Limitations of WRF land surface models for simulating land use and land cover change in Sub-Saharan Africa and development of an improved model (CLM-AF v. 1.0)

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- 10 Abstract. Land use and land cover change (LULCC) impacts local and regional climates through various biogeophysical processes. Accurate representation of land surface parameters in land surface models (LSMs) is essential to accurately predict these LULCC-induced climate signals. In this work, we test the applicability of the default Noah, Noah-MP, and CLM LSMs in the Weather Research and Forecasting Model (WRF) over Sub-Saharan Africa. We find that the default WRF LSMs do not accurately represent surface albedo, leaf area index, and surface roughness in this region due to various flawed assumptions,
- 15 including the treatment of the MODIS woody savanna LULC category as closed shrubland. Consequently, we developed a WRF CLM version with more accurate African land surface parameters (CLM-AF), designed such that it can be used to evaluate the influence of LULCC. We evaluate meteorological performance for the default LSMs and CLM-AF against observational datasets, gridded products, and satellite estimates. Further, we conduct LULCC experiments with each LSM to determine if differences in land surface parameters impact the LULCC-induced climate_<u>responsessignals</u>. Despite clear
- 20 deficiencies in surface parameters, all LSMs reasonably capture the spatial pattern and magnitude of near surface temperature and precipitation. However in the LULCC experiments, inaccuracies in the default LSMs result in illogical localized temperature and precipitation elimate-changessignals. Differences in thermal elimate-changessignals between Noah-MP and CLM-AF indicate that the temperature impacts from LULCC are dependent on the sensitivity of evapotranspiration to LULCC in Sub-Saharan Africa. Errors in land surface parameters indicate that the default WRF LSMs considered are not suitable for
- 25 LULCC experiments in tropical or Southern Hemisphere regions, and that proficient meteorological model performance can mask these issues. We find CLM-AF to be suitable for use in Sub-Saharan Africa LULCC studies, but more work is needed by the WRF community to improve its applicability to other tropical and Southern Hemisphere climates.

1 Introduction

Land use and land cover change (LULCC) has various biogeophysical impacts on climate by altering land surface albedo, 30 evapotranspiration, and surface roughness that in turn alter atmospheric circulations, energy budgets, and hydrologic cycles

(Pielke et al., 2011; Mahmood et al., 2014; Bright 2015; Smith et al., 2016; Quesada et al., 2017). Results from global modelling studies indicate a global reduction in surface temperatures due to deforestation, but the impacts of LULCC vary by region and season (e.g., Zhao and Pitman 2002; Lamptey et al., 2005; Lejune et al., 2017). Such studies have shown a latitudinal difference in the temperature response to deforestation, where higher latitudes experience cooling in winter as less tree cover brightens the surface when snow is present, and lower latitude tropical regions experience warming in response to a reduction

35 brightens the surface when snow is present, and lower latitude tropical regions experience warming in response to a reduction in evaporation (e.g., Longobardi et al., 2016; Quesada et al., 2017). This LULCC latitudinal dependence has been shown to occur in observations as well (Zhang et al., 2014).

Impacts of LULCC are simulated in climate and numerical weather prediction models through <u>a the</u> land surface model (LSM). Differences in LSM parameterizations can lead to significantly different <u>simulated</u> climate responses to LULCC in both

- 40 magnitude and sign (e.g., Olsen et al., 2004; Boisier et al., 2012; Burakowski et al., 2016), even when little difference exists in the mean simulated climate (Crossly et al., 2000). Errors and uncertainties in LSMs occur in response to errors in LULC classification maps and the wayin the prescription of land use properties, such as vegetation distributions and surface albedo, are prescribed (e.g., Lu and Shuttleworth, 2002; Olsen et al., 2004; Ge et al., 2007; Boisier et al., 2012; Boisier et al., 2013; Boysen et al., 2014; Meng et al., 2014; Hartley et al., 2017; Bright et al., 2018). As a result, improving LULC maps and LSM
- 45 parameters has been shown to significantly reduce biases and errors within global and regional climate models (RCMs) (e.g., Tian et al., 2004b; Kang et al., 2007; Lawrence and Chase, 2007; Lawrence and Chase, 2009; Moore et al., 2010; Karri et al., 2016; Thackeray et al., 2019). Having accurate representations of these parameters is especially important in regions with widespreadlarge surface heterogeneity, such as East Africa (Ge et al., 2008).
- Sub-Saharan Africa is a region of particular interest for simulating LULCC because it has already experienced dramatic LULCC (e.g., Collier et al., 2008), which has been shown to alter the West African monsoon system (e.g., Charney, 1975; Xue and Shakula, 1993; Abiodun et al., 2008; Wang et al., 2017). Various ensembles of RCMs have been applied to study the climate of Africa as part of both the COordinated Regional climate Downscaling Experiment (CORDEX) (e.g., Nikulin et al., 2012; Gbobaniyi et al., 2014; Kim et al., 2014; Mounkaila et al, 2015; Endris et al., 2016; Diasso and Abiodun, 2017; Adeniyi and Dialu, 2018; Odoulami et al., 2019) and the West African Monsoon Modeling and Evaluation Project Experiments
- 55 (WAMME) (e.g., Wang et al., 2016; Xue et al., 2016). Included as part of these ensemble modelling projects is the Weather Research and Forecasting (WRF) Model (e.g., Xue et al., 2016; Fita et al., 2019). The WRF model is a state-of-the-art numerical weather prediction model designed to be applicable in multiple world regions, across multiple spatial scales, and for short-term forecasting to longer term regional climate simulations (Skamarock and Klemp, 2008). Multiple studies have tested the sensitivity of the African climate to different ensembles of WRF physics
- 60 parameterizations, including LSMs (e.g., Pohl et al., 2011; Hagos et al., 2014; Noble et al., 2014; Alaka and Maloney, 2017; Noble et al., 2017; Igri et al., 2018). Results from these WRF simulations are somewhat contradictory as some studies found the National Centers for Environmental Prediction, Oregon State University, Air Force, and Hydrology Lab (Noah) LSM (Chen and Dudhia, 2001; Ek et al., 2003) to have superior performance compared to observations and reanalyse (Pohl et al., 2011; Igri et al., 2018), while others found no unambiguous difference in model performance between different LSMs (Noble

- 65 et al., 2014; 2017). In terms of LULCC applications, Hagos et al. (2014) found that WRF model configurations that simulate a climate which is too wet or too dry compared to observations and reanalysis do not produce a strong climate signal from LULCC over Africa. This weak signal is a result of the model falling into erroneous moisture or energy limited regimes. Despite these uncertainties, the Noah LSM is by far the most common LSM configuration applied in WRF studies over Africa (e.g., Vigaud et al., 2011; Cretat et al., 2012; Boulard et al., 2013; Ratna et al., 2014; Schepanski et al., 2014; Argent et al.,
- 70 2015; Diaz et al., 2015; Klein et al., 2015; Schepanski et al., 2015; Zheng et al., 2015; Arnault et al., 2016; Kerandi et al., 2017; Klein et al., 2017).
- In this work, we expand upon the current literature by testing five different LSM configurations within the WRF model for the purpose of evaluating the effects of LULCC over time on regional climate in Sub-Saharan Africa. First, we review four commonly used LSMs to determine if the LSM configurations reasonably represent land surface parameters such as albedo
- 75 and leaf area index (LAI). As shown below, we find that these four LSMs have significant deficiencies which limit their capabilities in applications to LULCC in this region. Consequently, we then detail how we modify one LSM for use in this study. We then evaluate the five WRF LSM configurations against available meteorological observations, reanalysis, and satellite estimates to determine how well they simulate the current climate of Sub-Saharan Africa. To the authors' knowledge, this is the first time the surface parameters of these LSMs have been robustly assessed is Sub-Saharan Africa. Finally, we
- 80 simulate the effects of LULCC over time on the simulated regional climate, and how these climate responses differ when using different LSMs. Understanding the deficiencies in how LSMs represent LULCC is key to accurately representing regional climate signals that impact not only climate change investigations, but also coupled natural and human system research regarding human decision making, air quality, and human/ecosystem health interactions.

2 WRF description and configurations

- 85 This study uses the WRF model version 3.9.1.1 (WRFv3.9.1.1), configured as shown in Table 1, to simulate the regional meteorology and climate within Sub-Saharan Africa. We define a Sub-Saharan Africa domain that ranges from ~19° N 35° S latitude and ~19° W 64° E longitude (Fig. 1) with a horizontal grid spacing of 36 km and 30 vertical layers from the surface to 50 hPa. Physics parameterizations common to all simulations include: the New Tiedtke cumulus parameterizationparametrization scheme (Zhang et al., 2011), the aerosol-aware Thompson microphysics scheme (Thompson and Eidhammer, 2014), the RRTMG long and shortwave radiation schemes (Clough et al., 2005; Iacono et al., 2008), and the MYNN surface/ planetary boundary layer physics (Nakanishi and Niino, 2004; 2006). These physics combinations were selected because they represent some of the most advanced science within the WRF model, and these physics options performed the best when validated against observations/satellite estimates relative to other physics options tested (not shown). All simulations also take advantage of the CLM4.5 lake model, which is calibrated to prognostically simulate lake conditions
- 95 for the African Great Lakes by adjusting the lower bound lake temperature from 4°C to 24°C consistent with Lake Victoria temperature profiles (Nyamweya et al., 2016). Meteorological initial and boundary conditions for the simulations are obtained

from the European Centre for Medium-Range Weather Forecasts Interim reanalysis (ERA-Interim), with the variables used listed in Table S1 (Dee et al., 2011). Because LULC inputs change each year, each every model year is simulated modelled individually, preceded by a three-month spin-up period that is discarded to allow the model to reach equilibrium and minimize the impact of initial conditions on the simulations.

2.1 WRF land surface model descriptions

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Here we briefly describe four commonly-used WRF LSM configurations used in this study and differences between them: the Noah LSM; the Noah LSM using satellite derived albedo and LAI (Noah-Sat); the Noah Multi-Parameterization LSM (Noah-MP) (Niu et al., 2011); and the default Community Land Surface model (CLM-D) (Subin et al., 2011; Jin and Wen, 2012; Lu and Kueppers, 2012). We focus on the different ways in which the LSMs prescribe and treat surface parameters such as LAI, albedo, and surface roughness length (RL) based on the Moderate Resolution Imaging Spectroradiometer (MODIS) 21 land category data. In addition to the LSMs used in this work, four other LSMs exist in WRF including: the five layer thermal diffusion scheme (Skamarock et al., 2008), the Rapid Update Cycle (RUC) LSM (Smirnova et al., 2016), the Pleim-Xiu (PX) LSM (Pleim and Xiu, 2003; Gilliam et al., 2007), and the Simplified Single Biosphere Model (SSiB) (Xue et al. 1991; Sun

- 110 and Xue, 2001). The five layer thermal diffusion scheme is omitted from these experiments because it is overly simplistic and not appropriate for climate scale studies. The RUC and PX LSMs are primarily designed for weather forecasting and for retrospective meteorological simulations commonly used as input for downstream air quality simulations, respectively. Although RUC and PX can be used for other applications, they require extensive detailed input data or data assimilation for peak performance (http://www2.mmm.ucar.edu/wrf/users/docs/user_guide_V3.9/users_guide_chap5.htm#Phys). Since this
- 115 detailed level of observational data is not available in Sub-Saharan Africa, both the RUC and PX scheme were excluded. The SSiB LSM is designed for climate applications, however it is also excluded both because its best performance occurs using its own LULC dataset and because it is not currently compatible with the MYNN surface/boundary layer parameterizations.

