Recovering Evapotranspiration Trends from Biased CMIP5 Simulations and Sensitivity to Changing Climate over North America[✉]

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ABSTRACT

Future projections of evapotranspiration (ET) are of critical importance for agricultural and freshwater management and for predicting land–atmosphere feedbacks on the climate system. However, ET from phase 5 of the Coupled Model Intercomparison Project (CMIP5) simulations exhibits substantial biases, bolstering little confidence in future ET projections. Despite poor predictive skill and large bias of ET from the global climate models, the information content necessary to calculate ET offline is available in the models' archived outputs: temperature T , water vapor pressure e , atmospheric pressure P , and surface net radiation R . A relatively simple three-source energy balance model [Penman–Monteith (PM)], along with the mean annual cycle of remotely sensed vegetation properties, can then be used to reconstruct ET with a substantially reduced bias relative to in situ turbulent heat flux measurements. This methodology is used here to reconstruct ET projections from 2006 through 2100 over North America using output from selected CMIP5 models and to attribute projected ET trends to specific atmospheric controls. CMIP5 ET exhibits substantial bias in annual ET relative to in situ flux measurements across North America (38%–73%; 2006–15), but ET reconstructed from the CMIP5 meteorology with the PM method greatly reduces this bias (−8% to +14%). Present-day North American ET is more sensitive to changes in atmospheric demand for ET (temperature and water vapor pressure) than energy limitation (net radiation), and to a lesser extent vegetation properties (leaf area index). Accordingly, ET is projected to increase $0.26\text{--}0.87\text{ mm yr}^{-1}\text{ yr}^{-1}$ over North America through 2100 driven primarily by trends in temperature.

1. Introduction

Evapotranspiration (ET) is the fundamental mediator of water vapor transport across the land–biosphere–atmosphere interface, returning the majority of terrestrial precipitation to the atmosphere (Fisher et al. 2017). Over the last half century, significant trends in in situ, remotely sensed, and modeled ET have been identified (Dirmeyer et al. 2013; Yao et al. 2016; Taichen et al. 2018; Y. Zhang et al. 2016; Zeng et al. 2016; Zhang et al. 2015), but the magnitude and sign of the trends are spatially variable and dependent on the dataset analyzed (Dong and Dai 2017; Hember et al. 2017), and attribution of observed ET trends to climatic and anthropogenic drivers is highly uncertain (Mao et al. 2015).

Future projections of ET are critical for agricultural and freshwater management (Fisher et al. 2017; Famiglietti 2014), especially in light of likely increased demand for irrigation (Levis et al. 2018; Pryor et al. 2016), but ET is poorly constrained and highly uncertain in current climate models (Mueller and Seneviratne 2014; Y. Zhang et al. 2016; Yao et al. 2016).

ET moderates atmospheric thermodynamic and stability profiles, and occurrence of precipitation (De Ridder 1997; Guillod et al. 2014; Findell et al. 2011; Miralles et al. 2014), and future water cycle intensification will further amplify the importance of land–atmosphere coupling (Dirmeyer et al. 2013; Zhang et al. 2015). Accordingly, poorly constrained ET and the resultant uncertainty in atmospheric feedbacks have been identified as a potential cause of model bias in near-surface meteorology (Ma et al. 2018; Cheruy et al. 2014; Seneviratne et al. 2013). Clearly, a better understanding of the processes that control ET, how ET feedbacks impact atmospheric processes, and how these interactions will change into the future is warranted (Fisher et al. 2017).

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A key challenge in stimulating policy response to climate science is building confidence that climate projections are accurate and realistic. One approach in building confidence in climate models is to quantify skill in reproducing historical and/or recent atmospheric states and processes. In light of high uncertainty and poor skill of current climate models in reproducing observed ET (Mueller and Seneviratne 2014; Yao et al. 2016; Y. Zhang et al. 2016), making projections of future ET trends can be a seemingly futile endeavor. However, an improved understanding of the atmospheric state variables and processes that control ET [e.g., temperature (T), water vapor pressure (e), net radiation (R), precipitation (ppt), soil moisture (SM), vegetation properties [e.g., leaf area index (LAI)]] can elucidate an alternate pathway for projecting future ET trends. In principle, if the controls on ET are moderately well understood and trends in those control variables can be robustly predicted, subsequent trends in ET can be reconstructed with greater confidence.

