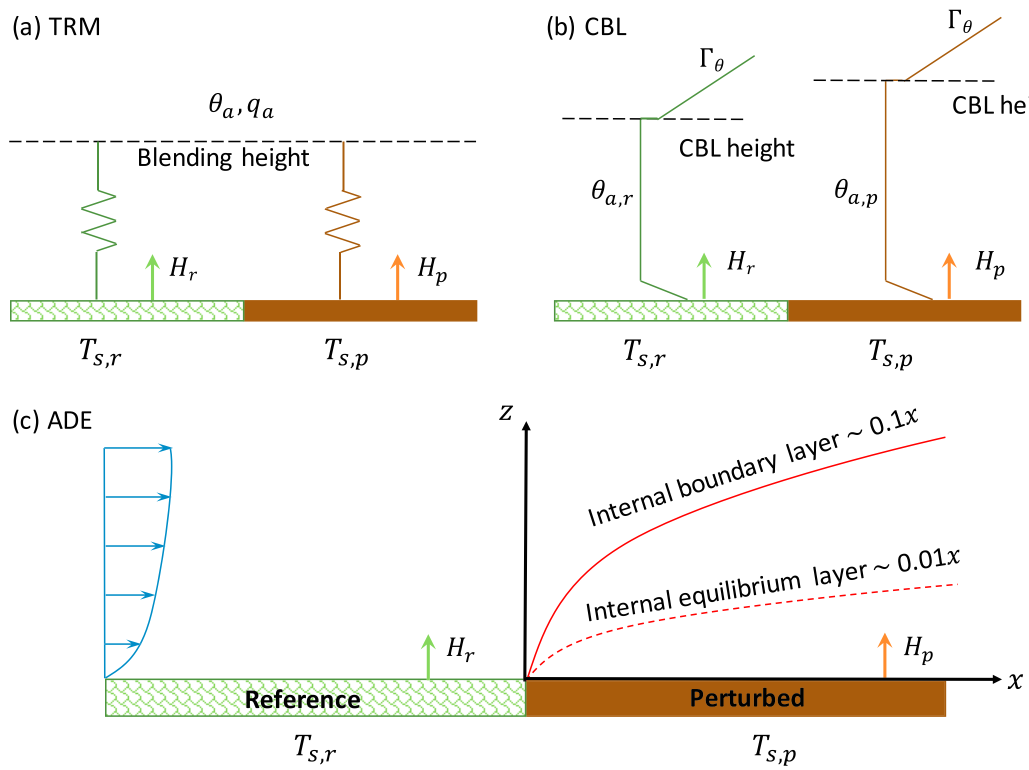

Figure 1. A schematic of different conceptualization of land-atmosphere coupling over heterogenous terrain. These different conceptualization apply to landscapes of different characteristic heterogeneity scales (not to scale). Panels (a) and (b) are one-dimensional models, and (c) considers horizontal advection across the transition. Here T_s refers to the surface temperature, H is the sensible heat flux, θ_a and q_a are the atmospheric potential temperature and specific humidity, respectively, and Γ is the lapse rate of potential temperature above the convective boundary layer (CBL). The subscripts "r" and "p" refer to the reference patch and the perturbed patch, respectively. TRM = Two-Resistance Mechanism; ADE = advection-diffusion equation.

Recently, there have been many studies employing simple models to quantify or interpret the sensitivities of surface temperature to LULCC-induced biophysical changes (Baldocchi & Ma, 2013; Boisier et al., 2012; Cronin, 2013; Juang, Katul, et al., 2007; Lee et al., 2011; Luyssaert et al., 2014; Rigden & Li, 2017). Nearly all of these models can find their roots in earlier work on local land-atmosphere interaction and coupling (see recent reviews by Betts, 2009 and Santanello et al., 2018). A common assumption in local land-atmosphere interaction studies is that the land surface is horizontally homogenous or uniform and thus land-atmosphere coupling is strictly a vertical problem. Simple models used to quantify and interpret the sensitivities of surface temperature to LULCC-induced biophysical changes often implicitly inherit this assumption. The outcome of this assumption is that changes in surface temperature are scale independent if the biophysical changes are spatially uniform.

This "one-dimensionality" assumption (Holgate et al., 2019) can be problematic particularly when the LULCC effects are derived from the differences between two neighboring land patches with contrasting land cover (e.g., forest vs. deforested open land, urban vs. rural, see Figure 1), a common approach used in the LULCC literature (Baldocchi & Ma, 2013; Chen & Dirmeyer, 2016; Duveiller et al., 2018; Lee et al., 2011; Li, Zhao, et al., 2015; Liao et al., 2018). The contrast between two patches, even when the two patches themselves are spatially uniform, inevitably creates surface heterogeneity in the horizontal direction, which can potentially lead to the breakdown of the one-dimensionality assumption (Stull, 1988).

