The Local Biophysical Response to Land-Use Change in HadGEM2-ES

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ABSTRACT

The biophysical response to a local change in land use is calculated using the HadGEM2-ES Earth system model. The biophysical temperature response is found to be a small residual of three large opposing flux responses: available energy, sensible heat, and latent heat. Deforestation reduces available energy, which is balanced by a reduction in heat lost via turbulent fluxes. However, the changes in turbulent heat fluxes are not simply a response to the reduction in available energy; rather, they are a direct response to land-use change, caused by reduced roughness length and, in the tropics, an increase in the Bowen ratio. Evaluation against satellite-derived observational datasets shows that in response to deforestation, the model has too much albedo-driven cooling and too little latent-heat-driven warming, leading to a large cooling bias.

1. Introduction

Land-use and land-cover changes (LULCC) affect surface albedo, roughness length, and transpiration, which in turn alter surface fluxes of energy, momentum, and moisture (Bonan 2008). The surface flux response to LULCC can have large impacts on climate (Bonan 1997; de Noblet-Ducoudré et al. 2012), although there is substantial model disagreement (Lejeune et al. 2017) that is often difficult to constrain using observations (Winckler et al. 2019). Recently, new observational estimates of the impacts of LULCC have been produced (Li et al. 2015; Alkama and Cescatti 2016; Bright et al. 2017; Duveiller et al. 2018a) and methods of quantifying model responses to land-use change developed (Kumar et al. 2013; Malyshev et al. 2015; Winckler et al. 2017). The new observational datasets and model analysis methods produce metrics that are directly comparable and have global coverage, providing a new opportunity to assess model predictions.

Deforestation increases albedo and this causes surface cooling; in the midlatitudes this mechanism dominates the biophysical response to land-use change and

historically it is as important as warming caused by increased CO₂ concentration in this region (de Noblet-Ducoudré et al. 2012). At higher latitudes, the albedo mechanism is enhanced because tall vegetation can mask snow on the ground, while shorter vegetation is covered by snow (Betts 2000). In the tropics, the dominant mechanism is expected to be reduced evapotranspiration (ET), which causes surface warming (Bonan 2008). Smaller roughness length after deforestation causes smaller sensible heat fluxes that can dominate the biophysical response in some regions (Winckler et al. 2017; Bright et al. 2017; Duveiller et al. 2018a). Observational estimates show a more extensive warming response than most general circulation model (GCM) studies, with deforestation warming not only in the tropics, but also the midlatitudes and some regions of the high latitudes (Li et al. 2015; Alkama and Cescatti 2016; Bright et al. 2017; Duveiller et al. 2018a). As well as latitudinal variations, differences in response between dry and moist regions are also seen (Winckler et al. 2017; Alkama and Cescatti 2016).

The effect of land-use change on climate can be difficult to quantify, because other climate forcers (e.g., aerosols) can have impacts that are collocated with land-use change, affect the same climate variables, and have stronger effects than land-use change. The surface flux responses caused by land-use change can cause climate responses that are remote from the land-use change forcing (Zhao et al. 2001; Davies-Barnard et al. 2014a; Winckler et al. 2019) and this makes it difficult to

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attribute a surface climate response to a specific LULCC event. These remote responses are scenario specific (Zhao and Pitman 2002; Davies-Barnard et al. 2014a; Winckler et al. 2017), that is, the pattern of response depends on the pattern of LULCC, so it is hard to generalize a model's sensitivity to LULCC. Additionally, the remote responses are hard to quantify in observations, for the same reasons they are difficult to attribute in GCM studies.

There have been many GCM studies that estimate the impact of land-cover change on climate (see McGuffie et al. 1995; Pielke et al. 1998; Findell et al. 2006; Pitman et al. 2009). More recently, a variety of different techniques have been used to isolate the effect of land-use change in GCM simulations (e.g., Pitman et al. 2009; Brovkin et al. 2013; Kumar et al. 2013; Malyshev et al. 2015; Andrews et al. 2017; Winckler et al. 2017).

Brovkin et al. (2013) compared simulations with and without future land-use change and found that climate response was hard to detect, even at the location of land-use change, because of substantial interannual variability and the lack of regions with near-total land-use changes.

Kumar et al. (2013) compared grid boxes with and without land-use change that are near to each other and so experience the same large-scale climate. Large-scale climate forcings, such as CO₂ concentration and changes in aerosol distribution, are generally not limited to a single grid cell in the same way that LULCC can be, so that when comparing nearby grid boxes with and without LULCC, differences can be attributed to LULCC. The remote responses to LULCC are expected to act as large-scale climate forcings by affecting regional climate as opposed to specific grid boxes remote from the source LULCC; this means that the methodology neglects the remote portion of the response. Kumar et al. (2013) applied this technique to historical and future climate simulations in which LULCC is inhomogeneous and the response to LULCC could only be calculated over some regions.

Winckler et al. (2017) compare paired simulations with idealized land-cover differences. The paired simulations address the issue of limited coverage by applying land-cover differences that are distributed uniformly across the world. The land-cover differences applied are large—at the selected grid boxes vegetation is either all trees or all grasses—which provides a stronger signal than the partial land-cover change seen in realistic scenarios. The large, globally distributed, land-cover changes produce substantial remote climate responses that are much greater than would be produced by a realistic LULCC scenario, but by applying a technique similar to Kumar et al. (2013) they remove the

remote response leaving only the, scenario-independent, “local” response (see section 2b for more details on methodology).

The strength of the Winckler et al. (2017) approach is that it provides global coverage of a scenario-independent response to land-cover change that is directly comparable to global observational estimates of the climate response to land-cover change. A number of new datasets are available that provide observational estimates of the local response to land-use change: Li et al. (2015), Alkama and Cescatti (2016), Bright et al. (2017), and Duveiller et al. (2018a). Each of these datasets provides extensive spatial coverage allowing comprehensive evaluation of global model output.