However, the dependence of ET on the controlling factors are likely nonlinear and are strongly coupled to local land cover (Eichmann et al. 2018) and climate type (Tabari and Talaei 2014). For example, in India ET was found to be most sensitive to perturbations in T and least sensitive to e , with R and wind speed (u) sensitivity middling (Goyal 2004). The strong dependence of ET on T and low sensitivity to e was also found in Australia (Guo et al. 2017) and Iran (Sharifi and Dinpashoh 2014), but Tabari and Talaei (2014) found that the sensitivity of ET to T in Iran was limited to arid regions, and that ET became more sensitive to R in humid areas of the country. Likewise, ET in China was found to be most sensitive to relative humidity followed by lower sensitivity to R , T , and u (Gong et al. 2006). ET was found to be most sensitive to vapor pressure deficit (VPD) in the United States (Irmak et al. 2006) where grassland ET is more strongly linked to e than ppt, with the sensitivity increasing with increased aridity of the vegetation (Konings et al. 2017). Accordingly, a better understanding of local controls on ET is essential.

The research presented herein is intended to add to the understanding of atmospheric and biogenic controls of terrestrial ET, how these controls may change under changing climate, and the potential impact on future ET trends. First, a remotely sensed, vegetation-index-based energy balance model [Penman–Monteith (PM)] (Monteith 1965; Mu et al. 2011; Sullivan et al. 2019) is used to estimate ET over North America from in situ meteorological and radiation measurements. The estimated ET are then recomputed after perturbing model inputs (T , e , R , LAI) to quantify the sensitivity

of ET to specific atmospheric, radiative, and vegetative forcing.

To understand future trends in ET in a changing climate, we also utilize model output from phase 5 of the Coupled Model Intercomparison Project (CMIP5; Taylor et al. 2012). Consistent with previous research indicating poor performance of CMIP5 ET, we demonstrate a substantial bias in modeled ET relative to in situ turbulent heat flux measurements. However, this bias can be substantially reduced by recomputing ET (CMIP-PM-ET) from the PM equation using the CMIP5 simulated meteorology and surface net radiation. We then compute CMIP-PM-ET through 2100 to evaluate future trends in North American ET over the remainder of the century. In addition to improving ET estimates relative to CMIP5 land surface model ET, CMIP-PM-ET is also computed by selectively using combinations of present-day and future inputs (T , e , R , LAI) to diagnose the specific drivers of ET trends.

2. Methods

a. ET algorithm

The implementation of the Penman–Monteith equation used here is following the National Aeronautics and Space Administration's (NASA) Moderate Resolution Imaging Spectroradiometer (MODIS) ET product (MOD16; Mu et al. 2011, 2007; Cleugh et al. 2007; Running et al. 2017), with constrained canopy surface resistance to transpiration following Sullivan et al. (2019) (Argonne-ET). MOD16 is a three-source PM model accounting for transpiration from vegetation, evaporation of water intercepted in the canopy, and evaporation from soil. Parameterization of the aerodynamic and surface resistance (r_a and r_s , respectively) terms are computed for each ET component separately as a function of T , e , P , LAI, and biome specific constants that are tuned to in situ eddy covariance flux tower measurements and global precipitation patterns.