2.1.1 Noah LSM and Noah-Sat

In Noah and Noah-Sat are the same LSM with different configurations for how surface albedo and LAI are prescribed. Within
the Noah LSM, surface parameters including surface albedo, <u>RLroughness length</u>, and LAI are prescribed based on the dominant MODIS LULC category in each grid cell with temporal interpolation between maximum and minimum values depending on the time of year. The Noah-Sat configuration uses a monthly average satellite derived climatology of surface albedo and LAI supplied from the WRF preprocessing system (WPS), as a more detailed replacement of the LULC based prescribed values. Noah and Noah-Sat have no explicit canopy layer, and instead simulate evapotranspiration using a satellite derived green fraction variable from WPS to weight the contribution of direct soil evaporation and evapotranspiration from vegetation in each grid cell. The land surface and underlying soil is simulated using 4 soil layers 0.1, 0.3, 0.6, and 1.0 meters thick centered at 0.05, 0.25, 0.7, and 1.5 meters below the ground surface, respectively.

Noah-Sat is limited in its ability to simulate LULCC because LAI and surface albedo are decoupled from changes in the LULC categories, and temporally varying satellite LAI and albedo products are influenced by other climate variations or changes

- 130 apart from effects of LULCC. Noah is also preferable to Noah-Sat for future climate simulations because the albedo and LAI products Noah-Sat requires would have to be-_generated as separate independently varying fields from the future LULC projection. However, Noah-Sat is useful for meteorological evaluations, because it has the most accurate surface parameters in the current WRF modeling system. Therefore, Noah-Sat can be used as pseudo-observations to understand deficiencies in the surface parameter methodologies of the other WRF LSMs.
- Additionally, the Noah LSM can be configured using a mosaic tile approach to represent the influence of sub-grid scale variations in LULC. The representation of sub-grid LULC variability can significantly alter the responses of climate models to LULCC (e.g., Boone et al., 2016), but this functionality is not considered in these experiments since any underlying errors in albedo, LAI, and <u>RLsurface roughness from within</u> Noah would be present in both the mosaic tile and dominant LULC configurations. Also, this approach has been shown to primarily impact urban regions (Mallard and Spero, 2019), which are not resolved well at the grid spacing of this study.

2.1.2 Noah-MP

The Noah-MP model is an updated version of the Noah LSM with multiple-parameterization options utilizing the same soil level structure as the default Noah LSM. The major updates in Noah-MP include: the addition of an explicit one-layer vegetation canopy and three layer snowpack, a tiling scheme that separates vegetation and bare soil to better calculate the

- 145 surface energy balance, separating permeable and impermeable frozen soils, new runoff and groundwater schemes, and new dynamic vegetation model options (Niu et al., 20113; Xia et al., 2017 and references therein). In this study, Noah-MP is configured with the default settings, which are the most similar to the default Noah LSM. With these default settings, dynamic vegetation is disabled and LAI is prescribed based on the dominant MODIS LULC category in each grid cell using monthly profile values. Noah-MP simulates surface reflectance using a modified two stream radiation scheme that accounts for gaps
- 150 within the vegetation canopy and between canopy crowns (Yang and Friedl, 2003; Niu and Yang, 2004); however, in WRFv3.9.1.1 Noah-MP uses a simplification that assumes all bare soil albedos are comparable to loam soil. As a result, surface albedo within Noah-MP is solely a function of soil moisture and vegetation cover.

2.1.3 Default CLM (CLM-D)

The default configuration of CLM in WRF divides the land surface into five types: glacier, lake, wetland, urban, and vegetated.
Vegetated land is further split into up to four patches of 16 plant functional types (PFTs) with distinct physiological parameters.
Calculations within each vegetated grid are done at the PFT level and then aggregated for atmosphere interactions. CLM contains a single-layer vegetation parametrization with a sunlit and shaded canopy and uses the two stream approximation (Sellers, 1985) to calculate the energy balance within the canopy. Temperature and humidity varies between the ground surface, the canopy, and the leaf surface (Subin et al., 2001 and references therein). The land surface and soil properties in CLM are

simulated using 10 layers ~0.018, 0.028, 0.045, 0.075, 0.124, 0.204, 0.336, 0.554, 0.913, and 1.134 meters thick centered at ~0.007, 0.028, 0.062, 0.119, 0.212, 0.367, 0.620, 1.038, 1.728, and 2.86 meters below the ground surface.
 In the version of CLM available in WRF, each dominant MODIS land use category is assigned a distribution of PFTs with

distinct monthly profiles for LAI that do not vary geographically. A list of the CLM PFTs with the percentages for each vegetated MODIS land use category is shown in Table S21 of the Supplementary Material. Bare soil albedos in CLM are not constrained like within Noah-MP and therefore a broader range of surface soil albedos is considered.

- Some simplifications in WRF-CLM lead to difficulties applying the default version for the Sub-Saharan Africa domain. For example, Table S³² of the Supplementary Material shows the monthly LAI profiles used for each PFT within the default CLM configuration. These profiles clearly show Northern Hemisphere growing cycles, which is problematic for Sub-Saharan Africa because it contains regions with bimodal tropical growing cycles and Southern Hemisphere growing cycles. Additionally, the
- visible spectrum dry soil albedo for the sandiest soils in the default CLM treatment is 0.24, considerably less than the 0.25-0.45 albedo from MODIS satellite estimates over most the Sahara (Wang et al., 2004).

3 Updated CLM for Sub-Saharan Africa (CLM-AF)

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To address these limitations with CLM-D, and deficiencies of other LSMs described in the results section, the WRF-CLM LSM has been modified to include PFT distributions more representative of the Sub-Saharan Africa domain, regionally varying monthly profiles for LAI and stem area index (SAI), minor improvements in vegetation optical properties (e.g., leaf

reflectance), and scaled surface albedos for sandy soils to better match satellite estimates. Each of these modifications is described in detail below.

3.1 CLM-AF PFT plant functional type distributions

- Updated PFT distributions are derived from a global three <u>3</u> arc minute PFT dataset for the year 2001 generated by the National
 Center for Atmospheric Research for the Model of Emission of Gases and Aerosols from Nature version 2.1 (https://bai.ess.uci.edu/megan/versions/megan21). To determine the percentages of each PFT representative of the various MODIS land use categories in Sub-Saharan Africa, the global PFT dataset is regridded to the 36 km WRF domain, and the average coverage of each PFT within each WRF-MODIS 2001 dominant land use category is calculated. Updated PFT distributions were generated for broad leaf evergreen/deciduous forests, mixed forests, closed and open shrublands, woody
 savannas/savannas, grasslands, and cropland/mosaic croplands (i.e., MODIS categories 2, <u>4</u>, <u>5</u>, <u>6</u>-10, 12, and 14). This limited subset of categories is used because the remaining MODIS categories did not cover a large enough area to be the dominant land use at 36 km resolution. Since CLM allows for up to four PFT patches, the top four most abundant PFTs within each
- MODIS land use category are scaled to represent <u>100%</u> one hundred percent of the land use category, with an exception for some inconsistencies that occurred between the PFT and the evergreen broad leaf forest, savanna, and mosaic cropland MODIS

190 categories (see Supplementary Material <u>ST1</u>). The resulting updated PFT distribution for these CLM vegetated land use categories is shown in Table 2.

Most of the updated PFT distributions in Table 2 are consistent with the MODIS International Geosphere-Biosphere Programme (IGBP) category descriptions from Friedl et al. (2002) (Table S43, Supplementary Material). However, there are two minor inconsistencies with the closed shrubland and grassland categories. The closed shrubland category contains slightly less than 60% shrubs and 8% deciduous tropical trees, indicating there is some sub-grid scale overlap with nearby woody

savannas or forests. The grasslands category contains 18% shrubs, which is higher than the 10% from the description in Table S43, indicating some overlap with sub-grid scale shrublands. Overall, compared to the CLM-D PFT distributions in Table S21, the updated values in CLM-AF have greater heterogeneity in plant types and contain more herbaceous cover. The largest deviations from the CLM-D distribution occur with shrublands and woody savanna. CLM-D prescribes all shrublands as broad

200 leaf evergreen shrubs, while the global PFT dataset indicates that shrublands in Sub-Saharan Africa contain broad leaf deciduous temperate shrubs. Additionally, the woody savanna category PFT distribution in CLM-D is identical to closed shrubland. This is potentially a large source of error as woody savanna should have forest cover between 30_-60% (Table S43, Supplementary Material). This error is removed in the CLM-AF PFT distribution with the woody savanna category containing 38% tree cover.

205 3.2 CLM-AF LAI and SAI profiles

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Since the Sub-Saharan Africa domain covers a wide range of tropical and sub-tropical latitudes, a single domain-wide LAI and SAI monthly profile for each PFT is not appropriate. Here, geographically varying monthly LAI profiles are generated by <u>using_dividing the Sub-Saharan Africa domain into</u>-17 distinct regions based on bioclimate characteristics used in LULCC modelling of Sub-Saharan Africa (Fig._1_and₅ Table 3).₅. These bioclimate regions <u>are constructed for land use modeling</u>

210 purposes as discussed in Section 4.3, were generated because landscape dynamics are known to be different between broad climatic zones, needing separate modelling parameterizations parametrizations (Soares-Filho et al 2006). These same bioclimate regions are ideal for parameterizing LAI and SAI profiles because they divide the region based on climate characteristics that impact vegetation. However, the central wet (CW), central moist (CM), and northeast semi-dry (NESD) bioclimate regions used in the land use modeling span a large latitudinal range and are subdivided based on latitude to generate more meaningful LAI seasonal profiles (Supplementary Material ST2).

The updated LAI profiles within each bioclimate region are derived from both the 36 km regridded global PFT dataset and the monthly LAI climatology data, provided by WPS, used in the Noah-Sat configuration. LAI profiles are calculated only from a subset of grid cells within the WPS Sub-Saharan Africa LAI climatology, where the 36 km regridded PFT data indicates that a given PFT comprises eighty percent80% or more of the grid cell (PFT80). For the broad leaf evergreen tree PFTs, the median monthly LAI value of the PFT80 grid cells within each bioclimate or sub-bioclimate region is used as the monthly prescribed LAI value for that PFT. Median values are used in place of mean values for the broad leaf evergreen tree PFTs because several

small LAI values near the edges of forested regions lead to unrealistically small LAI values for the Congo and other forests 7

compared to the WPS LAI satellite derived climatology. For the remaining PFTs, the mean monthly LAI value of the PFT80 grid cells within each bioclimate or sub-bioclimate region is used as the monthly prescribed LAI value for that PFT. The monthly LAI profiles for each PFT within each bioclimate and sub-bioclimate region are listed in Tables S54-S110 of the 225 Supplementary Material. If no grid cells within a bioclimate or sub-bioclimate region meet the PFT80 criteria for a required PFT, then a reduced threshold of sixty percent60% of the grid cell is utilized to calculate the monthly LAI profile for that PFT. If no grid cells meet the sixty percent60% criteria, the LAI profile for that PFT within the bioclimate or sub-bioclimate region is assumed to be the same as a nearby comparable bioclimate region. These comparable "alternative" bioclimate regions are 230 listed in Table 4. The first nearby alternative bioclimate region used to generate LAI profiles for the missing PFTs is listed as

- "First Region" in Table 4. If the "First Region" does not have all the missing PFT LAI profiles then these profiles are obtained from a second nearby bioclimate region ("Second Region"). -Some additional adjustments were also required for the broad leaf evergreen tree PFTs to make these areas more consistent with the satellite_derived climatology (Supplementary Material ST3).
- 235 SAI represents the area of stems and dead leaves. The values of SAI are poorly known, but SAI is generally parameterized to have a minimum in winter and maximum in autumn for each land cover type (Tian et al., 2004a). Since no readily available data on SAI exists, SAI within CLM-AF is based on relating decreases in LAI (ΔLAI) from month to month to the SAI values in the CLM-D configuration. This is done by fitting a simple linear regression between Δ LAI and the SAI value in CLM-D. If the LAI is not decreasing from the previous month then the SAI value is assumed to be the minimum value from CLM-D.
- 240 These assumptions are consistent with the definition of SAI as dead leaves/litter will only increase when LAI is decreasing. However, it was not possible to generate linear regressions for evergreen trees and corn from CLM-D because the evergreen tree LAI profiles in CLM-D do not change from month to month and the corn SAI profile is equivalent to the corn LAI profile. These assumptions are not appropriate for Sub-Saharan Africa because of the longer tropical growing season and small seasonal fluctuations in evergreen tree LAI in the satellite climatology. Therefore, corn within CLM-AF is assumed to have
- the same SAI profile as C4 grass, and evergreen trees follow a similar equation as C4 grass with an intercept equivalent to the 245 appropriate evergreen tree minimum SAI value of 0.5. A list of the SAI profile equations and minimum SAI values in the CLM-AF configuration for the updated PFTs are listed in Table 5.