Surprisingly, the Hadley Centre Global Environment Model, version 2, with Earth System configurations (HadGEM2-ES) cools in response to tropical deforestation (Brovkin et al. 2013). ET is reduced, but the albedo response is unusually strong, resulting in net cooling (Davies-Barnard et al. 2014b). The HadGEM2-ES response is also unusual in the midlatitudes, with large increases in both evapotranspiration and albedo, resulting in a strong cooling (Kumar et al. 2013). In response to historical land-use change, HadGEM2-ES is unique in predicting year-round cooling in South Asia (Lejeune et al. 2017) and consistently predicting a global mean cooling (Winckler et al. 2019). The model's equilibrium radiative forcing from historical land-use change is substantially more negative than other estimates, making it the fourth most important forcing of climate change in the HadGEM2-ES historical simulations (Andrews et al. 2017).

HadGEM2-ES's unusually strong cooling in response to land-use change makes a significant contribution to the multimodel spread. The model's albedo and ET responses are also found to be outliers but have yet to be evaluated against observational estimates. The net cooling response to deforestation produced by the model is of particular importance, because it falsely suggests that tropical deforestation will lead to surface cooling and this could be used as evidence to support future deforestation.

Here we quantify the mechanisms causing the HadGEM2-ES temperature response to land-use change and attribute errors in the temperature response to errors in specific flux responses. We use a slightly modified version of the Winckler et al. (2017) methodology to quantify the full energy budget response to land-use change and evaluate it using the Li et al. (2015) and Duveiller et al. (2018a) datasets. This is the first estimate of the local response to land-use change in HadGEM2-ES that has comprehensive spatial coverage. The increased understanding of the model

TABLE 1. HadGEM2-ES parameters and variables that describe the biophysical differences between the five plant functional types (PFTs). The asterisk (*) indicates that the values given are valid when the leaf-area index (LAI) is equal to its maximum. Height is not an input parameter but is calculated as a function of LAI, using Eqs. (58) and (61) of [Clark et al. \(2011\)](#), and roughness length is proportional to height.

PFT	Broadleaf tree	Needleleaf tree	Shrub	C3 grass	C4 grass
Maximum LAI	9.0	5.0	3.0	4.0	4.0
Height (m)*	28.1	19.0	2.1	1.3	1.3
Roughness length for heat and moisture (m)*	0.1405	0.095	0.021	0.013	0.013
Snow-free albedo*	0.143	0.088	0.115	0.192	0.159
Snow-covered albedo*	0.2375	0.2375	0.3800	0.5700	0.5700
Root depth (m)	3.0	1.0	0.5	0.5	0.5
Temperature of leaf drop (°C)	0.0	−45.0	−45.0	0.0	0.0

behavior informs which aspects of the HadGEM2-ES simulations are useful and potentially helps to constrain multimodel spread.

2. Methods

a. HadGEM2-ES

HadGEM2-ES is an Earth system model that was used in phase 5 of the Coupled Model Intercomparison Project (CMIP5) and includes components representing the atmosphere, vegetation structure, and surface hydrology ([Collins et al. 2011](#)). The model has 38 levels and a horizontal resolution of 1.875° longitude $\times$ 1.25° latitude, or approximately 140 km in the midlatitudes ([Martin et al. 2011](#)). The model is forced by concentrations of CO₂, surface concentrations of CH₄, anthropogenic emissions of aerosols and aerosol precursors, land-use change, volcanic aerosol emissions, and natural variations in solar irradiance ([Jones et al. 2011](#)).

HadGEM2-ES includes a dynamic global vegetation model (DGVM), which calculates the distribution of vegetation types in response to changes in climate and land-use ([Cox 2001](#); [Clark et al. 2011](#); [Burton et al. 2019](#)). Vegetation is represented by five plant functional types (PFTs), and the distribution of each PFT depends on its ability to grow under given environmental conditions (climate, CO₂ concentration, soil hydrology) and on competition for space between PFTs.

Biophysical characteristics of the vegetation vary between PFTs, causing land-cover change to alter the surface fluxes of energy, momentum, and moisture. [Table 1](#) provides some of the key parameters that control the biophysical properties of each PFT. Tree PFTs are tallest, have the highest leaf-area index (LAI) and the deepest roots, and most effectively mask snow on the ground (see snow covered albedo in [Table 1](#)). Grass PFTs are the shortest, with the shallowest roots and the highest albedo. The height of the shrub PFT lies in between that of the tree and grass PFTs, as does its ability

to mask snow on the ground, but the shrub PFT's snow-free albedo is lower than some trees, its roots are as shallow as grass's, and it has the lowest LAI of all PFTs.

The broadleaf tree and two grass PFTs are cold deciduous; leaf turnover becomes very rapid when the temperature drops below 0°C, this affects evapotranspiration and albedo. The roughness length for heat and moisture is 1/200th vegetation height for tree PFTs and 1/100th vegetation height from the other three PFTs; however, other model parameters act to ensure that the tree PFTs always have a larger roughness length than shrubs and grasses ([Clark et al. 2011](#)). Within each grid box, all PFTs uptake water from a single soil column with four levels and a maximum depth of 3 m ([Best et al. 2011](#)).