While many methods for estimating ET exist, the PM equation was selected as its meteorological inputs are routinely measured and archived in global climate model outputs (cf. ET models that require surface temperature, which is only available for clear-sky conditions). Additionally, it is amenable to physical interpretation and sensitivity analysis (K. Zhang et al. 2016). It is noted that as different ET models exhibit variable skill and are limited by inherent biases, the PM method is dependent on predefined, biome specific constants (Jiménez et al. 2011; Gonzalez-Dugo et al. 2009). When forced with in situ meteorology, the PM model used herein shows fidelity in reproducing in situ latent heat

flux measurements over the U.S. Southern Great Plains: correlation of 0.75, root-mean-square error (RMSE) of 36 W m^{-2} , and bias in mean annual ET of 1% (Sullivan et al. 2019). While Argonne-ET exhibits considerable skill relative to in situ flux measurements, future trends in ET should be interpreted with caution.

Sullivan et al. (2019) found that the MOD16 derivation resulted in estimated dry canopy r_s to transpiration that were much greater than observed values, leading to a substantial bias in annual cumulative ET estimates over the U.S. Southern Great Plains. However, by imposing a simple constraint whereby r_s values are rescaled to the range realistic values (Szeicz and Long 1969; Allen et al. 2006), the bias can be nearly eliminated (+1% relative to in situ measurements, cf. −38% from the original MOD16). In brief, r_s values are rescaled to $[0\text{--}150] \text{ m}^{-1} \text{ s}$ following Eq. (1). This range was selected to represent the approximate range of r_s values even in water stressed regimes (Szeicz and Long 1969; Allen et al. 2006):

$$r_{s,i,\text{new}} = \left\{ \frac{r_{s,i,\text{old}} - \min(r_s)}{[\max(r_s) - \min(r_s)]} \right\} \times r_{s,\text{limit}}, \quad (1)$$

where $r_{s,i,\text{old}}$ and $r_{s,i,\text{new}}$ are the original (i.e., following Mu et al. 2011) and constrained r_s , respectively, for time i , $r_{s,\text{limit}}$ is the constrained maximum r_s ($150 \text{ m}^{-1} \text{ s}$) and $\min(r_s)$ and $\max(r_s)$ are the minimum and maximum r_s , respectively, from the time series at each measurement site. Herein, $\min(r_s)$ is assumed to be zero and $\max(r_s)$ is limited to $10000 \text{ m}^{-1} \text{ s}$ to prevent larger outliers from skewing the rescaling. The original constraint was developed using the U.S. Department of Energy's Atmospheric Radiation Measurement (ARM) user facility's (Mather and Voyles 2013; Cook and Sullivan 2019a,b) Southern Great Plains (SGP) dataset over a region of primarily crop and grassland. In applying the Argonne-ET algorithm to FLUXNET sites with different vegetation types, it was found that 1) root-mean-square errors and biases in annual ET were lower when r_s was not constrained (i.e., following Mu et al. 2011) over forests, and 2) the constraint was overcorrective for shrubland and savannas, where r_s can be much larger than the original rescaling threshold developed over crop and grassland (Sullivan et al. 2019; Dhungel et al. 2014). Thus, no r_s constraint is applied to forest grid cells [i.e., r_s is calculated following Mu et al. (2011) with no rescaling [no Eq. (1)]], and $r_{s,\text{limit}}$ is set to $500 \text{ m}^{-1} \text{ s}$ and $\max(r_s)$ is set to $1000 \text{ m}^{-1} \text{ s}$ for shrubland and savannas grid cells (Dhungel et al. 2014).

b. Input data

MOD16 and Argonne-ET use net radiation and meteorological states from reanalysis and in situ