3.3 CLM-AF sandy soil albedo

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CLM-D sandy soil albedos and updated values for CLM-AF are listed in Table 6. CLM simulates surface albedo using a lookup table for different soil color classes with two different radiation streams that differentiate between saturated and dry soils. Albedo values in the sandy soils of the Sahara range from 0.25-0.45 (Wang et al., 2004), which is larger than the 0.24 dry sandy soil albedo in CLM-D. Accordingly, we increased the albedo values for sand and sand-loam combination soil types by 0.1 and 0.02, respectively. This puts the sandy soil albedos inside the range expected for the Sahara, while not leading to excessively large albedos in the deserts of southern and eastern Africa.

255 3.4 CLM-AF vegetation property adjustments

In order to bring the albedo of vegetated areas into better agreement with the satellite climatology from WPS, several adjustments are made to leaf/vegetation optical properties in CLM-AF. In CLM-D, shrubs in Sub-Saharan Africa are erroneously classified as broad leaf evergreen shrubs rather than temperate deciduous shrubs. In order to maintain a lower albedo for these African shrubs, the leaf transmittance, leaf angle, and leaf reflectance properties of the deciduous temperate shrubs are adjusted to match those of broad leaf evergreen shrubs. Additionally, the near-infrared leaf reflectance of all broad leaf tree species is lowered from 0.45 to 0.35 in CLM-AF, which is in better agreement with near-infrared leaf reflectance measured by unmanned aerial vehicle mounted hyperspectral imaging instruments over African forest canopies (Thomson et al., 2018).

4 Experimental design

265 This study consists of two experiments (Table 7). The first is a <u>meteorological evaluation model validation</u>-experiment to compare differences between the WRF LSM configurations and assess their <u>impact of their prescribed surface parameters on meteorological</u> model performance. The second is a LULCC experiment to determine if the errors and uncertainties of each LSM lead to differences in their climate responses to LULCC.

4.1 Meteorological evaluation Model validation experiment

- 270 The <u>meteorological evaluationmodel validation</u> experiment consists of five simulations conducted for the year 2013, each using one of the five LSM configurations discussed above. The year 2013 is selected because it is a neutral year for the El Niño Southern Oscillation (ENSO) and thus should be representative of the mean state of Sub-Saharan Africa's ENSO climate <u>variability</u>. While a single year comparison does not yield climate relevant statistics, it is sufficient to demonstrate differences in the meteorology between the five LSM configurations and the mechanisms responsible for these differences. This is because
- 275 the prescribed surface parameters from the LSM do not vary between years and thus the impact from these parameters on the simulated meteorology will be similar (or at least the impact from each LSM will remain similar relative to the others) regardless of the model's overall meteorological state. The meteorological evaluation model validation simulations are conducted with default greenhouse gas concentrations and MODIS 21 class land use data. These default settings are chosen to illustrate the performance that can be expected from the publicly available WRF model.

280 4.2 Land use and land cover change experiment

The LULCC experiment simulates recent climate responses from LULCC since the year 2001 by comparing simulations with static LULC from 2001 with dynamic LULC representing 2010–2015. In both cases, meteorology is simulated for the sixyear period of 2010–2015, the period 2010-2015 and represents recent climate responses from LULCC since the year 2001. These To accomplish this goal, the LULCC experiment consists of two simulations differing in LULCC are conducted for

- 285 <u>eachper</u> LSM configuration, using the Noah, Noah-MP, CLM-D, and CLM-AF LSMs. The first simulation for each LSM uses static LULC from <u>MODIS representing</u> the year 2001 for each simulated year (i.e., 2010_-2015), hereafter referred to as LU01. The second uses dynamic LULC from the MODIS 21 class land use dataset that is processed by the Dinamica EGO land use modeling framework (Soares-Filho et al., 2002 – described in more detail below) for each simulated year in the 2010_2015 period, hereafter referred to as LUD._-The six-year average dPifferences between the LU01 and LUD simulations delineate
- 290 the climate response to LULCC. These two simulations are carried out using the Noah, Noah MP, CLM-D, and CLM AF LSMs. The time period 2010–2015 is selected because it is far enough away from the year 2001 to show significant impacts from LULCC and because it contains athe full ENSO elimate variability cycle. Noah-Sat is excluded because LAI and albedo parameters derived from satellite data could be impacted by climatological variability-, and therefore do not only represent other than LULCC. The LULCC simulations also utilize MODIS 21 class land use data that was processed by the Dinamica EGO
- 295 land use modeling framework (Soares-Filho et al., 2002 described in more detail below) and global average greenhouse gas concentrations for each simulation year (2010–2015) from the National Oceanic and Atmospheric Administration's (NOAA) Earth System Research Laboratory (ESRL) Global Monitoring Division. In the LULCC experiments, each year is a discreet simulation with a 3-month spin-up in which the model LULC is updated at the start of each year. This is necessary because the WRF modelling framework treats LULC as a static field.
- 300 There are several non-trivial differences between the WRF default LULC used in the evaluation experiments and the MODIS data used in the LU01 simulation (Fig. S1), even though the WRF default LULC is intended to represent 2001. Overall, the default WRF LULC data has more area classified as grassland, savanna, and forest, with less areas classified as cropland, woody savanna, and barren land compared to the LU01 dataset. Spatially, the areas classified as cropland in LU01 are primarily classified as the nearest natural LULC type in the default dataset. In Central Africa, some areas classified as forests and
- 305 savannas in the default LULC dataset have been assigned as woody savanna in LU01. In southern Africa, some areas assigned as grasslands in the default LULC dataset are classified as open shrubland and in arid regions some areas classified as open shrubland in the default dataset are assigned as barren land in LU01.

4.3 LULC dataLand use / land cover data

The LULC dataset for the LULC<u>C</u> experiment is extracted from simulated annual maps of land use and land cover spanning
2001 to 2050. These maps are created by means of prospective landscape modelling techniques and while simulations contain some level of model error, this approach is used to reduce the impact of potential LULC misclassification errors and uncertainties in the MODIS product that could propagate into the WRF model leading to "noisy" and inconclusive climate impactssignals. To the authors' knowledge, this is a novel practice as many LULC studies in Africa do not simulate year to year changes (e.g., Otieno and Anyah, 2012) from the LULC datasets or use idealized LULC datasets (e.g., Abiodun et al., 2008; Wang et al., 2016). The use of a simulated LULC product is sufficient to support the goals of the LULCC experiment, which aims to determine if the climate signals from realistic LULCC simulated by the different LSMs make logical sense.

LULC is simulated using the Dinamica EGO environmental modelling platform (Soares-Filho et al., 2002). Dinamica EGO is a modelling tool designed to construct simple or complex spatiotemporal models involving multiple transitions and iterations, dynamic feedbacks, sub-region approaches, and several spatial algorithms for the analysis and simulation of a wide variety of

- 320 dynamic LULCC phenomena. Dinamica EGO has been used for many applications (Soares-Filho et al., 2002; De Almeida et al., 2005; Soares-Filho et al., 2006; Merry et al., 2009; Nepstad et al., 2009; Soares-Filho et al., 2010; Thapa and Murayama, 2011; Silvestrini et al., 2011; Bowman et al., 2012; Ghilardi et al., 2016; Oliveira et al., 2019; Cheng et al., 2020; De Almeida et al., 2005; Ghilardi et al., 2016; Merry et al., 2009; Nepstad et al., 2009; Oliveira et al., 2019; Cheng et al., 2020; De Almeida et al., 2005; Ghilardi et al., 2016; Merry et al., 2009; Nepstad et al., 2009; Oliveira et al., 2019; Silvestrini et al., 2011; Soares et al., 2006; Soares -Filho et al., 2010; Thapa and Murayama, 2011).
- 325 For input to our LULCC simulations, we use the MODIS Land Cover Type product (MCD12Q1) consisting of a suite of datasets that provides global land cover maps at 500 meter spatial resolution and annual temporal coverage from 2001 to 2013, and includes six different land cover classification schemes (Friedl et al., 2010; Friedl and Sulla-Menashe, 2015; Friedl et al., 2010). This product is generated using an ensemble of supervised classification algorithms that uses MODIS Nadir BRDF-Adjusted Reflectance data as input (Schaaf et al., 2002). Specifically, we use the IGBP classification legend since the land cover data <u>used ingested</u> by the WRF model (Skamarock, 2008) is based on MODIS-IGBP classification scheme. The MODIS
- Land Cover product has a post-process overall accuracy of 75% (Friedl et al., 2010). Using this approach, we detected spurious changes that toggle yearly between classes such as woody savannas, savannas, or grasslands. To reduce this temporal noise, we apply a cell-based temporal mode filter that replaces cell values with the most frequently occurring LULC class selected from a moving but non-overlapping 3-year window; or alternatively, a 6-year
- 335 window when no mode is found, and assigning No Data to the entire 12-year time series if still inconclusive. This filter preserves long lasting changes while drastically reducing short term changes between LULC classes. There is no edge preservation because windows do not overlap in time, i.e. LULC classes can change for 2001 or 2012. Consequently, the year of a "true" LULC change can be shifted forwards or backwards by one year.

Prospective landscape models covering very large areas need to be regionalized, meaning that during the calibration period,
explanatory variables and their spatial relationships with observed changes can be tuned separately to capture the heterogeneity
of landscape dynamics. Regions do not represent "hard borders" in modelling results, as the amount of projected change and
the probability of change occurrences are not boxed-in within regions, but the proximate causes of observed change can be
analysed separately.

- For Dinamica EGO, Africa is regionalized into 18 regions based on climatic zones, demographic factors, and anthropogenic
 activity (Fig. S₂+) consisting of three overlapping layers: 1) United Nations geographic regions for Africa: Northern, Eastern, Southern, Western and Central (UNSD, 1999); 2) a bioclimate layer from the modified version of the Global Environmental Stratification (GEnS) dataset (Metzger et al. 2013); and 3) residential sector emissions hotspots using DICE-Africa emissions (Marais and Wiedinmyer, 2016). The resulting 67 categories are generalized into the final 18 based on neighborhood. The process of generalization is done by comparing major change trends among regions, trying to avoid as far as possible the
- 350 presence of separate regions with similar LULC dynamics. Of these 18 regions, 17 are used in the WRF modelling and for the

generation of LAI and SAI profiles as described in Section 3.2 because the North Semi-dry region is outside the Sub-Saharan Africa domain.

LULC change rates by region are analysed by means of transition probability matrices, in order to quantify the amount of change in km^2 for each LULC change transition during the calibration period (2001 – 2007). Matrices are annualized and used to simulate expected annual LULC changes up to 2013 for validation purposes, and to 2050 for simulation purposes.