Whether the one-dimensionality assumption breaks down or not hinges on the horizontal scale characterizing the surface heterogeneity (hereafter called the heterogeneity scale) (Brutsaert, 1998; Mahrt, 2000). One can imagine that if the heterogeneity scale is sufficiently large (say orders of magnitude larger than the atmospheric boundary layer or the ABL height), the one-dimensionality assumption is probably a reasonable assumption for the whole land-ABL column. Under such conditions, a one-dimensional boundary layer model coupled with a surface energy balance model may be appropriate for studying the surface temperature difference between two adjacent patches (Baldocchi & Ma, 2013; Cronin, 2013). Such a model, however, is inappropriate when the heterogeneity scale becomes comparable to or smaller than the ABL height. This simple thought experiment illustrates that the validity of one-dimensional models is intrinsically linked to a range of heterogeneity scales.

The scale issue is not a new topic in hydrology and boundary layer research (Avissar & Schmidt, 1998; Baidya Roy & Avissar, 2000; Brutsaert, 1998; Gentine et al., 2012; Mahrt, 2000; Raupach & Finnigan, 1995; Taylor et al., 2013), and its importance in the LULCC research is also widely recognized (Baidya Roy & Avissar, 2002; D'Almeida et al., 2007; Khanna et al., 2017; Lawrence & Vandecar, 2015). However, the role of heterogeneity scale in controlling the sensitivity of surface temperature to LULCC-induced biophysical changes has not been studied systematically. The objective of this paper is to fill this research gap using three analytical/semianalytical models that are designed for three different scale ranges. The scenario to be considered in this paper is that part of an infinitely large and uniform reference patch is perturbed by altering certain biophysical factors such as surface albedo, which creates a perturbed patch of limited size x. In this case x can be also interpreted as the distance from the transition between the reference patch and the perturbed patch (see Figure 1c). The perturbations are assumed to be spatially uniform and hence the scale dependence is solely a result of advective effects in the atmosphere. For simplicity we treat this problem as either one-dimensional or two-dimensional, with three-dimensional considerations left for future research, and we only consider daytime conditions. In addition, we treat biophysical properties as external parameters to the models and thus ignore atmospheric feedbacks on biophysical properties (Raupach, 1998). However, we do consider atmospheric feedbacks on the surface energy budget.

2. Theory

Figure 1 shows a schematic of different conceptualization of land-atmosphere interaction over two contrasting patches (i.e., a reference patch and a perturbed patch). Specifically, Figures 1a and 1b represent the two major types of one-dimensional models. In Figure 1a, the reference and perturbed patches are assumed to share the same atmospheric conditions. That is, there exists a blending height above which the atmospheric properties become uniform due to the integrating power of turbulence (Brutsaert, 1998; Mahrt, 2000; Raupach & Finnigan, 1995). In Figure 1b, the whole boundary layer is assumed to be in equilibrium with the underlying patch.

Different from Figures 1a and 1b, Figure 1c shows that an internal boundary layer and an internal equilibrium layer develop due to the abrupt change in the surface characteristics. Their heights scale roughly as $0.1x$ and $0.01x$ under neutrally stratified conditions, respectively, where x is the distance from the transition between the reference and perturbed patches (Brutsaert, 1998). Above the internal boundary layer, the atmosphere is only affected by the reference patch, while within the internal equilibrium layer the atmosphere is only affected by the perturbed patch. Between the internal equilibrium layer and internal boundary layer, the atmosphere is affected by both the reference and perturbed patches. It is clear that this conceptualization goes beyond the traditional, one-dimensional paradigm, and explicitly takes horizontal advection into consideration.

In the following, three different models designed based on these three different conceptualization are discussed. We will primarily discuss the scales under which each model is applicable. Other details including model formulations are presented in the supporting information.

2.1. Surface Energy Balance Equation-Based Models

As just mentioned, models building on the conceptualization of Figure 1a assume that the reference and the perturbed patches share the same atmospheric conditions. In essence, this assumes that the LULCC-induced biophysical changes only affect the surface temperature but not atmospheric properties. This requires the internal boundary layer generated by the perturbed patch to be below z where the atmospheric conditions are assumed to be unchanged (e.g., imposed as the external forcing). Given that the internal boundary layer develops roughly as $0.1x$ under neutral conditions (Brutsaert, 1998), the size of the perturbed patch x has to be smaller than $10z$. Note that the unstable stratification does not significantly alter the scaling of internal boundary layer with x (Brutsaert, 1998).