measurements, respectively. Herein, ET is derived both from in situ measurements from the U.S. Climate Reference Network (2006–17; USCRN), and climate model output from CMIP5. Three CMIP5 models were selected based on the criteria that: 1) all requisite input meteorology are saved and freely available on the CMIP5 database (esgf-node.llnl.gov), 2) in addition to future time periods, simulation output cover the recent time period (2006–15) to allow evaluation relative to in situ measurements, and 3) the selected models span the range of equilibrium climate sensitivities (ECS) from all CMIP5 models. The models evaluated here are GISS-E2-R (hereafter GISS; NASA Goddard Institute for Space Studies; Schmidt et al. 2014), MIROC5 (hereafter MIROC; The University of Tokyo, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology; Watanabe et al. 2010), and GFDL-CM3 (hereafter GFDL; NOAA Geophysical Fluid Dynamics Laboratory; Donner et al. 2011) representing low, medium, and high ECS, respectively (Sherwood et al. 2014). GISS and GFDL are at $2.0^\circ \times 2.5^\circ$ resolution, MIROC is at $\sim 1.4^\circ \times \sim 1.4^\circ$ resolution, and 3-hourly mean output are used for all models (Fig. 1). For all models, two representative concentration pathways (RCP) for future climate scenarios are also used (RCP4.5, RCP8.5).

For the USCRN-ET, LAI is from the MODIS *Terra/Aqua* 0.5-km 4-day product (MCD15A3H), linearly interpolated to the hourly USCRN measurements. As LAI is not a saved output in all the CMIP5 models, the LAI annual cycle for CMIP-PM-ET is also taken from MODIS, approximated as the mean annual cycle of all available MODIS measurements within each model grid cell from the first decade of the simulations.

Land cover type is determined from the most common land cover type within each model grid cell from the MODIS *Terra/Aqua* 0.5-km yearly product (MCD12Q1; Fig. 1).

For USCRN-ET, net radiation is computed from measured global radiation and near surface air temperature, the MODIS combined *Terra/Aqua* daily 0.5-km albedo product (MCD43A3; where albedo is approximated as the arithmetic mean of the black- and white-sky shortwave albedos), and surface and atmospheric emissivity approximations following Mu et al. (2011). CMIP5 net radiation is computed as the sum of the surface incoming and outgoing, longwave and shortwave radiation. Surface soil (ground) heat flux is estimated as a function of net radiation and vegetation fraction following Su et al. (2001). Vegetation fraction (Fc) is derived empirically from LAI, using a power law

FIG. 1. CMIP5 grids from (a) GFDL-CM3 and GISS-E2-R and (b) MIROC5. Filled square colors are the MODIS derived land use type that characterizes the most pixels within each grid cell. The bold grid outline color represents the number of in situ measurement sites (ARM and FLUXNET) within each grid cell. The X marks are the land use type and location of the in situ flux measurements.

function fit to LAI and F_c from the sites in [Sullivan et al. \(2019\)](#).

c. Trends and sensitivity analysis

The USCRN data are used to estimate present-day ET rates (USCRN-ET; 2006–17), and quantify the sensitivity of these estimates to perturbations in the individual PM ET inputs (T , e , R , LAI). Specifically, ET is first computed using observed input variables, and then recomputed with each individual input variable decreased and increased by 20% (i.e., eight additional ET computations for $\pm 20\%$ for each of T , e , R , and LAI). This range was selected as it has routinely been used in previous literature examining the sensitivity of ET estimates to input meteorology, and ET changes generally scale linearly to changes in input meteorology

(e.g., ET changes $\sim$ twice as much due to a 20% change in an input variable cf. a 10% change in the input variable) ([Tabari and Talaei 2014](#); [Goyal 2004](#); [Sharifi and Dinpashoh 2014](#); [Gong et al. 2006](#); [Irmak et al. 2006](#)). While the meteorological variables inevitably exhibit covariability, the analysis presented here is intended to provide a first-order sensitivity analysis, and a comprehensive analysis of higher-order interactions is left to the previously referenced literature.