Land use is represented by preventing woody PFTs from growing in a fraction of each grid box reserved for agriculture (the “disturbed fraction”); within the disturbed fraction, only grass PFTs are allowed to grow ([Burton et al. 2019](#)). The two grass PFTs, C3 grass and C4 grass, represent natural grasses, crops, and pastures; the woody PFTs are broadleaf tree, needleleaf tree, and shrub. When an area of woody PFT is removed by land-use change it is initially replaced by bare soil and until the grass PFTs have fully colonized the newly available area. The period of bare soil after land-use change affects the biophysical properties of the grid box including dust emissions ([Andrews et al. 2017](#)). In the case of increases in disturbed fraction, the grass PFTs rapidly colonize the newly available space, but when disturbed fraction is reduced, either for natural regrowth or active afforestation, the simulated rate of colonization by tree PFTs is much too slow. The problem of slow regrowth of tree cover will cause errors in the simulation of land-use change impacts on climate; however, this model error is outside of the scope of the present study and is avoided by only using simulations of deforestation (increased disturbed area). We assume that after the regrowth period, the impact of afforestation will be the inverse of the impact of deforestation.

FIG. 1. Disturbed fractions used to force (a) the ensemble of control simulations and (b),(c) the two ensembles of test simulations. Some grid boxes contain lakes or urban areas, causing the maximum disturbed fraction to be less than 1. The disturbed fraction is modified globally; only a small region is shown here in order to make the chessboard pattern clear.

b. Experimental design

HadGEM2-ES is run without the ocean component, instead the atmosphere is forced with time-varying sea surface temperatures (SSTs), sea ice, and oceanic dimethyl sulfide emissions. These additional forcings are taken from CMIP5 historical simulations made with the coupled atmosphere–ocean configuration of HadGEM2-ES. All other forcings are the same as in the CMIP5 historical simulations (Jones et al. 2011), except for the land-use forcing, as discussed below. The CMIP5 simulations also provide the initial conditions of the land and atmosphere. There is an ensemble of four historical simulations, allowing us to also run a four-member ensemble. Our simulations run for 30 years, from December 1973 to November 2003.

To quantify the model's sensitivity to land-use change we compare simulations with different land-use forcing. All simulations use time-invariant patterns of disturbed fraction. The control simulation uses the 1974 disturbed fraction forcing from the CMIP5. In the test simulations, the disturbed fraction is increased to 1 in every other grid box in a chessboard pattern (Fig. 1), while the other grid boxes maintain the 1974 disturbed fraction. Increasing the disturbed fraction to 1 totally deforests the grid box.

The total response to land-use change is calculated as the difference between the chessboard deforestation simulation (test A) and a simulation with no change in disturbed fraction (control). For any variable V the total response is given by

$$\Delta_{\text{total}} V = V_{\text{test}} - V_{\text{control}}. \quad (1)$$

Grid boxes where the disturbed fraction has changed experience local and nonlocal responses, while those

with no change in disturbed fraction only experience the nonlocal response:

$$\Delta_{\text{total}} V = \Delta_{\text{non-local}} V + \Delta_{\text{local}} V. \quad (2)$$

And at grid boxes with no change in disturbed fraction D ,

$$\Delta_{\text{local}} V = 0, \quad \text{where} \quad \Delta_{\text{total}} D = 0, \quad (3)$$

so that

$$\Delta_{\text{non-local}} V = \Delta_{\text{total}} V, \quad \text{where} \quad \Delta_{\text{total}} D = 0. \quad (4)$$

The nonlocal response at grid boxes experiencing no land-use change is linearly interpolated to all grid boxes and then it is subtracted from the total response, leaving only the local response at grid boxes that do experience land-use change:

$$\Delta_{\text{local}} V = \Delta_{\text{total}} V - \Delta_{\text{non-local, interpolated}} V, \quad \text{where} \quad \Delta_{\text{total}} D \neq 0. \quad (5)$$

The difference in disturbed fraction, $\Delta_{\text{total}} D$, does not necessarily equate to a difference in woody PFT cover, $\Delta_{\text{total}} W$; the implementation of land-use change causes a transition from a woody, grass, and bare soil mixture to a grass and bare soil mixture. We address this problem by dividing the local response by the change in woody PFT cover, producing a sensitivity to change in woody PFT cover. At some locations, the change in woody PFT cover is small, which can lead to very large sensitivities; we arbitrarily remove locations where the change in woody PFT cover is less than 10% of the grid box. This means that we do not estimate a response at all grid boxes. To produce an estimate of the impact of

deforestation, we reverse the sign of the metric, effectively multiplying it by a change in woody PFT cover of -1 :

$$\Delta_{\text{local, deforestation}} V = -\frac{\Delta_{\text{local}} V}{\Delta_{\text{total}} W}, \quad \text{where} \\ \Delta_{\text{total}} W < -0.1 \quad \text{and} \quad \Delta_{\text{total}} D \neq 0. \quad (6)$$

The experiment is then repeated, with the disturbed fraction pattern shifted by one grid box (test B; Fig. 1), allowing us to estimate the local response at the grid boxes not tested by the first chessboard pattern.

Results presented in this paper are ensemble-mean local responses to deforestation, $\Delta_{\text{local, deforestation}} V$, that combine information from all four ensemble members and both checkboard disturbance patterns; for convenience we drop the subscripts and use the notation ΔV .

Using prescribing SSTs, instead of the atmosphere–ocean coupled setup of HadGEM2-ES, is not expected to alter the results, because the large-scale climate responses that ocean feedbacks can affect, are removed by the analysis methodology.

Winckler et al. (2017) showed that the estimation of the local response is independent of the pattern of land-use change used, but that using a chessboard pattern minimizes errors due to interpolation. The method of Winckler et al. (2017) includes two interpolation steps: interpolation of the nonlocal response [Eq. (5)] and interpolation of the local response ($\Delta_{\text{local}} V$). Instead of interpolating $\Delta_{\text{local}} V$, we repeat the analysis using the alternative chessboard disturbance pattern (test B) and this removes some potential errors caused by interpolation.