Another way to estimate the constraint on the size of the perturbed patch is to use the empirical relation between the blending height (z_b) and the heterogeneity scale (x), which can be expressed as $z_b = C\left(u_*/U\right)^p x$, where u_* is the friction velocity, U is the wind speed at z_b, and C is a nondimensional coefficient usually taken as unity (Mahrt, 2000). The value of p varies among studies but is often between 1 and 2 (Mahrt, 2000). With $p = 1$ and $u_*/U \approx 0.1$, $z_b \approx 0.1x$. Hence $z > z_b$ again requires $x < 10z$. Typically, values for z range from 2 (e.g., atmospheric conditions measured by weather stations) to 20 m (e.g., atmospheric conditions measured by flux towers), which correspond to $x <$ 20–200 m.

In this case, the sensitivities of surface temperature to any biophysical perturbations can be deduced from solving the surface energy balance equation. A notable example is the so-called Two-Resistance Mechanism (TRM) method proposed by Rigden and Li (2017), which solves the surface energy balance equation by introducing two resistances (aerodynamic and surface resistances) for parameterizing turbulent heat fluxes, neglecting the surface temperature dependence of ground heat flux, and linearizing the outgoing longwave radiation and the saturated specific humidity terms at the atmospheric temperature. The outcome is an analytical solution for the surface temperature from which changes in surface temperature (ΔT_s) due to changes in various biophysical factors, including albedo ($\Delta\alpha$), surface resistance (Δr_s), and aerodynamic resistance (Δr_a) can be derived. Here Δ indicates the difference between the reference patch and the perturbed patch.

In this study, we make one important modification to the TRM method, namely, we replace the surface resistance (r_s) by the surface water availability (β), defined as the ratio of surface specific humidity to its saturated counterpart, which thus can be interpreted as the relative humidity at the surface. The surface water availability defined here is similar to the evapotranspiration efficiency or moisture availability parameters used in other studies (Bateni & Entekhabi, 2012; Davin & de Noblet-Ducoudré, 2010). This modification is to ensure a consistent comparison between the TRM model and the other models, especially the advection-diffusion equation (ADE) model which uses β. The exact formulations for the modified TRM method can be found in the supporting information.

2.2. CBL Models

The second type of one-dimensional models, on the other hand, assumes that the whole boundary layer is in equilibrium with the underlying surface patch (see Figure 1b). This requires that the surface patch is large enough so that the whole boundary layer is within the internal equilibrium layer. A rough estimate based on the growth of the internal equilibrium layer ($\sim 0.01x$) suggests that the patch size x needs to be at least on the order of $100h$, where h is the boundary layer height. Given that $h \sim 1 - 2$ km, the patch size needs to be at least on the order of $100 - 200$ km. The effect of buoyancy may reduce this requirement by enhancing turbulent mixing in the boundary layer. For example, under convective conditions, the length scale required for the boundary layer (hereafter convective boundary layer or CBL) to be in equilibrium with the perturbed patch can be estimated as $x \sim U(h/w_*)$, where w_* is the Deardorff convective velocity scale (Deardorff, 1970). Given that $U \sim 10$ m/s and $w_* \sim 1$ m/s, $x \sim 10 - 20$ km. Throughout the paper, we will use $x \sim 10 - 20$ km as the criterion.

In this case, any biophysical perturbations at the surface will be "felt" by the whole boundary layer. It is thus important to treat the coupled land-boundary layer column as the system of interest. To model such a system, a CBL model (Betts, 1973; Carson, 1973; Tennekes, 1973) coupled with a surface energy balance model is often employed (Betts, 2000; Brubaker & Entekhabi, 1996; 1995; De Bruin, 1983; Ek & Mahrt, 1994; Entekhabi & Brubaker, 1995; Ek & Holtslag, 2004; Gentine et al., 2016; 2013; Jacobs & De Bruin, 1992; Juang, Katul, Porporato et al., 2007; Juang, Porporato, et al., 2007; Huntingford & Monteith, 1998; Manoli et al., 2016; McColl et al., 2019; McNaughton & Spriggs, 1986; Raupach, 2000; Siqueira et al., 2009; Yin et al., 2015). A review of applications of such coupled CBL and surface energy balance models can be found in Vilà-Guerau De Arellano et al. (2015). This coupled CBL-surface energy balance model will be simply referred to as the CBL model hereafter, which, in the LULCC context, can be used either in a time-dependent fashion (Baldocchi & Ma, 2013) or to explore the equilibrium behaviors (Cronin, 2013).

In this study, we use the time-dependent CBL model described in Porporato (2009) coupled with the surface energy balance equation, which is solved in a similar way as in the TRM model. This facilitates a direct comparison between the CBL model and the TRM model. The key difference between the TRM and CBL models is that the air temperature and specific humidity in the CBL model respond to biophysical perturbations following CBL dynamics, but not in the TRM model. Details of the CBL model are presented in the supporting information.