CMIP5 meteorology and surface net radiation (2006–15; run in forecast mode) are used as input into the PM equation to estimate ET (CMIP-PM-ET) to evaluate skill in reproducing ET from in situ flux measurements, compared to that of the original CMIP5 land surface model ET (CMIP-ET). CMIP-PM-ET are then used to evaluate projected ET trends (2006–2100), and examine

the dependence of projected trends to trends in individual input variables. Specifically, ET is computed from the CMIP5 meteorology, and then recomputed three times with individual inputs T (no ΔT), e (no Δe), and R (no ΔR) set to the mean annual cycle from the first decade of the simulation period (2006–15). To quantify the potential impact of vegetation greening on ET (Y. Zhang et al. 2016; Zeng et al. 2016; Zhang et al. 2015; Huang et al. 2018), a fifth CMIP-PM-ET experiment is conducted by recomputing ET with LAI increasing linearly up to a 30% increase by 2100 (approximate trend in satellite-based LAI measurements over the last ~30 years; Zeng et al. 2018).

d. Comparison to in situ measurements

It is hypothesized that although CMIP5 models perform poorly in reproducing observed ET, they perform with sufficient accuracy in reproducing the ET meteorological drivers (e.g., T , e , R), and therefore the information content of ET can be recovered without requiring modifications to the land surface models and rerunning the simulations. This hypothesis is tested by comparing ET from the CMIP5 land surface models (CMIP-ET) and ET reconstructed using CMIP5 meteorology and the PM equation (CMIP-PM-ET) with in situ turbulent heat flux measurements.

In situ flux measurements are from the ARM SGP site (Mather and Voyles 2013; Cook and Sullivan 2019b,a) and from the FLUXNET2015 tier 1 (open data) dataset (Baldocchi et al. 2001) (Fig. 1). The ARM dataset used here consists of measurements from 15 energy balance Bowen ratio (EBBR) and 8 eddy correlation (ECOR) flux measurement systems across Oklahoma and Kansas grassland and cropland (one forest site) [see Sullivan et al. (2019) for detailed description]. During the simulation periods there are 34 FLUXNET sites across the study area employing the eddy correlation flux technique over grassland, crop, savannas, open shrubs, and wetlands, and evergreen needleleaf, deciduous broadleaf, and mixed forest. While methods for averaging spatially discrete site measurements to coarse model grid cells have been proposed that account for land cover and/or spatial distributions of measurements, it was found that the resultant grid cell mean was less sensitive to averaging method than instrument uncertainty (Tang et al. 2019). Thus, a simple mean of all measurements within each grid cell is used for evaluation of CMIP-ET and CMIP-PM-ET.

Prior to analysis, all data with bad data quality flags are removed, and the FLUXNET data were gap-filled following Reichstein et al. (2005). It is noted that while ARM does not provide gap-filled data, thus potentially biasing annual ET estimates, the impact to the model

evaluation is not large: for example, the model correlation with and RMSE relative to in situ measurements changes on average only ~ 0.01 and 1 W m^{-2} , respectively, when only FLUXNET data are used compared to when both FLUXNET and ARM are used. Currently larger data gaps are not artificially in-filled, as it is expected that multiple sites within a grid cell will not be concurrently missing, but it is acknowledged that this may lead to jumps in the time series and thus increased uncertainty in the measurements. To minimize bias from missing data periods, annual ET is computed by multiplying the mean latent heat flux (converted to mm s^{-1}) by the number of seconds in a year.

Uncertainties in latent heat flux measurements can be $>10\%$ (Cook and Sullivan 2019a,b), the eddy correlation flux method routinely fail to achieve energy balance closure (Foken et al. 2011), and latent heat flux estimates can depend the measurement method (e.g., eddy correlation versus energy balance Bowen ratio; Tang et al. 2019). As these measurements are considered “ground truth” herein, these uncertainties must be recognized when interpreting evaluation of the CMIP5 and PM ET estimates.