The main difference between our method and that of Winckler et al. (2017) is that HadGEM2-ES includes a DGVM to determine land cover, while Winckler et al. (2017) forced their model with land cover. Forcing the model with disturbed fraction instead of land cover requires an extra analysis step [Eq. (6)] in order to produce a metric that is directly comparable to the observational estimates.

c. Surface temperature budget

We calculate the local response in surface temperature (T_s), albedo (α), downward shortwave radiation (R_{SWdn}), downward longwave radiation (R_{LWdn}), latent heat flux (L), and sensible heat flux (H). Again following Winckler et al. (2017), we use the energy budget decomposition of Luyssaert et al. (2014) to convert the flux responses into their impacts on surface temperature. The Luyssaert et al. (2014) budget includes an available energy term, which we expand into components due to changes in α , R_{SWdn} , and R_{LWdn} . The α response is

multiplied by the climatological seasonal cycle of R_{SWdn} from the control simulations in order to convert it into a measure of change in the upward shortwave radiation response. The budget also includes a residual term, which includes the ground heat flux:

$$\Delta T_s = a \Delta R_{\text{SWdn}} + a \Delta R_{\text{LWdn}} - a R_{\text{SWdn}} \Delta \alpha - a \Delta L \\ - a \Delta H - \text{residual}, \quad (7)$$

where

$$a = (4\epsilon\sigma T_s^3)^{-1}, \quad (8)$$

σ is the Stefan–Boltzmann constant, and ϵ , the emissivity, has a constant value of 0.97 as in HadGEM2-ES.

We can estimate how much of the latent and sensible heat flux responses is caused by the reduced available energy and how much is caused by changes in the efficiency of the turbulent heat fluxes at removing energy from the surface. The portion of each upward energy flux response caused by the change in available energy is estimated as the local available energy response (ΔQ) multiplied by the ratio (e.g., L/Q) of each flux to available energy in the control simulation [Eq. (9)]. The portion due to changes in efficiency is calculated as the control simulation available energy Q multiplied by the local response of the ratio term [e.g., $\Delta(L/Q)$]. There is also a residual term caused by both components changing simultaneously:

$$\Delta L = Q \Delta \left(\frac{L}{Q} \right) + \Delta Q \left(\frac{L}{Q} \right) + \text{residual}, \quad (9)$$

where

$$Q = R_{\text{SWdn}} + R_{\text{SWup}} + R_{\text{LWdn}}. \quad (10)$$

d. Evaluation

HadGEM2-ES is evaluated by calculating zonal-mean climatological seasonal cycles of biases against the observational estimates of Li et al. (2015) and Duveiller et al. (2018a). The comparison to the Li et al. (2015) dataset is straightforward, because estimates are of the response to deforestation and are provided as a zonal-mean climatological seasonal cycle with 1° latitudinal resolution and monthly time resolution (Li et al. 2016). The Duveiller et al. (2018a) data estimate the responses to transitions between six different surface cover types and are provided on a spatial grid, to evaluate HadGEM2-ES we compare similar transitions on a spatial grid and then take a zonal mean.

The Duveiller et al. (2018a) product is provided as a monthly climatology on a 1° spatial grid (Duveiller et al. 2018b). To compare to HadGEM2-ES, we identify the

TABLE 2. Vegetation transitions in HadGEM2-ES and Duveiller et al. (2018a).

HadGEM2-ES transition	Duveiller et al. transition
Broadleaf tree to C3 grass	Evergreen tree to crop
	Evergreen tree to grass
	Deciduous tree to crop
	Deciduous tree to grass
Needleleaf tree to C3 grass	Needleleaf tree to crop
	Needleleaf tree to grass
Shrub to C3 grass	Shrub to crop
	Shrub to grass

dominant PFT transition within each model grid box and regrid the observations to the model grid. We exclude grid boxes where the same transition is not present in both model and observations, and we exclude latitudes with fewer than 10 comparable grid boxes. The Duveiller et al. (2018a) vegetation classifications are not identical to our PFTs, but they are similar, Table 2 lists the model and observational transitions that we compare.

Li et al. (2015) estimate ΔT_s , $\Delta\alpha$, and daytime and nighttime ΔET , and we use the mean of the daytime and nighttime ΔET . Duveiller et al. (2018a) estimate ΔL , the response of the upward longwave radiation flux (ΔR_{LWup}), and the response of the upward shortwave radiation flux (ΔR_{SWup}). They assume that downward radiation fluxes do not respond to land-cover change and then close the energy budget with a residual term

that combines responses of H and the ground heat flux and we use this term to evaluate ΔH .

Both studies apply a space-for-time approximation to 0.05° Moderate Resolution Imaging Spectroradiometer (MODIS) data, where differences in surface climate between pixels are attributed to differences in land cover and used as a proxy for land-cover change. Li et al. (2015) use data from 2002 to 2013 and Duveiller et al. (2018a) use data from 2008 to 2012. To close the energy budget, Duveiller et al. (2018a) also use data from the Clouds and the Earth's Radiant Energy System instrument. Surface temperature and albedo are closely tied to radiation measurements made by MODIS, but it should be noted that ET relies on a surface energy balance model and meteorological reanalysis data (Mu et al. 2011).

3. Results

a. Understanding the model response to deforestation

Deforestation reduces the shortwave radiation absorbed by the surface (Fig. 2). The total turbulent heat flux is also reduced; however, there is a change in partitioning between the latent and sensible heat fluxes causing the sensible heat flux to increase in parts of the tropics (Figs. 2c,d). The shortwave response is largest in the high latitudes, and the latent heat flux response is largest in the tropics. The sensible heat flux response is negative at high latitudes and positive in the moist tropics, while in dry regions it is strongly negative.