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2.3. ADE-Based Models

It is now clear that models corresponding to Figure 1a should apply to heterogeneity scales that are smaller than 1 km, while models corresponding to Figure 1b should apply to heterogeneity scales that are larger than 10–20 km. When the heterogeneity scale is in the intermediate range (from ∼1 to ∼10 km), the assumptions of the previously mentioned models are no longer satisfied. The two neighboring patches are neither under the influence of the same atmospheric conditions nor are in equilibrium with their respective boundary layer columns. In this case (see Figure 1c), the connection between the reference and perturbed patches through horizontal advection needs to be explicitly taken into account.

In this study, a model based on simultaneously solving the ADEs for temperature and water vapor with their boundary conditions constrained by the surface energy balance equation is utilized (Li & Bou-Zeid, 2013). Hereafter this model will be called the ADE model. To ensure a consistent comparison between the ADE model and the other two models, the effect of surface water availability on latent heat flux in the surface energy balance equation is considered in a similar way as in the TRM model. In addition, we also improve the original ADE model presented in Li and Bou-Zeid (2013) to consider the longwave radiation feedbacks since the longwave radiation feedbacks are considered in the TRM model. Considering longwave radiation feedbacks means that the outgoing longwave radiation is treated as a function of surface temperature when solving the surface energy balance equation, which is also called the radiatively coupled situation in Raupach (2001). This is in contrast to the classic Penman-Monteith equation where the outgoing longwave radiation is not treated as a function of surface temperature (see discussions in Raupach, 2001). The details of the ADE model, including the improvement compared to the model presented in Li and Bou-Zeid (2013), can be found in the supporting information.

Although the effect of surface water availability on latent heat flux and longwave radiation feedbacks are considered in the ADE model as in the TRM and CBL models, the comparison between the ADE model and the other two models remains complicated due to the fact that aerodynamic resistance does not explicitly show up in the ADE model formulations. Instead, the ADE model considers the aerodynamic effects through complex parameterizations of mean wind and turbulent transport. Moreover, the ADE model does not consider changes in the mean wind or turbulent transport when the atmosphere flows from the reference patch to the perturbed patch. As a result, in this study we assume that the reference and perturbed patches have the same aerodynamic resistance in the TRM model and CBL model, and use this aerodynamic resistance to determine the parameters used in the parameterizations of mean wind and turbulent transport in the ADE model.

Given that the ADE model works in the intermediate range of heterogeneity scales, we expect that the ADE model behaves more like the CBL model as x increases but more like the TRM model as x decreases. In other words, the differences between large x and small x in the ADE model should resemble "qualitatively" the differences between the CBL and TRM model results. Such resemblance is only qualitative, not quantitative, because the ADE model uses complex parameterizations of mean wind and turbulent transport while the TRM and CBL models use the aerodynamic resistance concept. However, this does not mean that the ADE model results themselves cannot be compared quantitatively.

3. Results

Figure 2 gives an example of how the surface temperature changes as the surface albedo value changes from 0.2 (reference patch, $x < 0$) to 0.3 (perturbed patch, $x > 0$; left panels) and as the surface water availability value changes from 0.5 (reference patch, $x < 0$) to 0.4 (perturbed patch, $x > 0$; right panels), which mimics the contrast between a forest land (reference patch) and an open grassland (perturbed patch) as forests tend to have lower surface albedo and higher surface water availability values. Compared to the top panels, the bottom panels use logarithmic scales for x axes to emphasize the horizontal variations of ΔT_s over the perturbed patch.

A few interesting features stand out in Figure 2. First, the surface temperature over the perturbed patch decreases (increases) in all three models as α increases (as β decreases), as expected. However, the magnitude of ΔT_s differs among models. For example, compared to the TRM model, the CBL model generates a larger ΔT_s with the same $\Delta\alpha$ (considering the magnitude of ΔT_s), but a smaller ΔT_s with the same $\Delta\beta$. Second, while both TRM and CBL models produce uniform increases in T_s over the perturbed patch due to their