3. Results

a. Sensitivity of ET to meteorological state

Consistent with previous estimates (Reitz et al. 2017; Sanford and Selnick 2013; Velpuri and Senay 2017), USCRN-ET exhibits a strong spatial gradient across the contiguous United States (CONUS) with ET approaching 1000 mm yr^{-1} in the southeast, $\sim 500 \text{ mm yr}^{-1}$ in the Midwest and Great Plains, and $<400 \text{ mm yr}^{-1}$ west of the Rocky Mountains (Fig. 2a). Over the entire CONUS, ET is strongly responsive to changes in T , with a median change in ET of $+1.0\%$ per percent change in T across the study area (i.e., $\sim \pm 20\%$ change in ET when T is changed $\pm 20\%$; Figs. 2b–d). ET is also strongly responsive to changes in e , with a median change in ET of -0.8% per percent change in e (Figs. 2e–g). ET is modified by T and e primarily due to the changes in VPD (increased VPD with increased T and decreased e) and the resultant impact on the atmospheric demand component of the PM equation. Conversely, the energy limitation component of the PM equation is about half as responsive, with a median change in ET of $+0.5\%$ per percent change in R (Figs. 2h–j). Contrary to expectation of strong vegetation–ET coupling (Y. Zhang et al. 2016; Zeng et al. 2016; Zhang et al. 2015), ET is least responsive to LAI, with a median change in ET of $+0.2\%$ per percent change in LAI (Figs. 2k–m). As with the annual ET, there is a strong spatial gradient with ET sensitivity increasing east of the Great Plains. Thus,

FIG. 2. (a) Mean annual ET (mm yr^{-1}) at USCRN sites calculated from the PM equation, and percent change in mean annual ET at USCRN sites calculated from the PM equation with $\pm 20\%$ change in (b)–(d) temperature, (e)–(g) water vapor pressure, (h)–(j) net radiation, and (k)–(m) LAI. The first column and red in the third column are -20% for each input variable; the second column and blue in the third column are $+20\%$ for each input variable.

regions with the highest ET rates also exhibit the strongest sensitivity of ET (derived from the PM equation) to changes in meteorological states, and could be regions subject to strong land–biosphere–atmosphere feedbacks in a changing climate.

b. Comparison of CMIP5 land surface model and Penman–Monteith ET to in situ measurements

Deficiencies in ET from climate models are well documented. It is proposed here that, despite inaccuracies in the land surface models, the information content

of ET is not inevitably lacking, and thus ET can be recovered from simulated meteorological and radiative states. Specifically, the Penman–Monteith equation is used with climatological, remotely sensed LAI, and T , e , R , and atmospheric pressure P from three CMIP5 models with variable climate sensitivities (Sherwood et al. 2014). The improvement (or lack thereof) in skill in predicting ET is quantified relative to 3-h averaged in situ latent heat flux measurements from ARM and FLUXNET (Baldocchi et al. 2001; Mather and Voyles 2013; Cook and Sullivan 2019a,b).

FIG. 3. Skill metrics for ET from CMIP5 (squares) and computed from the PM equation using CMIP5 meteorology (circles) for RCP4.5 (cool colors) and RCP8.5 (warm colors) at 3-h (blue and red) and daily (cyan and magenta) frequency relative to in situ measurements from ARM and FLUXNET. Markers and whiskers are the mean $\pm$ 1 standard deviation for all grid cells in which in situ data are available. Note GFDL-CM3 RCP8.5 ET is not available before 2036 in the CMIP5 database. Annual ET bias is computed as the cumulative annual ET estimated from CMIP5 or PM minus in situ measured ET, normalized by in situ measured ET. Spatial distributions of the metrics are shown in Figs. S1–S3.

For all skill metrics used here (RMSE, Pearson's correlation coefficient r , and annual ET bias), CMIP-PM-ET outperforms CMIP-ET for all three models (GFDL, GISS, and MIROC) and both RCP4.5 and RCP8.5 (Fig. 3). While the specific RCP scenario does not largely impact model skill, there are discrepancies between the three models: MIROC has the lowest RMSE of $53\text{--}55\text{ W m}^{-2}$ (cf. $68\text{--}70\text{ W m}^{-2}$ for GFDL and GISS) and highest r of $0.68\text{--}0.70$ (cf. 0.62 for GFDL and $0.65\text{--}0.66$ for GISS). In contrast, CMIP-PM-ET RMSE ranges from 44 to 51 W m^{-2} and r ranged from 0.69 to 0.75 using meteorological outputs from the three models and two RCPs. When diurnal variability is removed (i.e., daily averaged ET), the increase in r from CMIP-ET to CMIP-PM-ET is even larger: improvement in $r = \sim 0.12$ (cf. ~ 0.06 for 3-h averages) when averaged across the models.