- While transition matrices project the expected amount of LULC change into the future, they say nothing about where this change is likely to occur. For each meaningful transition, a map depicting the probability of that transition happening in the future is built by means of analysing the spatial relationship between observed changes and a set of explanatory variables (Table S124, Fig. S32). Static and dynamic explanatory variables were related by means of conditional probabilities with the spatial occurrence of observed LULC changes for a subset of meaningful transitions during the calibration period. All maps were resampled to 1 km² resolution and projected to the Africa Albers Equal Area Conic coordinate system. Annual transition matrices (how much change is expected at each year) are integrated with annual probability maps (also generated for each year) to produce simulated land cover maps.
- To evaluate the accuracy of simulations within the present time, simulated annual maps outside the calibration period (2008– 365 -2013) are compared with the MODIS product for the same year, using a fuzzy-logic method (Hagen, 2003) (Fig S3)<u>4</u>). This approach incorporates a moving window neighborhood context, since predicting the location of LULC transition at a pixel level is virtually impossible. The comparison is done between simulated and observed cells undergoing a certain LULC change within the windows. To measure the spatial agreement between maps we used window sizes ranging from 1 to 9 cells (corresponding to spatial resolutions between 500 x 500 m and 4,500 x 4,500 m). For most transitions and regions, simulations 370 correctly predict change within 4,500 x 4,500 m windows 50% and 75% of cases, which is among the range of reported results
- in other prospective modelling studies (e.g. <u>Soares-Filho et al., 2006; Soares-Filho et al., 2010; Thapa and Murayama, 2011;</u> Carlson et al., 2012; Soares et al., 2012; Soares et al., 2006; Thapa and Murayama, 2011; Yi et al., 2012).

4.4 Model evaluation datasets and protocol

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A list of data used to evaluate WRF's meteorological performance <u>isare</u> shown in Table 8, and the WRF model variables evaluated against these datasets are listed in Table 9. Surface meteorological and climate quantities are validated against both hourly surface observations from the National Climate Data Center's Integrated Surface Dataset (NDCD-ISD) and monthly average gridded estimates from the University of East Anglia's Climate Research Unit version 4.02 (CRU TS4.02) dataset (Harris et al., 2014). Precipitation (PRE) is evaluated against CRU TS4.02, monthly average Global Precipitation Climatology Project (GPCP) estimates, and three-hour average Tropical Rainfall Measurement Mission (TRMM) estimates. Cloud fraction

380 (CF) and precipitable water vapor (PWV) are compared against estimates from the MODIS Terra Aerosol Cloud Water Vapor Ozone level three product (MOD08_M3). Additionally, radiation balance variables are compared against satellite estimates from the Clouds and Earth's Radiant Energy System – Energy Balanced and Filled (CERES-EBAF) dataset.

To compare WRF to the gridded datasets, the WRF output is averaged to the appropriate temporal resolution and regridded to the native horizontal resolution of the gridded products to calculate performance statistics. Comparisons against NCDC-ISD are made for each hour by pairing the monitoring station values to the value of the WRF 36 km grid cell containing the monitoring station. All comparisons with MOD08_M3 are done by averaging the WRF data during the daytime MODIS Terra overpass times of Sub-Saharan Africa (i.e., 600 - 1200 UTC). Model performance is determined by calculating the mean bias (MB) and normalized mean bias (NMB). Statistical quantities are calculated for the domain as a whole and each bioclimate region to show regional variability in model performance. Additionally, spatial patterns for the simulations and observations are shown.

5 Results - surface parameters

It is important to illustrate the different surface properties from each LSM, within WRF, using the same LULC because these surface properties differences will drive simulated changes in the meteorology. Figuress- 2-4 depict the surface properties for each of the five LSM configurations from the 2013 evaluation simulations. Since the albedo and LAI of Noah-Sat are generated from satellite estimates, these values can be considered similar to observations.

- In general, all of the LSM configurations that prescribe albedo overpredict surface albedo in vegetated areas. However, the Noah LSM severely overpredicts surface albedo throughout the entirety of the domain with albedo values ranging from ~20_ -28% for regions containing woody savanna, savanna, and shrubland (Fig. 2b), compared to 10_20% over the same areas in Noah-Sat (Fig. 2a). This is because Noah's prescribed albedo values for many of the MODIS-IGBP categories are significantly
- 400 larger than those derived from satellites (Table S1<u>3</u>2, Supplementary Material). The annual average surface albedos prescribed by Noah-MP (Fig. 2e) and CLM-D (Fig. 2d) are similar in magnitude and spatial pattern, with overpredicted albedo in vegetated areas and underpredicted albedo in arid regions. However, Noah-MP underpredicts surface albedo in the Sahara to a greater extent due to the loam soil simplification (Sect. 2.2.2). The Noah, Noah-MP, and CLM-D LSM configurations all contain errors where woody savanna and closed shrubland are treated as either identical or similar. In the Noah LSM, this
- 405 leads erroneously to the woody savanna regions having greater surface albedos than nearby savanna regions. In Noah-MP and CLM-D, this leads to woody savannas erroneously having lower albedos than nearby broad leaf evergreen forests, because shrubs are assumed to have a lower leaf reflectance than broad leaf trees. In general, CLM-AF is the closest match to the satellite spatial pattern, despite differences in magnitude (Fig. 2e). The prescribed albedo values in CLM-AF improve the representation of surface albedo in the arid regions of northern and eastern Africa, but the scaled values lead to overpredictions
- 410 in southern Africa. Vegetated regions also contain higher albedo values than the satellite estimates. These errors suggest that better representations of soil color and leaf reflectance are needed in WRF-CLM.

In general, all of the LSM configurations that prescribe LAI overpredict the LAI of arid regions compared to satellite estimates (Fig. 3). Due to the lack of geographically varying LAI in CLM-D, the seasonality of LAI in Sub-Saharan Africa in this configuration is incorrect with elevated LAI values throughout the entire domain for June, July, and August (JJA) and

415 minimum LAI values throughout the domain in <u>December</u>, January, <u>and</u> February, <u>and December (DJFJFD</u>). Additionally, woody savanna (see Fig. 10)-LAI in CLM-D is significantly underpredicted because it has the same LAI profile as closed shrubland.

Unlike CLM-D, the Noah and Noah-MP configurations account for differences in seasonality in the northern and southern hemispheres by shifting the northern hemisphere LAI profiles by six months for the southern hemisphere. This approach leads
to differentiated northern and southern hemisphere LAI values in Noah and Noah-MP (Fig. 3); however, distinct discontinuities occur in LAI at the equator. In Noah-MP this LAI discontinuity only impacts East Africa due to the presence of broad leaf evergreen forest with a time invariant LAI profile (category 2 in Table S143) in Central Africa. This issue is more apparent in the Noah LSM as the LAI discontinuity occurs in both eastern and central Africa, since all the LULC categories in this region have time variable maximum and minimum LAI values (Table S154 of Supplementary Material). Additionally, the LAI

- 425 profiles in Noah-MP (Table S143) have a stronger seasonality than the Noah values due to many LULC categories having much lower minimum values of ~0.0_-0.5 during the winter months. This leads to an overall underpredicted LAI during the winter periods in both hemispheres and overpredicted LAI during the summer periods. The net effect of this error is an overall underprediction in the annual average LAI of tropical heavily vegetated regions and slightly overpredicted annual LAI in sub-tropical arid regions. The generally higher minimum and maximum LAI values in the Noah LSM lead to generally accurate
- 430 annual average LAI values in tropical regions, but significantly overpredicted annual LAI values in sub-tropical arid regions. The errors in the LAI profiles of Noah and Noah-MP likely occur because they have been developed mainly for application in the Northern Hemisphere Mid-Latitudes.

CLM-AF, generates annual and seasonal average LAI spatial patterns that largely mimic the satellite estimates (Noah-Sat). The use of LAI profiles prescribed in smaller regions has eliminated any large and obvious discontinuities and better represents

435 the latitudinal variability and seasonality in LAI compared to the other LSM configurations. CLM-AF slightly underpredicts LAI values in the south-eastern portion of the domain and slightly overpredicts LAI near the Sahara. These errors likely result from the lack of spatial heterogeneity that can be expected from a look-up table methodology.

An observational RL dataset is not available for comparison with model estimated RL. However, a comparison of the modelled RL (Fig. 4) reveals several critical issues with the default representations. Despite having accurate LAI and surface albedo from satellite estimates, the Noah-Sat configuration uses the same methodology as Noah to prescribe RL and therefore both LSMs possess the same limitations. The values of RL in Noah and Noah-Sat are very low in comparison to other LSMs, with a maximum value over forested regions of 0.5 m. This is inconsistent with the MODIS-IGBP evergreen broad-leaf forest definition of canopies larger than 2 m (Table S43), indicating that both of these configurations likely underestimate RL.

Additionally, the spatial patterns in Noah, Noah-Sat, and CLM-D are all incorrect due to prescribing woody savanna regions
 as having shrubland RL values. The Noah-MP and CLM-AF LSMs have the most realistic spatial patterns and magnitudes of
 RL. The key differences are higher RL values for herbaceous land cover types in Noah-MP and larger maximum RL values
 over forested regions in CLM-AF.

For both latent (LH) and sensible (HFX) and latent heat (LH)-fluxes (Fig. 5 and Fig. 6), all LSMs produce similar annual average spatial distributions. LH are more similar amongst LSMs (Fig. 5), with the key difference being larger LH (~10-20)

- 450 W m²) in the most heavily vegetated portions of the domain for the CLM-D and CLM-AF configurations. The similar LH for CLM-D and CLM-AF suggests a mechanistic difference that may be related to the vegetation canopy approximation in CLM that does not account for gaps within the canopy or between vegetation crowns. However, the values are the largest for CLM-AF in regions containing savanna, likely due to the larger values of LAI in these regions during the drier seasons (Fig. 3). For HFX (Fig. 6), the Noat-Sat LSM produces the largest fluxes, especially in the semi-dry regions of eastern and southern
- 455 Africa. This is likely a combination of Noah-Sat having the lowest albedo in vegetated regions leading to more surface energy absorption and Noah-Sat having consistently low LAI values in these regions throughout the year compared to other LSMs (Fig. 2 and Fig. 3). Both CLM-D and CLM-AF have lower HFX compared to the other LSMs in vegetated areas, again likely due to the vegetation canopy assumptions. However, CLM-D has higher HFX in southern Africa comparable to those of Noah and Noah-MP. This is likely the result of Noah, Noah-MP, and CLM-D having much larger than realistic fluctuations in LAI
- 460 <u>between the wetter and drier seasons in this region (Fig. 3).</u>

6 Results - 2013 meteorological evaluation

The primary meteorological variable impacted by surface albedo is the upwelling surface shortwave radiation flux at the Earth's surface (USRS)), shown for comparison with CERES EBAF estimates (Fig. 5). <u>A</u>The annual average spatial plots of USRS compared with CERES-EBAF estimates are shown in <u>urfaceFig. 7</u>, with seasonal average spatial plots shown in Fig.

- 465 <u>S5 of the supplementary material. Additionally, -annual average difference plots with CERES-EBAF for each LSM are shown in Fig. S6. plots-All plots</u> illustrate that the Noah-Sat configuration, with satellite albedo estimates, has the best agreement between simulated USRS and CERES-EBAF. The performance of the remaining LSMs follows their agreement with the satellite albedo climatology (Fig. 2), where CLM-AF has the best performance and Noah the worst. Model performance is further quantified using soccer plots (Fig. <u>86</u>) of domain-wide and African bioclimate region NMB and NME statistics for simulated USRS and <u>2-m Temperature (T2)</u> compared to CERES-EBAF and CRU/NCDC-ISD observations. These statistics confirm that Noah-Sat has the best overall USRS performance and that Noah significantly overpredicts USRS in nearly all
- regions with overpredicted surface albedo. The statistical performance of CLM-D, Noah-MP, and CLM-AF are similar in many African bio-climate regions, with CLM-AF generally having the best overall agreement. In particular, CLM-AF simulates USRS more accurately in the arid ND and ED regions than both Noah-MP and CLM-D, which indicates that the
 increased sandy soil albedos in CLM-AF improve model performance. Additional radiative budget variables are evaluated against CERES-EBAF estimates in the supplementary material (Figs. S<u>74</u>–S<u>96</u>). We find that most other radiative parameters
- have minimal differences between LSMs, with most errors resulting from underestimated cloud radiative forcing consistent with other WRF experiments in Africa (e.g., Diaz et al., 2015). The underestimated cloud radiative forcing seems to indicate

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the model is not generating clouds of sufficient optical thickness, since cloud fractions are overestimated compared to satellite estimates (Fig. 10, Fig. S15).