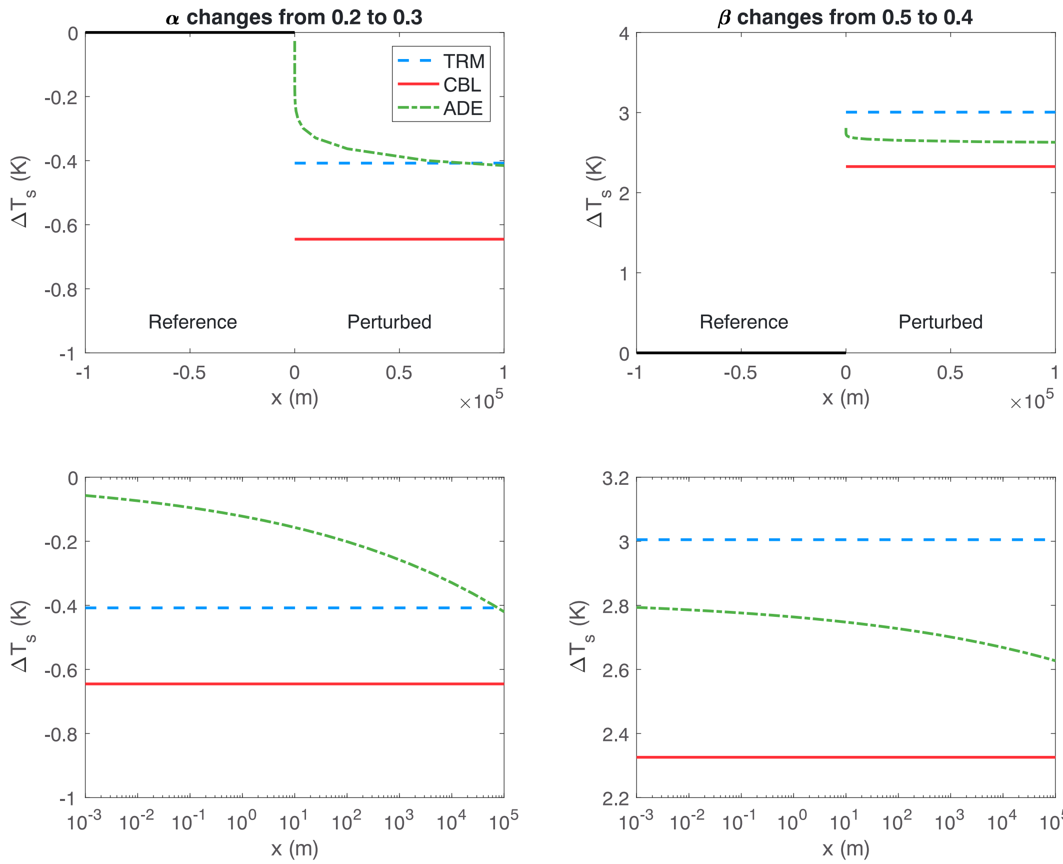

Figure 2. An example of how the surface temperature is altered as the surface albedo value changes from 0.2 (reference patch, $x < 0$) to 0.3 (perturbed patch, $x > 0$; left panels) and as the surface water availability value changes from 0.5 (reference patch, $x < 0$) to 0.4 (perturbed patch, $x > 0$; right panels). Compared to the top panels, the bottom panels use logarithmic scales for x axes and to emphasize the horizontal variations of ΔT_s over the perturbed patch. Note the difference in the y axes. TRM = Two-Resistance Mechanism; CBL = convective boundary layer; ADE = advection-diffusion equation.

one-dimensional nature, the ADE model generates nonuniform decreases or increases in T_s over the perturbed patch ($x > 0$). Interestingly, the ΔT_s in the ADE model increases with increasing x when α increases (again considering the magnitude of ΔT_s), but decreases with increasing x when β decreases. This demonstrates that the differences between large x and small x in the ADE model indeed resemble qualitatively the differences between the CBL and TRM models, which is consistent with the expected asymptotical behaviors of the ADE model. Lastly, changes in α do not create discontinuity in the surface temperature field in the ADE model. However, changes in β produce discontinuity at the transition between the reference patch and the perturbed patch (i.e., at $x = 0$).

Figure 3 further presents the sensitivity of $\Delta T_s/T_s$ to $\Delta\alpha/\alpha$ and $\Delta\beta/\beta$. We normalize the sensitivities so that the sensitivities to changes in α and β can be compared. It is clear that compared to changes in α, the same fractional change in β yields a fractional change in T_s that is an order of magnitude larger (note the difference in the y axes). This implies that surface temperature is much more sensitive to changes in the partition of available energy into sensible and latent heat fluxes (controlled by β) than changes in the available energy itself (controlled by α). This finding is consistent with previous studies (Li & Bou-Zeid, 2013; Li, Sun, et al., 2015; Philip, 1959; Rider & Philip, 1960, Rider et al., 1963).

When the three models are intercompared, Figure 3 shows that the CBL model produces larger ΔT_s than the TRM model with the same fractional change in α but smaller ΔT_s with the same fractional change in β. The differences between large x and small x in the ADE model are again consistent with the differences between the CBL model and the TRM model. These findings are in agreement with those from Figure 2.