FIG. 2. The local response of the surface fluxes of (a) net shortwave radiation (downward positive), (b) net longwave radiation (downward positive), (c) upward latent heat flux, and (d) upward sensible heat flux.

FIG. 3. Surface temperature budget of the local response to deforestation in HadGEM2-ES. (a) The local temperature response and its components due to responses in (b) albedo, (c) latent heat flux, (d) sensible heat flux, (e) downward radiation fluxes, and (f) the residual term [see Eq. (7)].

The local response of downward longwave radiation is small (not shown), and the net longwave response is primarily caused by surface temperature change. In dry regions, where there is a large reduction in sensible heat, the surface warms and the longwave response is negative. Outside of the dry regions, the surface cools and the longwave response is positive.

The energy budget responses are converted into surface temperature budget responses using Eq. (7). The net surface temperature response is a balance of three large, opposing, flux responses (Fig. 3). The residual term is small (Fig. 3f). Radiative cooling dominates the high-latitude response as expected, and it also dominates the midlatitude response. Sensible heat flux dominates in some drier areas of the midlatitudes and tropics. In the tropics, warming caused by the latent heat flux response is often greater than the albedo-driven cooling, as expected; however, the increase in the sensible heat flux results in a net cooling in the tropics.

Deforestation increases albedo everywhere, but the effect is much stronger at higher latitudes where removing taller vegetation un.masks snow (Fig. 3b). The

albedo response is strongest for the transition from needleleaf tree, which has the lowest albedo of all PFTs and most effectively masks snow on the ground because it is evergreen (Table 1). In the far north, reduced insolation limits the effect of albedo changes on temperature. At high latitudes an increase in downward shortwave radiation has a warming effect (Fig. 3e), but it is not large enough to change the net temperature response (see the online supplemental material). The latent heat flux response causes warming everywhere, but the sensible heat flux response is mixed, causing warming in some locations and cooling in others (Fig. 3d). At high latitudes, the sensible heat flux is reduced, warming the surface and acting as the main process countering the albedo-driven cooling. In the moist tropics, the sensible heat flux is increased, cooling the surface; although the magnitude of the response is small, it is enough to ensure a net cooling in the moist tropics (Fig. 3a). In drier regions, there is a strong reduction in sensible heat flux resulting in a substantial net warming despite the albedo response.

FIG. 4. Changes in surface energy loss fluxes, due to changes in available energy and changes in partitioning between fluxes. Three energy loss fluxes are shown: (top) latent heat, (middle) sensible heat, and (bottom) upward longwave radiation. For each loss flux the (a),(e),(i) total change is shown along with the components due to (b),(f),(j) changes in available energy and (c),(g),(k) changes in partitioning, along with (d),(h),(l) a residual term as described by Eq. (9).

We find that changes in the efficiencies of the turbulent fluxes explain almost the entire pattern of the total responses of each turbulent flux (Fig. 4), with the other terms in Eq. (9) being small. Only a small fraction of available energy is used to drive the turbulent fluxes ($L/Q = 0.12$, $H/Q = 0.05$), with the majority being used to produce the upward longwave radiation flux ($R_{LWup}/Q = 0.83$). The reduction in available energy therefore translates to small drops in the turbulent fluxes and a large reduction in R_{LWup} . For the turbulent fluxes, changes in the fraction of available energy used to drive each loss flux, is much more important. The fraction of available energy used for R_{LWup} increases and the fraction used for turbulent fluxes decreases; this suggests that the reduction in roughness length caused by deforestation is of leading order importance in determining the surface temperature response. In the tropics, the fraction of energy lost as sensible heat increases despite the reduced roughness length and must be caused by the reduction in latent heat flux. The reduction in latent heat flux is not only caused by reduced roughness length and is partly due to some other mechanism.

Figure 5 shows evidence of three important plant physiology factors. Roughness length (Fig. 5a) is reduced everywhere, which will cause lower turbulent fluxes. Gross primary productivity (GPP) is tightly linked to transpiration. In HadGEM2-ES converting tropical forest to grassland actually increases GPP (Fig. 5b), which must act to increase the latent heat

flux. While there is no net increase in latent heat flux the GPP response pattern is consistent with the latent heat flux response pattern, for example, the lower latent heat response seen in the Amazon compared to other regions of South America (Fig. 2c). Transpiration is also linked to plant-available water, and trees have deeper roots that can access more soil moisture. Deforestation results in increased deep soil moisture (Fig. 5d), because it can no longer be extracted by vegetation, but reduced surface soil moisture that is now in greater demand by vegetation (Fig. 5c). The larger reduction in latent heat flux seen in the tropics may be caused by change in soil moisture, or by atmospheric feedbacks; however, we have been unable to identify the mechanism responsible.

b. Evaluating the model response to deforestation

Figure 6 shows the comparison with the Li et al. (2015) dataset. The seasonality and magnitude of the surface temperature response is captured outside of a broad equatorial band (Figs. 6d–f). Within the equatorial band (20°S – 20°N), the observations show a strong warming, while the model has a very weak temperature response.