- To understand the impact of surface parameters on near surface temperatures, the spatial plots of annual average T2 compared with CRU estimates are shown in Fig. 9, with seasonal spatial plots shown in Fig. S10 of the supplementary material. Annual average differences between CRU and the LSMs are also shown in Fig. S11. Interestingly, despite clear deficiencies in surface parameters and USRS in many of the LSMs, all LSMs reasonably capture the spatial distribution and magnitude of annual 485 (Fig. 9) and seasonal (Fig. S10) T2 as compared to CRU estimates (Fig. 7). The only clear impact of surface albedo inaccuracy on annual average T2 is the relatively stronger cold bias in the Noah LSM (Fig. <u>974, Fig. S11</u>). A closer inspection of T2 within Fig. 86 for the CRU dataset indicates that Noah-Sat, Noah, and Noah-MP all contain a domain-wide cold bias in annual average T2, while CLM-D and CLM-AF have minimal domain-wide T2 biases due to offsetting warm and cold biases in various regions. Several prior studies illustrate similar simulated T2 biases for African regions using WRF (e.g., Kerandi et 490 al., 2017; Li et al., 2015). The evaluation differences above indicate that the mean T2 bias/errors likely result from differences in the way radiative and surface energy fluxes are parameterized in the LSMs, since the patterns in T2 predictions do not follow differences in surface parameters and incoming solar radiation is roughly equivalent for all LSMs. This is further illustrated by the evaluation of daily maximum temperature (T2MAX) and daily minimum temperature (T2MIN) (Fig. S127). T2MAX is generally similar amongst all LSMs, except for Noah which contains a cold bias from the albedo overpredictions. The cold 495 bias in Noah propagates to T2MIN, likely due to thermal inertia from underestimated daytime heating. Both Noah-Sat and Noah-MP have various offsetting cold and warm T2MIN biases in the African-bioclimate regions, but CLM-D and CLM-AF
- both distinctly overpredict T2MIN. The overprediction of T2MIN in CLM-D and CLM-AF likely arises from the larger LH latent heat flux(Fig. 5) and upward surface long wave fluxes (not shown) predicted by these LSMs (not shown), which may be related to the vegetation canopy approximation in CLM, -previously discussedmentioned above that does not account for gaps within the canopy or between vegetation crowns. These T2MIN overpredictions for CLM-D and CLM-AF also account for the lack of annual average cold bias in these simulations. Additionally, the underpredicted T2MAX in the Noah LSM and overpredicted T2MIN in CLM-D and CLM-AF result in underpredicted diurnal temperature range (DTR) for these three
- The WRF comparison with the hourly NCDC-ISD dataset confirms the presence of a cold bias for the Noah LSM, andbut 505 provides more insight into regional model performance. Across all the LSMs the wettester regions (e.g., MAD, WW, WWN, CW, LVW, EW) contain the strongest cold biases, while the semi-arid regions (e.g., SESD, WSD, NESD, SSD) contain the strongest warm biases. This would appear to indicate that hourly temperature biases are modulated by inaccuracies in cloud radiative forcing or evaporative cooling.

LSMs.

The evaluation of the moisture variables PWV, CF, and PRE against MODIS and TRMM estimates (Fig. <u>108</u>) and the spatial comparison of WRF PRE to observations (Fig. <u>119</u>) show a <u>reduced more muted</u> impact from LSM differences compared to temperature variables. Most regions have reasonable agreement in moisture variables with observations and satellite estimates, with a few <u>select</u> regions experiencing <u>very</u> poor agreement (Fig <u>108</u>). All LSM simulations overpredict PWV and CF, while

underpredicting PRE. This indicates a possible underrepresentation of moisture recycling in this WRF configuration, whereby insufficient moisture convergence or insufficient activation of the cumulus parameterization fails to trigger precipitation,

- 515 leading to excess water vapor that forms cloud cover. These findings are consistent with underpredictions in precipitation from the modified Tiedtke cumulus parametrization found by Igri et al. (2018), indicating that this cumulus scheme may be less efficient at removing moisture from the atmosphere. The evaluation of <u>2-m dewpoint temperature (Td2) and 2-m vapor pressure (E2) against NCDC-ISD and CRU (supplementary Figs. S<u>1459</u> and S<u>160)5</u>) provide further evidence to support the possibility of insufficient moisture recycling as surface humidity is underpredicted, likely as a result of underpredicted PRE.</u>
- 520 For a more detailed look at PRE, annual average spatial plots of PRE compared with CRU, GPCP, and TRMM estimates are shown in Fig. 11. Additionally, seasonal spatial plots of PRE compared with TRMM and annual average differences between TRMM and the LSMs and shown in Fig. S16 and Fig. S17, respectively. All LSM simulations reasonably capture the annual spatial pattern and magnitude of PRE compared to CRU, GPCP, and TRMM estimates (Fig. 119) and seasonal (Fig. S16) spatial patterns and magnitude of PRE. Across all LSMs, PRE is better simulated in the wetter regions of West and Central
- 525 Africa. The greatest underpredictions occur in arid regions (ND, ED, SD, NESD, and WSD) and portions of East Africa (EM, CM, and LVW), while regions in South Africa (SSD and SM) and EW typically experience the strongest overprediction across the LSMs (Fig. 10, Fig. S13, Fig. S17). Similar regional model biases have been reported in other studies (Alaka and Maloney, 2017; Argent et al., 2015; Cretat et al., 2012; Ratnam et al., 2018), indicating that our results are comparable to the large body of work utilizing WRF to study African precipitation. More details regarding moisture variable evaluation can be found in the
- 530 Supplementary Material <u>ST4</u>.
- Lastly, comparisons of <u>10-m wind speed (WSP10)</u> to NCDC-ISD observations (Fig. S<u>149</u> supplementary material) show a few key differences in WSP10 performance between LSMs. Noah and Noah-Sat have nearly identical overpredictions in the magnitude of WSP10, associated with an underestimation of RL. CLM-D also underpredicts the magnitude of WSP10, associated with the underrepresentation of RL in woody savannas and the inaccurate seasonal profile of RL. Both Noah-MP
- 535 and CLM-AF have offsetting overpredictions and underpredictions in various regions, but both LSMs underpredict WSP10 in equatorial forested areas, moderately underpredict or overpredict WSP10 in most moist vegetated regions, and largely overpredict WSP10 in more arid regions. The LSM regional model performance distribution may indicate that RL values in the forested regions are too large and the RL values in more semi-arid regions are too small in the Noah-MP and CLM-AF configurations.
- 540 Overall, the <u>meteorological evaluation</u>-model validation experiments reveal little impact from inaccurate surface parameters on most meteorological parameters. The lack of poor meteorological performance may indicate that errors in surface parameters have minimal impacts on African meteorology for certain applications. However, these errors can impact the trajectory of LULCC-induced climate signals as demonstrated in Sect. 7.

7 Results - impact of LULCC on regional climate using different LSMs

- 545 Changes in land use and land cover, as represented by Dinamica EGOgo, between 2001 and 2015 are shown in Fig. 1210. Broadly, the LULC changes can be broken down into three categories: agricultural expansion, deforestation/degradation, and greening. Agricultural expansion is defined here as the change in the LULC category from a natural vegetation type to either the MODIS cropland or cropland/natural mosaic category. This LULCC is most prevalent across the northern and central portions of the domain. In West Africa, a loss of evergreen broadleaf forest is found along the coasts of Ghana and Côte 550 d'Ivoire, with woody savanna significantly lost in Nigeria to cropland/natural vegetation mosaic. There are losses of savanna
- and grasslands to cropland in Ethiopia, Sudan, and South Sudan, while losses of woody savanna to cropland/natural vegetation occur in the western Republic of the Congo, western Democratic Republic of the Congo, and northwestern Angola. Deforestation/degradation, defined here as the transition from a more forested MODIS natural vegetation type to a less forested natural vegetation type, is commonly found in the southern and eastern portions of the domain. Major
- 555 deforestation/degradation transitions include: a loss of woody savanna to savanna (e.g., central Angola, Mozambique, Zambia, and Tanzania), loss of savanna to grasslands (e.g., Somalia and Kenya), and loss of savanna to open shrubland (e.g., Namibia, Botswana, and Madagascar). Finally, greening, defined here as the reclamation of the barren MODIS category by a vegetated category or a transition from a less forested vegetation category to a more forested vegetation category, is found along the Saharan border, the boundary of the Namib Desert, within the Horn of Africa, and along the eastern coast of Madagascar.
- 560 While it is difficult to compare the LULCC predicted by Dinamica EGO to other African LULCC studies because these studies either use idealized LULCC (e.g., Abiodun et al., 2008; Wang et al., 2016) or do not simulate year-to-year changes, the increased agricultural expansion and deforestation/degradation are consistent with the LULCC seen in Otieno and Anyah (2012) for the period of 1986–2000.

7.1 LULCC impact on surface properties

- 565 A comparison of surface albedo changes between the LU01 and LUD simulations using the Noah, Noah-MP, CLM-D, and CLM-AF LSMs is shown in Fig. 13.2+. The CLM-AF LSM is consistent with expected changes. Regions with a loss in vegetation from either agricultural expansion or deforestation/degradation experience surface albedo increases, while areas with greening experience albedo decreases. However, Noah, Noah-MP, and CLM-D all deviate from expected changes because of errors and differences in their treatment of surface albedo. Additionally, due to the increased PFTs per LULC category in
- 570 the CLM-AF treatment there is greater overlap in PFTs between LULC categories, which results in albedo changes between vegetation categories that are less extreme than the other LSMs.

The LULCC-induced albedo changes in Noah deviate the most from the other LSMs. This is largely because of the erroneous treatment of woody savanna albedo as higher than croplands, cropland/natural vegetation mosaic, and savanna (Table S132). The result of this flawed treatment is an erroneous albedo decrease in areas where woody savanna is lost to agricultural

575 expansion or deforested/degraded to savanna. While both CLM-D and Noah-MP also have inaccurate treatments for woody

savanna, these LSMs do not have erroneous albedo responses. For Noah-MP, this is because the savanna and cropland categories are prescribed albedos less than woody savanna. In CLM-D, this is a result of the shrub leaf reflectance being less than that of grass and broad leaf deciduous trees. Noah-MP and CLM-D predict reductions in surface albedo for savanna to open shrubland transitions because both LSMs prescribe shrubs as having much lower leaf reflectance than grasses. In CLM-

- 580 AF, the impact of lower shrub leaf reflectance is not as strong on the savanna to open shrubland transitions because open shrublands contain more bare soil than savannas (Table 2), leading to albedo increases for savanna to open shrubland transitions. Noah-MP also does not show a change in albedo from the greening around the Sahara because its flawed soil color treatment does not simulate a significant difference in the albedo of grasslands and bare soil in that region (Fig. 2).
- Among LSMs, there is greater similarity in LAI projections-(Fig. 1<u>4</u>2) than for surface albedo (Fig. 1<u>3</u>4). The LAI projections
 from LULCC for CLM-AF and Noah-MP have the same spatial pattern and direction with slightly different magnitudes. The projected LAI changes from CLM-D are also very similar to CLM-AF and Noah-MP across the northern half of the domain, but CLM-D has erroneous increases in LAI for woody savanna to savanna transitions. Again, these LAI errors are caused by erroneously treating woody savanna as a closed shrubland with a temporally uniform 1.0 m² m² LAI (Table S<u>3</u>2). The Noah LSM shows the greatest deviations from the other LSMs. This is mostly a result of erroneous increases in prescribed LAI
 values associated with agricultural expansion because croplands are prescribed higher LAI values than <u>most</u> natural vegetation.
- Additionally, the LAI of the woody savanna and savanna categories in Noah have the same prescribed values, hence this transition shows no change (see Table S154).