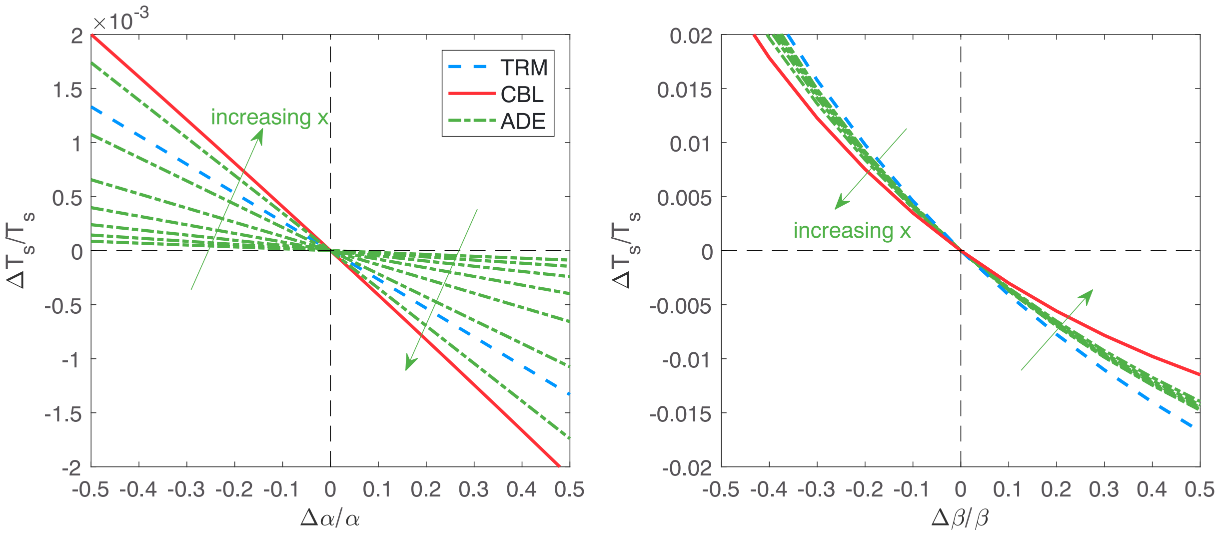

Figure 3. The sensitivities of surface temperature (T_s) to changes in surface albedo (left) and surface water availability (right). The changes in surface temperature, albedo, and water availability are normalized by their values over the reference patch, respectively. Note the difference in the y axes. TRM = Two-Resistance Mechanism; CBL = convective boundary layer; ADE = advection-diffusion equation.

4. Discussions

First, we explain why the CBL model generates a larger ΔT_s with the same $\Delta\alpha$, but a smaller ΔT_s with the same $\Delta\beta$ than the TRM model, which is summarized in Figure 4. The direct effect of increasing surface albedo (α) is that the net radiation decreases, which likely leads to decreases of sensible heat flux, latent heat flux, and outgoing longwave radiation. As such, the surface temperature will also decrease as it is directly related to the outgoing longwave radiation. Under such conditions, the atmospheric temperature is likely to also decrease, which would cause the sensible heat flux to increase if such feedbacks were considered. This would further cause the outgoing longwave radiation to decrease in order to balance the increase of sensible heat flux due to atmospheric feedbacks. As such, the CBL model, which does consider such feedbacks, yields a larger outgoing longwave radiation decrease and hence a larger surface temperature decrease for the same increase in surface albedo.