The poor performance of CMIP5 ET is particularly evident in the annual cumulative ET. Annual ET is drastically overestimated by 63% , $68\%\text{--}73\%$, and $38\%\text{--}39\%$ for GFDL, GISS, and MIROC, respectively, relative to the in situ measurements (although these are subject to nontrivial uncertainties themselves). This substantial bias has significant implications for water budget analyses and may lead to poorly represented land–atmosphere feedbacks that can impede the performance of predicting other meteorological variables as well (Seneviratne et al. 2013). On the other hand, this bias can be substantially reduced by recomputing ET

from CMIP5 meteorology: CMIP-PM-ET annual ET biases are on average -6% to -8% , 0% , and 14% when computed from GFDL, GISS, and MIROC meteorology, respectively. Interestingly, while MIROC predicts ET with the greatest skill of the three models, CMIP-PM-ET shows the largest bias when using MIROC meteorology, potentially indicating some confounding feedbacks between modeled ET and meteorology.

The spatial distribution of the validation statistics is shown in Figs. S1–S3 in the online supplemental material. There are notable similarities in performance of the different models in different regions. In general all models and PM estimates show the highest correlation with in situ measurements in the Great Plains and Midwest regions, with lower correlation in the southwest. However, the lower performance in the southwest diminishes for the RMSE metric.

c. Future projections of ET and controls on ET trends

Consistent with the high bias in annual ET from CMIP-ET relative to in situ measurements discussed above, the domain average annual ET (2006–16) is largely reduced when recomputed in CMIP-PM-ET. The intermodel range is $690\text{--}750\text{ mm yr}^{-1}$ from CMIP-ET compared to $420\text{--}530\text{ mm yr}^{-1}$ from CMIP-PM-ET, indicating an overestimation of ET by the land surface models of $\sim 30\%\text{--}81\%$ relative to the reconstructed PM ET (Fig. 4). While CMIP-PM-ET substantially reduces ET bias relative to in situ measurements, it is

FIG. 4. Mean annual ET (mm yr^{-1}) from 2006 to 2016 from (a)–(f) CMIP5 land surface models (CMIP-ET) and (g)–(l) the PM equation driven by CMIP5 meteorology (CMIP-PM-ET) from (left) GFDL, (center) GISS, and (right) MIROC for RCP4.5 in the first and third rows and RCP8.5 in the second and fourth rows.

noted that there is still a large uncertainty as characterized by the spread across the PM estimates derived from the different models' meteorology (e.g., $\sim 100 \text{ mm yr}^{-1}$ spread in domain average annual ET). However, this could be considered an observational constraint of the uncertainty as it is on the same order of magnitude as the uncertainty derived from spatially averaging different point flux measurement systems (e.g., ECOR and EBBR) to model grid cells (Tang et al. 2019).

Trends in CMIP5 land surface model ET are markedly model dependent (Figs. 5a–f and 6). All three models predict significant increases in ET over the Midwest, Northeast, and Southeast, with the smallest changes in magnitude calculated from GISS. Reductions in ET are predicted for the Southwest, with the largest

reductions in magnitude and areal extent calculated when using MIROC. Conversely, while all models predict significant ET trends over the Great Plains, there is lack of consensus in the sign of the trends: positive from GISS, negative from MIROC, and positive to the north and negative to the south from GFDL. Similarly, strong and weak positive increases are predicted in the northwest from MIROC and GISS, respectively, while GFDL RCP8.5 suggests decreasing ET in this region. Despite divergence in the models, all three are in general agreement of a greater magnitude trend from RCP8.5 than RCP4.5, indicating the trend can potentially be moderated by changes in anthropogenic emissions. As discussed in section 3b, ET from the CMIP5 land surface models is highly biased relative to in situ