7.2 LULCC impact on 2 m temperature

- Changes in T2 between the LU01 and LUD simulations for each LSM are shown in Fig. 1<u>5</u>3. Locations that have the largest magnitude differences in T2 align with the more localized changes in LAI and albedo. Similar T2 patterns occur across the northern half of the domain when comparing Noah-MP, CLM-D, and CLM-AF simulations, while Noah predicts the most unique changes. To further investigate the LULCC impacts, <u>annual average</u> T2 differences are calculated for grid cells with different LULC transitions (see Table 10).-<u>Additionally, we generate annual average differences of the surface energy budget</u> and near surface temperature profiles for these grid cells, separately for daytime (SWDOWN > 0 W m²) and nighttime
- 600 (SWDOWN = 0 W m²) conditions. The diurnally split radiative flux differences for USRS, SWDOWN, upwelling longwave radiation at the earth's surface (ULRS), and GLW for each LSM are listed in Tables S16–S19. Additionally, the diurnally split surface heat flux differences for HFX, LH, and the ground fluxes (GRDFLX) are listed in Tables S20–S23. Lastly, the diurnally split surface temperature profile differences for surface skin temperature (TSK), T2, lowest model layer temperature (TATM), and the surface to lowest model layer vertical temperature gradient (TGSATM) for each LSM are listed in Tables S24–S27.
- 605 Similarly, differences in the surface sensible and latent heat fluxes for these LULCCs are provided in supplementary tables S15 and S16.

Agricultural expansion induces annual average localized warming of ~0.1_0.2 °C using Noah-MP, CLM-D, and CLM-AF, but a localized cooling of -0.12 °C using Noah-because of its erroneous increase in LAI (Fig. 12) and subsequent enhanced

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		evaporative cooling and cloud radiative forcing (not shown) in cropland transitions. The cooling from Noah for most
	610	agricultural expansion transitions occurs in response to erroneous increases in LAI (Fig. 14) that result in erroneous daytime
		LH increases and evaporative cooling (Table S23). However, in the transition of evergreen broad leaf forest to mosaic cropland
		along the coasts of Ghana and Côte d'Ivoire the LAI transition follows the other LSMs (Fig. 14), indicating that this cooling is
		the result of excessive daytime average USRS increases of 37.3 W m ² (Table S19) from surface albedo increases (Fig. 13). In
		the other LSMs, this evergreen broad leaf forest to mosaic cropland transition results in the The strongest warming response
	615	from agricultural expansion results from the loss of evergreen broad leaf forest to mosaic cropland along the coasts of Ghana
		and Côte d'Ivoire, with. This LULCC results in an average 0.6 °C warming using Noah-MP and ~1.31.4 °C of warming
		using CLM-D and CLM-AF, due to reductions in evapotranspiration (Table S16). This warming is the result of reduced
		daytime evaporative cooling, as evidenced by the largest daytime LH reductions of any LULC transition (Tables S20-S22).
		However, this warming is somewhat indirect as the greatest T2 increases occur during the nighttime. This is because the
	620	reduced daytime LH leads to greater land surface heat storage via the GRDFLX, which is then released at night heating the
		atmosphere. For most other agricultural expansion transitions, CLM-AF predicts nighttime warming consistent with reduced
		daytime LH and increased daytime GRDFLX, as described above. The exception is the grassland to mosaic cropland transition,
		where most warming occurs during the daytime due to reductions in USRS from albedo increases that increase TSK and HFX
		warming the atmosphere (Tables S16, S20, and S24). Noah-MP predicts less warming amongst agricultural expansion LULC
	625	transitions than CLM-AF with no clear signal as to the mechanism behind the warming. This is caused by the relative
		insensitivity of LH the surface latent heat fluxes (Table S2146) to agricultural expansion in Noah-MP, which allows for a
		lossother processes such as surface albedo changes, biogeophysical in energy as the albedo increases (Fig. 11) effects of RL
		changes (Winckler et al., 2019; Breil et al., 2020), and along with other secondary feedbacks such as changes in cloud cover
		and precipitation discussed more below to compensate each other resulting in a weaker climate signal. CLM-AF consistently
	630	predicts reduced latent heat fluxes across the various agricultural expansion LULC transitions, resulting in the most overall
		warming-The behaviorbehaviour of CLM-AF is also consistent with the global remote sensing work of Duveillier et al. (2018),
1		which indicates losses in latent heat flux for all natural vegetation to cropland transitions. CLM-D has many T2 changes similar
		to CLM-AF with some exceptions. TFor instance, the erroneous treatment of albedo for woody savanna in CLM-D, being too
		high, leads to excessive daytime increases in USRS of 29.8 W m ² (Table S18) for the transitions from woody savanna to
	635	mosaic cropland, which cools the surface (Table S26), reduces the surface sensible heat fluxHFX (Table S2215), and
		resultsting in minor cooling. In the other transitions from grasslands to different types of cropland, CLM-D does not have as
		strong a daytime LH reduction as CLM-AF, leading to either similar or weaker T2 warming that may be affected more by
		feedbacks from other model processes.

Deforestation/degradation grid cells experience an average 0.22 °C warming using CLM-AF, while the remaining LSMs 640 predict almost no change in- T2 for these grid cells (e.g., -0.03 - 0.04 °C). The strong warming signal in CLM-AF-can potentially come from multiple mechanisms, but in all deforestation transitions the reduced daytime LH and increased daytime GRDFLX that leads to nighttime T2 warming appears to dominate (Tables S20 and S24). Unlike agricultural expansion, Formatted: Superscript

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deforestation in CLM-AF causes decreases in daytime HFX. This could potentially be the result of biogeophysical effects of reduced RL making surface heating less efficient, or it may be related to the relatively larger increases in USRS from 645 deforestation reducing energy input, is again related to larger evapotranspiration reductions with surface latent heat reductions exceeding 2 W m² for all transitions (Table S16), In while Noah-MP, has smaller changes in evapotranspiration coupled with greater enhancements in surface reflectance for the woody savanna to savanna transition lead to little to no climate signal in T2with surface latent heat reductions below 2 W m² for all transitions. For the other deforestation transitions, Noah-MP predicts daytime TSK increases unlike CLM-AF (Tables S24 and S25), but little to no change in annual average T2. This may 650 be related to the effects of RL reductions reducing daytime HFX (Table S21) and increasing TGSATM (Table S25). The reduced heating efficiency coupled with reduced available energy from either increased daytime USRS or reduced daytime SWDOWN leads to small daytime T2 cooling in these transitions that compensates any nighttime warming from reduced evapotranspiration. -In CLM-D, has the smallest overall small change in annual average T2 from associated with deforestation/degradation is due to offsetting changes in different LULC transitions. This offsetting behavior behaviour is 655 primarily related to the woody savanna albedo and LAI errors that when combined do not substantially reduce thethat increases LAI and the daytime LH (-0.1 W m²) latent heat flux and excessively enhance daytime USRS (18.9 W m²) in grid cells with woody savanna to savanna transitions (Tables S22 and S26). Since woody savanna to savanna transitions comprise a substantial portion of the total deforestation/degradation grid cells, this signal cancels the warming from other transitions. The warming from CLM-D in the other deforestation transitions appears somewhat similar to CLM-AF. The daytime LH reduction / 660 nightime T2 increase mechanism appears to be responsible for the warming in the savanna to grassland transition. However,

- the nightime warming in the savanna to open shrubland transition appears to be related to reduced daytime HFX that increases the daytime GRDFLX, which could be related to either reductions in USRS from albedo reductions or biogeophysical impacts from reduced RL.__Noah also experiences offsetting impacts from different deforestation/degradation transitions; however, these changes are primarily driven by albedo and changes in the surface sensible heat flux (Table S15). Noah predicts_annual
- 665 average warming for the woody savanna to savanna transitions warming in the woody savanna to savanna transitions because of significant erroneous albedo reductions, which causes substantial increases in the surface sensible heat flux. This is caused primarily by large daytime decreases in USRS (-35.0 W m²) and increases in HFX (23.9 W m²), which increases daytime T2 despite decreases in daytime TSK (Tables S19, S23, and S27). This suggests that the warming in this transition for Noah is primarily related to either excessive surface albedo changes or the erroneous increase in RL in this transition that increases the
- 670 heating efficiency of the atmosphere. Noah predicts cooling <u>T2</u> for the other dominant deforestation/degradation transitions, primarily due to albedo reductions that are not countered by any substantial reduction in <u>LH</u>lbedo increases that are not sufficiently compensated for by latent heat reductions. This behaviour indicates that the overpredicted albedo in Noah may substantially shift the thermal sensitivity of <u>LULCC</u> to shortwave radiative effects rather than evapotranspiration effects.

Grid cells that experience greening have annual average cooling using Noah-MP, CLM-D, and CLM-AF (Table 10). -CLM AF and CLM-D predict similar cooling (-0.41°C and -0.33°C, respectively). In the transitions from barren lands to vegetation, the primary mechanism responsible for the cooling in both LSMs is enhanced daytime LH that reduces the daytime GRDFLX,

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which reduces nighttime heat release. In the grassland to savanna transition, the cooling for both LSMs results from reduced daytime GRDFLX that appears to be related to either other model feedbacks that reduce daytime SWDOWN or enhanced daytime HFX via the biogeophysical impacts of increased RL. In CLM-AF, the savanna to woody savanna transition

- 680 experiences cooling via the increased daytime LH / nighttime cooling mechanism discussed above. However, CLM-D predicts slight annual average warming due to the erroneously large reduction in daytime USRS of -18.7 W m² (Table S18) due to the treatment of woody savanna as closed shrubland in CLM-D. This large reduction in USRS overwhelms the daytime LH increases and increases the daytime GRDFLX, causing nighttime warming. The strong cooling in CLM-AF (-0.41 °C) and CLM-D (-0.33 °C) is the result of enhanced evapotranspiration, with CLM-D predicting less cooling due to inaccurate surface
- 685 property changes in savanna to woody savanna transitions. Noah-MP predicts slightly weakerpredicts annual average cooling much weaker cooling (-0.13 °C) from greening. The mechanisms responsible for the cooling in Noah-MP for most transitions are similar to CLM-AF with similar daytime LH increases, except the daytime GRDFLX reductions are not as large (Tables S20–S21). -However, because Noah-MP does not predict any change in LAI between savanna and woody savanna, this transition has little change in LH and a negligible change in T2. because vegetated to vegetated transitions experience little to no latent heat sensitivity, as discussed above. -Finally, the Noah simulations continue to be an outlier with almost no change
- (0.02 °C) due to offsetting inaccurate surface property changes in different greening LULC transitions. The three types of transition-based changes discussed above lead to very different spatial T2 changes (Fig. 153). The T2 changes using the Noah LSM are largely incoherent due to various surface parameter errors. The T2 changes using Noah-MP are much weaker than CLM-D or CLM-AF because only the starkest LULC transitions using Noah-MP impact local
- 695 temperatures (i.e., transition from broad leaf evergreen forest to mosaic cropland within West Africa, transition from grassland to cropland in northeastern Africa, and transition from barren soil to grassland along the Sahara border). The simulated T2 changes associated with LULCC in CLM-D and CLM-AF are largely the same above the equator, but improper treatment of woody savannas and southern hemisphere growing cycles result in erroneous cooling in southern Africa using CLM-D. CLM-AF is the only LSM that captures warming from agricultural expansion in Nigeria, as well as the large-scale annual average warming associated with deforestation/degradation in south-western Africa (e.g., Angola, Namibia, and Botswana).