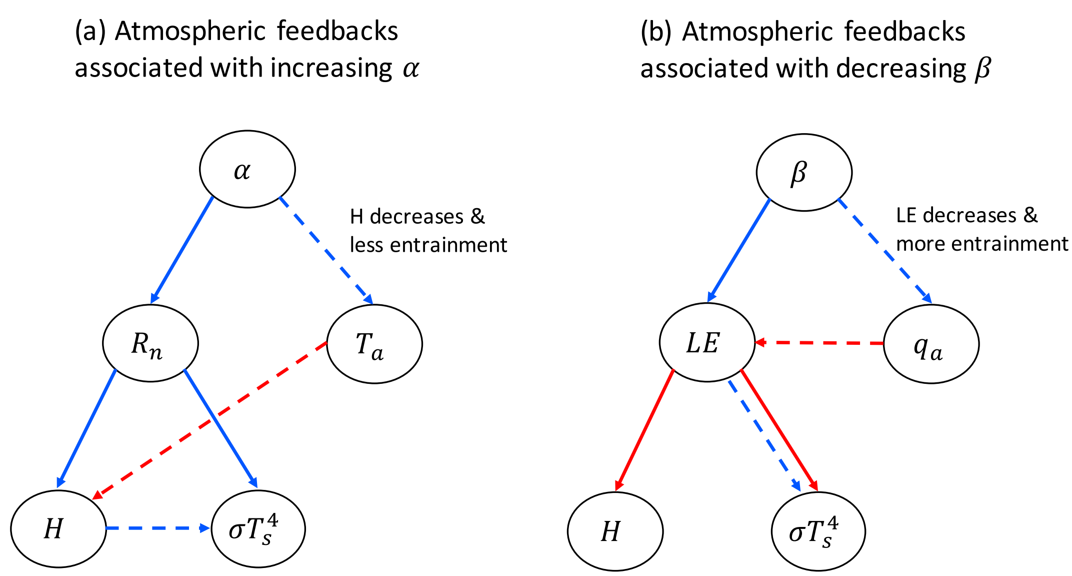

Figure 4. Atmospheric feedbacks associated with (a) increasing surface albedo (α) and (b) decreasing surface water availability (β). Arrows with lines are direct effects and arrows with dashed lines are indirect effects from atmospheric feedbacks. The red arrows are positive effects and the blue arrows are negative effects.

On the other hand, the direct effect of reducing surface water availability (β) is that the latent heat flux decreases. To balance such a direct effect, the outgoing longwave radiation will likely increase and hence the surface temperature will also increase. The sensible heat flux is also likely to increase. Under such conditions, the atmospheric humidity most likely would decrease (due to both the decrease of latent heat flux from the direct effect and the enhanced entrainment of dry air from the increase of surface sensible heat flux), which would cause the latent heat flux to increase if such feedbacks were considered. This would further cause the outgoing longwave radiation to decrease in order to balance the increase of latent heat flux due to atmospheric feedbacks, thereby hindering the direct effect. As a result, the CBL model yields a smaller surface temperature sensitivity to $\Delta\beta$ than the TRM model.

The differences between the CBL model and the TRM model are modulated by the initial boundary layer height and the integration time used in the CBL model. Figure S1 (top) shows that as the initial boundary layer height increases, the CBL model results become closer to the TRM model results. This is consistent with the asymptotic behavior of the CBL model. Namely, if the initial boundary layer height was sufficiently large, the CBL model would behave very similar to the TRM model because the atmospheric temperature and specific humidity would respond very little to changes in surface biophysical factors (note that the initial atmospheric conditions used in the CBL model are identical to those in the TRM model). The integration time is a unique input to the CBL model. The TRM model (and also the ADE model) are time independent and thus are only applicable to steady-state scenarios, in which case the time dependence has to come from the forcing conditions such as the incoming shortwave radiation. The CBL model is however by design time dependent even when the forcing conditions are time independent. As such, we need to specify an integration time period for the CBL model. Figure S1 (bottom) shows that changing the integration time does not change the CBL model behavior qualitatively. A further departure from the TRM results is observed as the integration time of the CBL model increases.

Second, we examine the behavior of the ADE model, especially the x dependence of ΔT_s and the discontinuity of T_s at $x = 0$. In the ADE model, the difference in the surface temperature between the perturbed patch and the reference patch can be expressed as

$$\Delta T_s = T_{s,p} - T_{s,r} = (1 - f_{\mathrm{ADE}})(-\Delta\beta)T_1^* + f_{\mathrm{ADE}}(-\Delta\alpha)T_2^*. \tag{1}$$

where T_1^* and T_2^* are two temperature scaling factors which principally characterize the sensitivity of surface temperature to $\Delta\beta$ and $\Delta\alpha$, respectively, and

$$f_{\mathrm{ADE}} \sim 0.01x^{1/9} \tag{2}$$

is the x dependence factor. Here the subscripts p and r indicate the perturbed and reference patches, respectively.

With equations (1) and (2), it is now clear why the magnitude of ΔT_s in the ADE model increases with increasing x when the surface albedo value changes, but decreases with increasing x when the surface water availability value changes. The sensitivities of surface temperature to changes in α and β are dependent on x in an opposite way through f_{ADE}. Specifically, as x increases, f_{ADE} increases. Hence, the sensitivity to changes in α increases but the sensitivity to changes in β decreases. It is also clear why ΔT_s in the ADE model shows discontinuity at $x = 0$ when β changes. At $x = 0$, $\Delta T_s = (-\Delta\beta)T_1^*$ when only β changes, which remains nonzero. On the other hand, $\Delta T_s = 0$ at $x = 0$ when only α changes.

Lastly, the ADE formulations explain why T_s is much more sensitive to changes in β than those in α. Since f_{ADE} scales with $0.01x^{1/9}$, the scales of practical interest to us ($x < 10^5$ m) yield f_{ADE} values smaller than or on the order of 0.01. Hence, although T_2^* is often an order of magnitude larger than T_1^*, the sensitivity of surface temperature to changes in β is at least an order of magnitude larger than the counterpart to changes in α (see Figure 3). Given that the surface temperature is so sensitive to changes in β, the scale dependence of the sensitivity of surface temperature to changes in β becomes less important than its counterpart to changes in α, which is consistent with the results shown in Figure 3.