HadGEM2-ES captures the seasonality of the large high-latitude albedo response (Figs. 6a–c). The winter response is too strong, suggesting misrepresentation of snow–vegetation interactions. Near the equator, HadGEM2-ES predicts too large an albedo response and south of this, the response is too weak. To allow comparison with the turbulent flux evaluation below, we

FIG. 5. The local responses in (a) roughness length (m), (b) gross primary productivity (GPP; $\text{kg m}^{-2} \text{ yr}^{-1}$), (c) surface soil moisture (kg m^{-2}), and (d) deep soil moisture (kg m^{-2}). Surface soil moisture represents the top soil level (0.0–0.225-m depth), and deep soil moisture represents the lowest soil level (1.325–3.0-m depth).

estimate the error in ΔR_{SWup} by scaling the $\Delta\alpha$ error by R_{SWdn} from the control simulations (Fig. 7). We find biases of about 5 W m^{-2} north of 10°S and biases of about -2 W m^{-2} to the south. Larger biases are seen in high-latitude spring, but the winter albedo error is not apparent due to low insolation at this time.

HadGEM2-ES agrees with observations that deforestation reduces ET, but the model underestimates the magnitude of response and does not capture the correct variability with latitude and season (Figs. 6g–i). At high latitudes, the seasonality of response is in antiphase, with HadGEM2-ES predicting increased summer ET after deforestation when the observations show a strong reduction. The observed ET response is largest in the tropics; here HadGEM2-ES underestimates the ET reduction throughout the year.

Compared to the Duveiller et al. (2018a) dataset, the model captures the seasonality of the net radiation response ΔR_n at high latitudes ($>40^\circ\text{N}$), with a strong reduction during the snowy and well-lit spring months. However, the magnitude of the reduction is overestimated (Figs. 8a–i), consistent with the positive $\Delta\alpha$ bias (Fig. 6c). When snow is not present, at high latitudes during the summer and low latitudes throughout the year, the model underestimates the reduction in net radiation (Figs. 8d–l). This is consistent with the negative ΔT_s bias (Fig. 6f) causing too small an increase in R_{LWup} .

In snowy conditions (October–April, north of 40°N), deforestation is predicted to greatly reduce the latent heat flux, which is not observed. While in summer at high latitudes a small increase in latent heat flux is

predicted, when the observations show either no response (Figs. 9b,e) or a strong reduction (Fig. 9h). At lower latitudes, both model and observations show a reduced latent heat flux, but here the model underestimates the response and fails to capture its seasonality (Figs. 9g–l) or latitudinal variation (Figs. 9j–l).

At high latitudes, there is an observed reduction in sensible heat flux in response to deforestation and HadGEM2-ES captures this response (Figs. 10a–f). At low latitudes, the model fails to capture the seasonality of response, resulting in large negative/positive biases in the northern/southern tropics during May–September (Figs. 10g–i). South of about 15°S , a year round increase in sensible heat flux is observed but not simulated (Figs. 10j–l).

HadGEM2-ES predicts reductions in downward radiation fluxes, but the Duveiller et al. dataset assumes that these terms do not respond to land-use change. We test the significance of these terms by removing their effects on surface temperature and net radiation and find no qualitative difference in the results of the evaluation (Figs. S2 and S3 in the online supplemental material).

We summarize the model evaluation by considering four latitude bands, and Tables S1–S4 in the supplemental material show biases averaged over each band. North of 40°N , albedo-driven cooling is damped by a reduced sensible heat flux resulting in a net cooling; the model captures magnitude and seasonality of this response well, but over estimates the albedo-driven cooling throughout the year (model mean -0.60 K , bias -0.48 K ; Table S1).

FIG. 6. Time-latitude comparison of the response to deforestation in HadGEM2-ES and the Li et al. (2015) dataset. (a)–(c) Albedo, (d)–(f) surface temperature, and (g)–(i) evapotranspiration. Shown are (left) the HadGEM2-ES response, which is the local response per tree cover change, ΔV , as described in the methods section; (center) the Li et al. (2015) data; and (right) the model – observation difference.

FIG. 7. Error in upward shortwave radiation response estimated from comparison to the albedo response in the Li et al. (2015) dataset.

Between 10° and 40°N a strong reduction in evapotranspiration is observed, but not captured by the model and it seems likely that this is responsible for the model also failing to capture the strong warming observed (model mean +0.57 K, bias −0.57 K; Table S2). An overestimation of the albedo response also contributes to the underestimation of the warming response.

Between 10°S and 10°N the model predicts cooling when a large warming is observed (model mean −0.08 K, bias −3.01 K; Table S3). The error is caused by errors in both the radiative and turbulent responses. The overestimation of the albedo response causes a large increase in upward shortwave radiation and an anomalous increase in sensible heat flux also has a large cooling effect. The role of the latent heat flux response remains unclear, with differing results from the comparisons to the two observational datasets.

South of 10°S the observed warming is underestimated because ΔL is too small (model mean +0.50 K, bias −0.92 K; Table S4). Generally, the albedo response is overestimated everywhere and the turbulent responses are underestimated south of 40°N (Tables S2–S4), but overestimated north of 40°N (Table S1).

4. Discussion

Previous studies have found that HadGEM2-ES produces a strong cooling response to deforestation; here

we have found that the local component of the temperature response is also a cooling in most regions. Deforestation of the moist tropics causes cooling, which is inconsistent with other models and with observational estimates. The Max Planck Institute Earth System Model (MPI-ESM) was also found to substantially underestimate the tropical warming response (Winckler et al. 2017); however, the error in the sign of HadGEM2-ES's temperature response makes it much more significant. The prediction of a biophysical cooling response to tropical deforestation could be used to support arguments for more deforestation, when in reality tropical deforestation will have a detrimental effect on local climate. The result that in HadGEM2-ES the local component of the temperature response greatly underestimates tropical warming confirms that there are errors in the representation of surface processes and not only in large-scale feedbacks. This narrows the investigation into the mechanisms at fault and focuses the development of a solution.