7.3 LULCC impact on precipitation

In general, PRE changes between the LU01 and LUD simulations for each LSM (Fig. 164, Table 11) are more regional and much more chaotic than changes in temperature. However, there are a few localized changes in PRE from LULCC. Along the coast of Ghana and Côte d'Ivoire, the lost broad leaf evergreen forest decreases PRE in all four LSMs by 0.12_-0.45 mm day. ¹ on average. This is in response to reduced moisture availability due to reduced evapotranspiration, enhanced stability from increased surface albedo, and possible reduced moisture convergence from reduced surface roughness. Additionally, both Noah-MP and CLM-D also predict reduced PRE for grid cells that experience woody savanna to mosaic cropland transitions (e.g., Nigeria), due to enhanced atmospheric stability from erroneous reductions in surface albedo.

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The most significant regional PRE changes occur within southern Africa. During the southern Africa rainy season (October – March), the Angola Low is assumed to form in response to dry convection processes associated with surface heating in Angola (Mulenga 1998), however, the exact processes responsible for the Angola Low's formation are poorly understood (Munday and Washington, 2017). The strength and position of the Angola Low have been shown to significantly alter the gradients and magnitude of precipitation over southern Africa (e.g., Cook et al., 2004; Cretat et al., 2019). All LSMs predict excess heating from deforestation/degradation between the LU01 and LUD simulations in Angola. This heating results in a persistent reduction of surface sea level pressure (Fig. S184), during southern Africa's rainy season (DJFJFD), within Angola and nearby countries. The sea level pressure changes strengthens either the Angola Low or the associated Kalahari thermal low, which

- induces a stronger cyclonic circulation (Fig. S192) over southern Africa that opposes moist on-shore flow over Mozambique. This reduces moisture transport into south-western Africa, leads to drying in Angola and surrounding areas, and enhances moisture convergence in south-eastern Africa increasing PRE in Mozambique and surrounding areas. The exact location and strength of this LULCC-induced PRE climate signal varies between LSMs due to differences in the strength and spatial location
- of maximum heating, but this feature appears robust.

8 Summary and conclusions

In this work the applicability of commonly used WRF LSMs (i.e., Noah, Noah-MP, and CLM-D) with WRF's default MODIS LULC data are explored in Sub-Saharan Africa. Each default WRF LSM is found to have unique deficiencies in representing African surface parameters including: 1) significantly overestimated surface albedo and underestimated surface roughness<u>RL</u> using the Noah LSM, 2) the same underestimated <u>surface roughness<u>RL</u></u> as Noah using Noah-Sat, 3) significantly underestimated surface albedo in arid areas due to inaccurate soil albedo treatments using Noah-MP, and 4) geographically invariable surface parameters using CLM-D that make it unsuitable for use outside the Northern Hemisphere Mid-Latitudes. Additionally, all default WRF LSMs inaccurately treat the MODIS woody savanna land use category as closed shrubland.

730 These deficiencies likely have a minimal impact on simulations in middle or high latitudes of the Northern Hemisphere, but lead to substantial inaccuracies in Africa. Consequently, we developed a version of the CLM LSM in WRF that more accurately represents these properties in Africa (CLM-AF).

Despite clear deficiencies in surface parameters, all WRF LSMs reasonably capture the spatial pattern and magnitudes of precipitation and T2. The only detectable impact of inaccurate surface parameters is the slightly stronger cold and dry bias

735 using the Noah LSM that occurs because of its overestimated albedo. The WRF model with each LSM reasonably captures the climate of Sub-Saharan Africa, despite errors with cloud parameters and radiative forcing that are common to most climate models (e.g., Lauer and Hamilton 2013).

Regardless of the similar meteorological performance, the land surface parameter errors amongst the default WRF LSMs substantially impact the magnitude and direction of LULCC-induced changes in temperature and to a lesser extent localized changes in precipitation. The surface parameters in the Noah LSM and CLM-D are the most flawed, and as a result neither

LSM is suitable for LULCC experiments in Africa. Additionally, great care should be taken when utilizing these LSMs for other scientific applications in these regions. Noah-MP is least flawed of the default LSMs and with several updates may also be suitable for use in tropical regions (e.g., Spera et al., 2018).

- Although several of the default LSMs produced erroneous LULCC-induced climate signals, there are several common features
 that stand out as potentially robust. Losses of broad leaf evergreen forest along the coasts of Ghana and Côte d'Ivoire to agricultural expansion between 2001 and 2015 appear to have caused warming and drying in this region for LSMs that accurately treat this transition. Additionally, warming from deforestation in Angola, Namibia, and Botswana are modelled to have altered the DJFJFD average atmospheric circulations in this region, decreasing precipitation in south-western Africa and increasing precipitation in south-eastern Africa. Important mechanistic differences also stand out between the Noah-MP and
- CLM-AF LSMs. Noah-MP predicts little change in LH latent heat flux-between vegetated to vegetated LULC transitions unless they are particularly stark (e.g., broad leaf evergreen forest to mosaic cropland), while CLM-AF consistently predicts LH latent heat flux-change between vegetation transitions resulting in stronger thermal changes from gains or losses in evaporative cooling. This indicates that the accuracy of the LH latent heat sensitivity in of LSMs to LULCC is is-crucial to the accuracy of LULCC climate signal predictions in the tropics. Additionally, the incoherent temperature and moisture climate
- 755 signals in the Noah LSM indicate that albedo accuracy may play a role in determining whether evapotranspiration, <u>RL change</u>, or shortwave radiative effects will dominate LULCC climate signals.

Overall, this study serves as a cautionary tale to illustrate that proficient meteorological performance can mask severe flaws in model treatments, and that special care is needed to evaluate LSM parameters when conducting LULCC studies in Africa. While this study focuses on Africa, we expect that these LSMs would encounter similar problems in applications to other

- 760 regions of the tropics or Southern Hemisphere. More work is required by the scientific and model development communities to not only improve meteorological model processes, but to ensure that these scientific improvements are applicable to as many climate regimes and localities as possible. Additionally, this work documents the development of the WRF CLM-AF configuration for use in LULCC studies of Sub-Saharan Africa. Future companion manuscripts will explore the climate change signals attributable to LULCC in Sub-Saharan Africa, their statistical significance, and their impact on air quality. This
- 765 development is a first step towards better global LULC representations in WRF, but additional improvements are needed to accurately represent land surface and vegetation parameters across the various global climate regimes.

Code and data availability. The default WRF model is publically available for download from the WRF website (https://www2.mmm.ucar.edu/wrf/users/downloads.html). The CLM-AF code, additional code to recreate the experiments shown here, the African bio-climate region data, the Dinamica EGO generated land use and land cover data, and instructions

for using these codes and input data are all available on the UNC Dataverse Archive (https://dataverse.unc.edu/dataverse/CLM-AF1). The ERA-Interim reanalysis data for meteorological initial and boundary conditions can be found on the NCAR Research Data Archive website (https://rda.ucar.edu/datasets/ds627.0/). All observational data used to evaluate the WRF model are publically available from the websites listed in Table 8.

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Author contributions. Timothy Glotfelty developed and tested the CLM-AF code, conducted all WRF simulations, and wrote the manuscript. Jared Bowden and J. Jason West provided scientific input on the code development and experimental design. Jared Bowden processed and refined the manuscript figures. Diana <u>Ramírez-MejíaRamírez</u> and Adrian Ghilardi designed the land use modelling framework. Diana <u>Ramírez-MejíaRamírez</u> generated all the land use and land cover modelling products. All authors reviewed and modified the manuscript.

Competing interests. The authors declare that they have no conflict of interest

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African Bioclimate Regions

 $1130 \quad \mbox{Figure 1: African bioclimate and sub-bioclimate regions defined in this study within the Sub-Saharan domain.}$



Figure 2: Comparison of annual average albedo (%) between LSM configurations. Since Noah-Sat is based on satellite observations, it can be treated as observations.



Figure 3: Comparison of annual, summer (JJA), and winter (<u>DJFJFD</u>) average LAI (m² m⁻²) between LSM configurations. Since Noah-Sat is based on satellite observations, it can be treated as observations.

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Figure 4: Comparison of annual average surface roughness length (m) between LSM configurations.

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0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9



Figure 5: Comparison of annual average latent heat flux (W m^{-2}) between LSM configurations.



Figure 6: Comparison of annual average sensible heat flux (W m²) between LSM configurations.



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Figure 75: Year 2013 annual average upwelling shortwave radiation at the Earth's surface (W m²) for CERES-EBAF estimates and WRF simulations.



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Figure <u>8</u>6: Normalized mean error and mean bias statistics of USRS and 72 relative to observations, CERES-EBAF USRS estimates and CRU/NCDC 72.



Figure 24: Year 2013 annual average 2 m temperature (°C) from CRU and WRF simulations with five different LSMs. NCDC-ISD 2 m temperature observations are overlaid.



Figure 108: Normalized mean error and mean bias statistics of PWV, cloud fraction, and precipitation relative to observed MODIS PWV/cloud fraction and TRMM precipitation.



Figure 119: Year 2013 annual average precipitation rate (mm day-1) from CRU, GPCP, TRMM, and the five WRF LSM simulations.



Figure 120: Processed MODIS land use and land cover categories for 2001, simulated categories for 2015, and grid cells that experience transitions due to agricultural expansion, deforestation/degradation, and greening.









Figure 142: Differences in leaf area index (m² m⁻²) between the LUD and LU01 (<u>LUD-LU01</u>) simulations using Noah, Noah-MP, CLM-D, and CLM-AF.



Figure 1<u>5</u>3: Differences in 2 m Temperature (°C) between the LUD and LU01 <u>(LUD-LU01)</u> simulations using Noah, Noah-MP, CLM-D, and CLM-AF.



Figure 1<u>6</u>4: Differences in precipitation rate (mm day⁻¹) between the LUD and LU01 <u>(LUD-LU01)</u> simulations using Noah, Noah-MP, CLM-D, and CLM-AF.

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	Table 1: Model Configurations						
	Simulation Configuration	Setting					
	Domain	Sub-Saharan Africa					
	Horizontal Resolution	36 km					
	Vertical Layers	30 Layers from the Surface to 50 mb					
	Initial/Boundary Conditions	ERA-Interim (D11)					
	Physics Parameterization	Option					
	Cumulus	New Tiedtke Scheme (Z11)					
	Cloud Microphysics	Aerosol-Aware Thompson Scheme (TE14) RRTMG (C05; I08)					
	Radiation						
	Planetary Boundary Layer	MYNN (NN04; NN06)					
	Surface Layer	MYNN (NN04; NN06)					
	Land Surface Models	Noah (CD01; E03)					
		Noah-MP (N11)					
		CLM 4.5 (S11; JW12; LK12)					
	Lake Model	CLM 4.5 (S12; G13)					
	reanalysis; RRTMG – Rapid Radiative Trans Mellor Yamada Nakanishi Niino; Noah - Nat	fer Model for General Circulation Models; MYNN – ional Centers for Environmental Prediction, Oregon State					
1190	Community Land Model version 4.5.	MP – Noan Multi-patameterization options; CLM 4.5 –					
1195	References: D11 – Dee et al., (2011); Z11 – Z (2014); C05- Clough et al., (2005); I0 (2004); NN06 – Nakanishi and Niino, al., (2003); N11 – Niu et al., (2011); S LK12 – Lu and Kueppers, (2012); S12	Zhang et al., (2011); TE14 – Thompson and Eidhammer, 8 – Iacono et al., (2008); NN04 – Nakanishi and Niino, , (2006); CD01 – Chen and Dudhia (2001); E03 – Ek et S11 – Subin et al., (2011); JW12 – Jin and Wen, (2012); 2 – Subin et al., (2012); G13 – Gu et al., (2013).					
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Table 2: Percentage of Plant Functional Types Assigned to MODIS Land Use Categories in the Updated CLM-AF

MODIS Land Use Category		4	5	6	7	8	9	10	12	14
Bare Soil		3	-	14	48	-	-	21	10	-
Broad Leaf Evergreen Tropical Tree		-	20	-	-	12	-	-	-	-
Broad Leaf Evergreen Temperate Tree		-	15	-	-	-	-	-	-	-
Broad Leaf Deciduous Tropical Tree		55	-	8	-	26	21	-	-	24
Broad Leaf Deciduous Temperate Shrub	-	18	-	57	31	-	-	18	-	-
C3 Non-Artic Grass	-	-	40	-	8	27	31	36	24	17
C4 Grass	-	24	25	21	13	35	48	25	15	33
Corn	-	-	-	-	-	-	-	-	51	26

MODIS Land Use Categories: 2 - Evergreen Broad Leaf Forest; 4 - Deciduous Broad Leaf Forest; 5 -

1215 Mixed Forest; 6 - Closed Shrublands; 7 - Open Shrublands; 8 - Woody Savanna; 9 - Savannas; 10 -Grasslands; 12 - Croplands; 14 - Cropland/Natural Mosaic.