5. Conclusions and Implications

In this study, we address the scale dependence of the sensitivities of surface temperature to changes in surface albedo and surface water availability induced by LULCC. Results indicate that the sensitivities of surface temperature to changes in surface albedo and surface water availability are scale dependent but in an opposite way. The sensitivity of surface temperature to changes in surface albedo increases with x, while the sensitivity of surface temperature to changes in surface water availability decreases with increasing x, where x is the distance from the transition between the reference and perturbed patches (or the size of the perturbed patch). Such scale dependence can be understood from the perspective of atmospheric feedbacks, which tend to enhance the direct effect of changing surface albedo but hinder the direct effect of changing surface water availability.

All models suggest that the surface temperature is much more sensitive to changes in the partition of available energy into sensible and latent heat fluxes (controlled by β) than changes in available energy itself (controlled by α). Since the surface temperature is so sensitive to changes in β, its scale dependence becomes less critical. For example, one can see from Figure 2 that when β changes from 0.5 to 0.4, changes in T_s range from 2.8 K (for $x = 10^{-3}$ m) to 2.6 K (for $x = 10^5$ m). Namely, an eighth-order increase of x only changes the sensitivity by less than 10%. On the other hand, it is exactly the relatively small sensitivity of surface temperature to changes in α that makes its scale dependence important to consider.

Our study has a few implications that are important to appreciate. First, our results demonstrate that even when the perturbed patch has uniform biophysical parameters, its surface temperature is not uniform due to advective effects, making the surface temperature change scale dependent. This conclusion is impossible to reach without going beyond the one-dimensional paradigm of land-atmosphere interaction. This suggests that when quantifying the biophysical impacts of LULCC (especially using paired observations), it is important to report the scale of the perturbed patch and discuss the potential influence of atmospheric feedbacks. In the meantime, we should stress that nonuniform changes in biophysical parameters over the perturbed patch, which are not considered in this study, will also contribute to the scale dependence of surface temperature change.

Second, the parameterization of subgrid-scale surface heterogeneity effects in numerical models has been studied for more than three decades now but continues to be one of the most challenging issues facing the land and atmospheric modeling communities (Bou-Zeid et al., 2004; 2007; Brutsaert, 1998; Chen & Avissar, 1994a; 1994b; Dalu et al., 1996; Li & Avissar, 1994; Mahrt, 1996; 1987; 2000; Maronga & Raasch, 2013; Miller & Stoll, 2013; Patton et al., 2005; Pielke & Uliasz, 1993; Pielke et al., 1997; Stoll & Porté-Agel, 2009; Zeng & Pielke, 1995a; 1995b; Zhou et al., 2019). Currently, many land surface models use the so-called mosaic or tiling approach to parameterize the subgrid-scale surface heterogeneity effects on land-atmosphere exchanges (Avissar & Pielke, 1989; Giorgi & Avissar, 1997; Koster & Suarez, 1992; Li et al., 2013), which in essence is based on the conceptualization shown in Figure 1a. As such, this approach sets a strong constraint on the sizes of subgrid patches (i.e., $x <\sim 10z$ where z is the height of the lowest atmospheric grid). Given that the height of the lowest atmospheric grid is typically 10–50 m, the sizes of subgrid patches need to be smaller than 100–500 m, which can be easily violated in mesoscale and global models. Our study demonstrates that the mosaic or tiling approach, by removing feedbacks due to atmospheric inhomogeneity, tends to underestimate the subgrid-scale surface temperature variability (e.g., the surface temperature difference between two patches like urban vs. rural) caused by surface albedo differences, but overestimate the subgrid-scale surface temperature variability caused by surface water availability differences. This calls for proper parameterizations of atmospheric feedbacks when using the mosaic or tiling approach in mesoscale and global models.

Third, although this paper is primarily a theoretical study, the results can still shed some insights into answering practical questions. For example, remote sensing studies have found that the difference between urban and rural surface temperatures strongly increases as x increases, where x is the distance from the edge of the city, until it reaches the center of the city (Zhou et al., 2015; 2017). Based on the ADE model results, this cannot be simply attributed to the imperviousness of the city as the reduction of β would cause the opposite behavior. Hence, changes in surface albedo and other biophysical factors (such as aerodynamic features) over the urban terrain, which might also be nonuniform, must contribute to the observed behavior.

Lastly, in addition to neglecting changes in aerodynamic resistance, the current study does not consider the atmospheric feedbacks on biophysical factors such as the surface water availability, which can be of great importance and remains a hotly debated topic (Guillod et al., 2015; Hohenegger & Stevens, 2018; Tuttle & Salvucci, 2016). These feedbacks are not considered in this study because they will greatly complicate the calculation. Future studies considering these feedbacks and also changes in aerodynamic resistance through, for example, numerical simulations are recommended.

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