The albedo responses of HadGEM2-ES is broadly consistent with observational estimates and other modeling studies: deforestation increases albedo everywhere with larger changes at high latitudes than in the tropics. Multimodel studies predict smaller reductions in available energy (de Noblet-Ducoudré et al. 2012; Brovkin et al. 2013) and smaller increases in albedo (Lejeune et al. 2017) than we find, probably because they impose less deforestation than is used here. GCM simulations of total deforestation predict tropical mean albedo increases of up to 0.028 and high-latitude mean increases of up to 0.130 (Deveraju et al. 2018), HadGEM2-ES has stronger albedo responses of 0.033 and 0.144, respectively. Previous studies have found that the albedo response to land-use change is larger in HadGEM2-ES than in other models (Davies-Barnard et al. 2014b; Kumar et al. 2013) and have identified this as a reason for the model's unusually strong cooling response. Our evaluation against the Li et al. (2015) dataset supports this hypothesis. The R_{SWup} error is the dominant reason for the overestimation of high-latitude cooling and is also a major cause of the tropical temperature error. Our comparison of the R_{SWup} , L , and H errors is not entirely fair because of different sets of grid boxes are used to compare to different datasets. In particular, the model produces different responses in dry and moist regions and the mixture of dry and moist regions sampled may change the zonal-mean biases. A further consideration is that our R_{SWup} error relies on the model simulation of R_{SWdn} and may be caused by biases in R_{SWdn} as well as in albedo.

Andrews et al. (2017) showed that the radiative forcing concept can be used to explain the temperature

FIG. 8. Time–latitude comparison of net radiation response (ΔR_n) to deforestation in HadGEM2-ES and in the Duveiller et al. (2018a) dataset. Transitions are (a)–(c) from shrub to grass, (d)–(f) from needleleaf tree to crop, (g)–(i) from deciduous tree to crop, and (j)–(l) from evergreen tree to crop. Shown are (left) the HadGEM2-ES response, which is the local response per tree cover change, ΔV , as described in the methods section; (center) the Duveiller et al. data, and (right) the model – observation difference.

response to historical land-use change in HadGEM2-ES. Our results show that while the net temperature response may be correlated with changes in shortwave radiation, the nonradiative fluxes are also of leading-order importance. When land-use change occurs outside of the midlatitudes, the correlation between radiative response and temperature breaks down, as Andrews et al. (2017) speculated. Over most of the world, deforestation is observed to increase albedo but to also increase temperature, therefore the turbulent flux response must be the dominant process determining the temperature response to land-use change. The HadGEM2-ES results are consistent with the observational evidence for a large turbulent flux response; however, the magnitude of the response is too small in the model.

The turbulent flux responses are not simply a feedback on the reduction in available energy caused by the albedo response; turbulent fluxes are reduced because of a reduction in roughness length and in the tropics, there is also a change in the Bowen ratio (ratio of H to L ;

Bonan 2008). Devaraju et al. (2018) find that, before atmospheric feedbacks are included, reduced roughness length is the dominant mechanism of response to deforestation in most models. Davin and de Noblet-Ducoudré (2010) simulated global deforestation in the L'Institut Pierre-Simon Laplace (IPSL) climate model and found that reduced roughness length was the most important process countering albedo-driven cooling. Changes in Bowen ratio were important in some places and did dominate in some tropical forest regions, which is consistent with the HadGEM2-ES results. Reductions in roughness length in HadGEM2-ES (Fig. 5a) are similar to those in the IPSL climate model (from -1.0 to -1.5 m in the tropics and from -0.1 to -1.0 m in the midlatitudes), but smaller than those observed at paired sites (from -0.96 to -3.16 m; Luyssaert et al. 2014). Increasing the change in roughness length in line with Luyssaert et al. (2014) would cause a larger warming response and smaller temperature errors.

Brovkin et al. (2013) report that HadGEM2-ES has a relatively strong latent heat response in South America,

FIG. 9. As in Fig. 6, but for latent heat flux (L).

although it is not an outlier in this respect. Duveiller et al. (2018a) find ΔL can be as large as -30 W m^{-2} in the tropics and is generally less than -10 W m^{-2} in the midlatitudes. HadGEM2-ES also produces a larger ΔL in the tropics than in the midlatitudes, but it underestimates the magnitude of variation. Generally, ΔL is underestimated and this is the dominant cause of the temperature error in the midlatitudes. In the tropics, the two observational datasets produce different conclusions, ΔET is greatly underestimated, but the error in ΔL is relatively small. This difference may be caused by the different subsets of grid boxes used in each evaluation.

The change in partitioning between L and H in response to land-use change varies a lot between GCMs (Lejeune et al. 2017; de Noblet-Ducoudré et al. 2012). In HadGEM2-ES, the change in H is as important as the change in L . The sensible heat flux can increase or decrease in response to deforestation: smaller roughness length causes reductions in sensible heat flux and lower surface resistance to moisture transport causes increases in sensible heat flux. Malyshev et al. (2015) also find a mixed sign of ΔH in the Geophysical Fluid Dynamics Laboratory Earth System Model. At high latitudes, the Duveiller et al. (2018a) dataset supports the reduction in

sensible heat flux seen in HadGEM2-ES. There is some observational evidence of an increase in H at lower latitudes that counteracts the strong reductions in L (Figs. 9k and 10k, south of 15°S), although not over such a large area as in the model (Figs. 2c,d). Luyssaert et al. (2014) found that warming due to a reduction in H was the dominant mechanism in the midlatitudes, but in HadGEM2-ES the H reduction is not large enough to overcome the albedo-driven cooling. The largest reduction in H is seen in dry regions, where the initial H is large and it causes a strong warming response. A large ΔH was also responsible for the strong warming of arid regions in MPI-ESM (Winckler et al. 2017) and other studies have also found the strongest warming in response to deforestation happens in dry regions (Alkama and Cescatti 2016; Bright et al. 2017).