Table 3: Dominant MODIS-IGBP Land Use Categories within African Bioclimate Regions at 36 km 1220 Resolution

Region					MOI	DIS-IO	GBP C	Catego	ry		
Name	Acronym	2	4	5	6	7	8	9	10	12	14
North Dry	ND	-	-	-	-	Y	-	-	Y	Y	Y
East Dry	ED	-	Y	-	-	Y	-	-	Y	-	Y
Northeast Semi-Dry*	NESD	-	-	-	Y	Y	Y	Y	Y	Y	Y
West Semi-Dry	WSD	-	-	-	-	Y	-	Y	Y	Y	Y
East Wet	EW	Y	-	-	-	-	Y	Y	Y	Y	Y
West Moist	WM	-	-	-	-	-	Y	Y	-	Y	Y
West Wet	WW	Y	-	-	-	-	Y	Y	Y	-	Y
Central Wet*	CW	Y	-	-	-	Y	Y	Y	Y	-	Y
West Wet Nigeria	WWN	Y	-	-	-	-	Y	Y	-	Y	Y
Central Moist*	CM	Y	-	-	-	-	Y	Y	Y	Y	Y
Lake Victoria Wet	LVW	Y	-	-	-	-	Y	Y	Y	Y	Y
East Moist	EM	Y	-	Y	-	-	Y	Y	Y	-	Y
Southeast Semi-Dry	SESD	-	-	-	-	Y	Y	Y	-	-	-
Madagascar	MAD	Y	Y	-	-	Y	Y	Y	Y	-	Y
South Dry	SD	-	-	-	-	Y	-	-	-	-	-
South Semi-Dry	SSD	Y	-	-	Y	Y	Y	Y	Y	Y	-
South Moist	SM	Y	-	-	-	Y	Y	Y	Y	Y	Y

*: Indicates bioclimate regions that are subdivided into a north, a south, or other sub-bioclimate regions for better LAI geographical distributions.

Region	First Region	PFTs	Second Region	PFTs
ND	WW	4,5	WSD	6,10,11
ED	EW	4,5	NESD-N	13,14,15
NESD-N	EW	4,5	-	-
NESD-S	EW	4,5	-	-
NESD-SH	EW	4,5	NESD-S	6,15
WSD	WW	4,5	-	-
EW	NESD-N	10	-	-
WM	WW	4,5	WSD	10,13
WW	WSD	10	-	-
CW-N	WSD	10	-	-
CW-S	SESD	15	-	-
CW-SA	CW-S	6	SESD	15
WWN	WW	6	WSD	10
CM-N	CW-N	4,5,6	NESD-S	10
CM-S	CW-S	6,10	-	-
LVW	NESD-S	6,10	-	-
EM	CW-S	6	SESD	10
SESD	EM	4,5	-	-
MAD	SESD	15	-	-
SD	SSD	4,5,6,14,15	-	-
SSD	-	-	-	-
SM	SSD	14	-	-

Table 4: Regional Interpolation of Missing PFT data

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Table 5: Equations for Calculating SAI for Each PFT in CLM-AF

PFT	SAI Equation	SAI Minimum
Broad Leaf Evergreen Trees	$SAI = -\Delta LAI + 0.5$	0.5
Broad Leaf Deciduous Tropical Trees	$SAI = -1.0385(\Delta LAI) + 0.2$	0.3
Broad Leaf Deciduous Shrubs	$SAI = -0.8(\Delta LAI) + 0.12$	0.1
C3 Non-Arctic Grass	$SAI = -0.9(\Delta LAI) + 0.32$	0.1
C4 Grass and Corn	$SAI = -\Delta LAI + 0.3$	0.3
CAL Chains Amer Indian ALAL D'ffemanes	hat a second	

SAI: Stem Area Index; Δ LAI: Difference between the LAI of the current and previous month.

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Moisture	Radiation Band	CLM-D		CL	M-AF 1240
		Sand	Sand-Loam	Sand	Sand-Loam
Saturated	Visible	0.12	0.11	0.22	0.13
	Infrared	0.24	0.22	0.34	0.24
Dry	Visible	0.24	0.22	0.34	0.24
	Infrared	0.48	0.44	0.58	0.46
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Experiment	Period	Land Use	LSM
Meteorological	2013	Default	Noah
Evaluationodel Validation			
			Noah-Sat
			Noah-MP
			CLM-D
			CLM-AF
Land Use Land Cover Change	2010	MODIS 2001 (LU01)	Noah
	2015		
			Noah-MP
			CLM-D
			CLM-AF
		Dinamica EGO 2010-2015	Noah
		(LUD)	
			Noah-MP
			CLM-D
			CLM-AF

Table 8: Datasets for Meteorological Evaluationodel Validation

Datasets	Temporal	Spatial	Website
	Resolution	Resolution	
CRU TS4.02 ^a	Monthly	0.5°×0.5°	https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.02/
NCDC-ISD ^b	Hourly	n/a	https://www.ncdc.noaa.gov/land-based-station-data/integrated-surface-database-isd
CERES-EBAF ^c	Monthly	1°×1°	https://ceres.larc.nasa.gov/
GPCP ^d	Monthly	2.5°×2.5°	http://www.esrl.noaa.gov/psd/data/gridded/data.gpcp.html
TRMM ^e	3-Hour	0.25°×0.25°	https://pmm.nasa.gov/data-access/downloads/trmm
$MOD08_M3^{f}$	Monthly	1°×1°	https://modaps.modaps.eosdis.nasa.gov/services/about/products/c61/MOD08_M3.h tml

1265 ^a: University of East Anglia, Climate Research Gridded Climate Data version 4.02; ^b: National Climate Data Center - Integrated Surface Data; c: Clouds and Earth's Radiant Energy System - Energy Balanced and Filled; d: Global Precipitation Climatology Project; e: Tropical Rainfall Measuring Mission; f: MODIS/Terra Aerosol Cloud Water Vapor Ozone Monthly L3 Global 1Deg CMG.

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Table 9: Evaluated Variables and Evaluation Datasets

Variable	Acronym	Evaluation Dataset
2m Temperature	T2	CRU TS4.02 and NCDC-ISD
Daily Maximum Temperature	T <mark>2</mark> MAX	CRU TS4.02
Daily Minimum Temperature	T <mark>2</mark> MIN	CRU TS4.02
Diurnal Temperature Range	DTR	CRU TS4.02
2-m Vapor Pressure	E2	CRU TS4.02
2m Dew point Temperature	T _d 2	NCDC-ISD
Precipitable Water Vapor	PWV	MOD08_M3
Cloud Fraction	CF	CRU TS4.02 and MOD08_M3
Precipitation	PRE	CRU TS4.02, GPCP, and TRMM
10 m Wind Speed	WS <mark>P</mark> 10	NCDC-ISD
Dow <u>nw</u> elling Shortwave Radiation (Surface)	<u>SWDOWNDSR</u>	CERES-EBAF
Downwelling Longwave Radiation (Surface)	<u>GLW</u> DLR	CERES-EBAF
Upwelling Shortwave Radiation (TOA*)	<u>SWUPTUSRT</u>	CERES-EBAF
Upwelling Shortwave Radiation (Surface)	USRS	CERES-EBAF
Upwelling Longwave Radiation (TOA*)	<u>OLR</u> ULR	CERES-EBAF
Shortwave Cloud Forcing	SWCF	CERES-EBAF
Longwave Cloud Forcing	LWCF	CERES-EBAF
*: Top of the Atmosphere.		

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1285 Table 10: Annual Average 2 m Temperature Change (°C) in WRF Grid Cells that experience LULCCs between 2001 and 2010_-2015

Transition	Noah	Noah-MP	CLM-D	CLM-AF
Agricultural Expansion [*]	-0.12	0.1	0.1	0.17
10 to 12	-0.09	0.16	0.18	0.17
2 to 14	-0.3	0.6	1.34	1.38
8 to 14	-0.06	0.01	-0.12	0.15
10 to 14	-0.1	0.06	0.03	0.07
Deforestation/Degradation*	0.04	-0.01	-0.03	0.22
8 to 9	0.17	-0.03	-0.22	0.18
9 to 7	-0.16	-0.04	0.12	0.36
9 to 10	-0.11	-0.05	0.1	0.11
Greening*	0.02	-0.13	-0.33	-0.41
9 to 8	-0.12	0.0	0.08	-0.13
10 to 9	0.18	-0.02	-0.28	-0.26
16 to 7	-0.01	-0.13	-0.39	-0.40
16 to 10	0.09	-0.2	-0.81	-0.8

*: Shows average difference for a broad class of LULCC followed by the average difference in the major MODIS LULC transitions that comprise that class. MODIS Land Use Categories: 2 - Evergreen Broad Leaf Forest; 7 - Open Shrublands; 8 - Woody Savanna; 9 - Savannas; 10 - Grasslands; 12 -290 Croplands; 14 – Cropland/Natural Mosaic; 16 – Barren/ Sparsely Vegetated.

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Table 11: Annua	l Average Precipitatio	n Rate Change (1	nm day-1) in W	VRF Grid Cells that	experience
LULCCs betwee	n 2001 and 2015				

Transition	Noah	Noah-MP	CLM-D	CLM-AF
Agricultural Expansion*	0.02	-0.13	-0.08	-0.03
10 to 12	0.02	-0.04	0.05	-0.02
2 to 14	-0.12	-0.25	-0.45	-0.38
8 to 14	0.07	-0.18	-0.10	0.00
10 to 14	0.04	-0.01	0.04	-0.02
Deforestation/Degradation*	0.02	-0.01	-0.04	-0.08
8 to 9	0.07	-0.03	-0.01	-0.04
9 to 7	-0.05	0.05	0.12	-0.05
9 to 10	-0.01	-0.01	-0.02	-0.04
Greening*	0.00	0.03	0.15	0.05
9 to 8	-0.02	0.03	0.14	-0.03
10 to 9	-0.03	0.06	0.01	0.02
16 to 7	-0.01	0.02	0.05	0.00
16 to 10	0.05	-0.01	0.02	0.02

*: Shows average difference for a broad class of LULCC followed by the average difference in the 1315 major MODIS LULC transitions that comprise that class. MODIS Land Use Categories: 2 – Evergreen Broad Leaf Forest; 7 – Open Shrublands; 8 – Woody Savanna; 9 – Savannas; 10 – Grasslands; 12 – Croplands; 14 –Cropland/Natural Mosaic; 16 – Barren/ Sparsely Vegetated.