Comparing to the results of Winckler et al. (2017) shows that HadGEM2-ES is behaving quite differently from MPI-ESM. First, MPI-ESM produces a warming throughout the tropics, while HadGEM2-ES does not; second, the mechanisms causing the temperature response differ. At most latitudes, MPI-ESM has opposing changes in L and H , which suggest that roughness length is not the primary mechanism, while in HadGEM2-ES,

FIG. 10. As in Fig. 6, but for sensible heat flux (H).

both turbulent fluxes are reduced, which is consistent with reduced roughness length. The two models are structurally different in their implementation of vegetation dynamics and land-use change (Clark et al. 2011; Reick et al. 2013); however, the idealized simulations used here and in Winckler et al. (2017) remove these differences. There are no processes included in only one of the models that would obviously cause a different biophysical response to land-use change.

In both the HadGEM2-ES predictions and the observational datasets, the local responses are produced by changes in surface properties and atmospheric feedbacks. The inclusion of atmosphere feedbacks in the model should provide a fairer comparison to the observations than methods that do not allow for feedbacks in response to land-use change (e.g., Meier et al. 2018; Duveiller et al. 2018c; Malyshev et al. 2015). However, the lower spatial resolution of HadGEM2-ES, compared to the satellite data, may result in different atmospheric feedbacks being present (Pielke et al. 1998). HadGEM2-ES has a resolution of about 140 km, while the satellite data are used at a 5.5-km resolution. The mechanisms of feedback between the surface and the bulk properties of the boundary layer are similar at

both scales, because neither scale resolves turbulent eddies. The representation of convection and clouds in HadGEM2-ES is not appropriate for estimating feedbacks at the 5.5-km scale, and so these feedback mechanisms may not be comparable in the model and observational data (Prein et al. 2015). Cloud feedbacks will affect the response of downward radiation fluxes: we have quantified these responses in the model and found that they do not qualitatively affect our results.

In GCM simulations of realistic scenarios, differences in the implementation of land-use change between models has been identified as a major reason for the large spread in the climate responses to land-use change. For example, for a given scenario, models will produce not only a different sensitivity to tree cover change but also different amounts of tree cover change (Pitman et al. 2009). The idealized simulations we use avoid some of the model-specific implementation practices; because we apply a total deforestation, tree cover change is less sensitive to the order in which natural PFTs are removed, or to the choice of gross or net transitions (Wilkenskjeld et al. 2014). These implementation methods can still influence our result, because they affect the historical simulation from which we take our

initial conditions. HadGEM2-ES uses a DGVM to determine vegetation distribution. The extent of tree cover simulated is not important because we calculate a sensitivity to change in tree cover. However, the specific grass and woody PFTs simulated are still a source of intermodel differences. The most important difference from other models implementation of land-use change is probably the lack of land management and crop-specific physiology. Representation crop physiology and management will affect the annual mean and seasonality of the response to deforestation by affecting roughness, ET, and albedo (Bonan 2008; Lobell and Bonfils 2008; Mahmood et al. 2008; Erb et al. 2017; Malyshev et al. 2015; de Noblet-Ducoudré et al. 2012). Wood harvest affects forest biophysics and so alters the response to deforestation; wood harvest can reduce albedo and ET and ultimately have as large a temperature effect as deforestation (Erb et al. 2017; Luyssaert et al. 2014).

The model overestimates the albedo response causing too small a warming response and to reduce this error the difference between the PFT's albedo parameters should be reduced. An evaluation of the control simulations would indicate whether grasses are too bright or trees too dark. Where there is no snow, the latent heat flux response is usually underestimated, partly because grass GPP is too high. Meier et al. (2018) found the Community Land Model also underestimated the latent heat flux response to deforestation, they increased ΔL by altering the productivity of different PFTs and how each accesses soil moisture. It seems likely that the same solutions would work in HadGEM2-ES. Once albedo and ET are improved, the more complex problems of snow interactions and partitioning between L and H could be addressed. The albedo impacts of vegetation masking snow can simply be tuned (see Table 1), but a more thorough approach would also evaluate the background snow distribution and its seasonality. The two turbulent fluxes could be simultaneously tuned by varying the stomatal resistance, as described above, and by varying the sensitivity of turbulent transport to vegetation height. With any development of a GCM, there are likely to be impacts on the broader system, not just on its response to land-use change, and a balance must be found between improving one process to the detriment of another.

5. Conclusions

HadGEM2-ES is an outlier among CMIP5 models because of its cooling response to deforestation. Our evaluation confirms that this response is unrealistic and shows it is caused by both too strong an albedo response and too weak an ET response. The weak ET response

means that HadGEM2-ES will continue to predict too much cooling under future scenarios, even if land-use change occurs in the tropics or snow cover is reduced due to climate change. The model includes the same mechanisms of response as other models, but gets the relative magnitudes of the mechanisms wrong. This means that the changes in the strengths of the mechanisms under future climates may still be informative and that the model may not require a great deal of development in order to correct its temperature response. The analysis provided a useful global evaluation of the representation of land-use change, but it would be improved by including smaller scales (regional, seasonal, and diurnal) and by the availability of an observational estimate of the shortwave response. The analysis should be repeated for the CMIP6 model U.K. Earth System Model, version 1 (UKESM1), the successor to HadGEM2-ES. While no developments to UKESM1 were aimed at modifying its biophysical response to land-use change, UKESM1 does include a number of developments that may alter the response, such as new set of PFTs (Harper et al. 2016), a new snow scheme (Walters et al. 2019), and adjustments to the masking of snow by vegetation (Sellar et al. 2019, manuscript submitted to *J. Adv. Model. Earth Syst.*).

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