FIG. 5. Trend in annual ET ($\text{mm yr}^{-1} \text{yr}^{-1}$) from 2006 to 2100 from (a)–(f) CMIP5 land surface models (CMIP-ET) and (g)–(l) the PM equation driven by CMIP5 meteorology (CMIP-PM-ET) from (left) GFDL, (center) GISS, and (right) MIROC for RCP4.5 in the first and third rows and RCP8.5 in the second and fourth rows. The trend is computed as the slope of the linear regression fit; cyan and magenta stippling indicate positive and negative trends, respectively, that are significantly ($\alpha = 0.05$) different from zero.

measurements and following the strong intermodel discrepancies in both magnitude and sign of predicted trends, little confidence is maintained in future trends in CMIP-ET.

Conversely, CMIP-PM-ET exhibits relatively small bias in annual cumulative ET, and there is convergence between the models on the sign and location of strongest trends (Figs. 5g–l). Over the entire domain (with the exception of a few individual grid cells) in all three models, CMIP-PM-ET projects an increase in ET from 2006 to 2100 ranging from $+0.26$ to $+0.87 \text{ mm yr}^{-1} \text{yr}^{-1}$, with the smallest and largest trends in GISS and MIROC, respectively (Fig. 6). There is also general

agreement of the greatest increase in ET over the central portion of the domain, with MIROC also predicting a strong increase through the east. When comparing emissions scenarios, the trends are from $+0.17$ to $+0.34 \text{ mm yr}^{-1} \text{yr}^{-1}$ higher in RCP8.5 than RCP4.5, highlighting the large uncertainty in future ET trends that can be attributed to uncertainties in anthropogenic emissions. Notably, the decreasing ET predicted in the Southwest in CMIP-ET becomes increasing ET in the reconstructed CMIP-PM-ET trends.

In addition to improved skill in prediction of ET, and thus anticipated improved skill in predicting ET trends, CMIP-PM-ET also affords the opportunity to diagnose

FIG. 6. Distribution of trends in mean annual ET ($\text{mm yr}^{-1} \text{yr}^{-1}$) across all grid cells from CMIP-ET, CMIP-PM-ET, and CMIP-PM-ET with no change in temperature (no ΔT), water vapor pressure (no Δe), and net radiation (no ΔR) (i.e., constant mean annual cycle from 2006 to 2015), and with a linear increase in LAI of 30% by 2100 (greening). Note outliers have been truncated for legibility. Spatial distributions of trends are shown in Figs. S4–S6.

the meteorological drivers of the predicted trends. To do this, we recomputed CMIP-PM-ET while holding each of T (no ΔT), e (no Δe), and R (no ΔR) individually to their mean annual cycle from 2006 to 2015, thus removing their trend from the calculated ET trend. Consistent with section 3a that ET was most sensitive to changes in T , removing the T trend results in a reversal of the sign of the ET trend across the central portion of the domain, where the strongest positive ET trends were predicted in CMIP-PM-ET (Fig. 6 and Figs. S4–S6d). GFDL and GISS also predict this sign reversal into the southwest. When trends in e are removed, the spread in ET trends across the domain widens (Fig. 6). In particular, positive trends increase in magnitude in the central portion of the domain, and negative trends emerge in the east and northwest in all three models, as well as the southwest in MIROC (Figs. S4–S6e). In light of expected warming trends and resultant increased energy for evaporation and thus increasing e , the change in sign in no ΔT and increased magnitude in the ET trend in no Δe in the central portion of the domain is consistent with changing VPD and atmospheric demand component of the PM equation. However, the contrasting change in sign in the ET trends from no Δe in the east and west highlights this relationship is likely not a straightforward, linear response. In contrast to the no ΔT and no Δe experiments, when net radiation is held to 2006–15 climatology, the magnitude and spatial pattern of ET trends is relatively unchanged, with the exceptions of a slight negative ET trend in a few western most grid cells in GFDL and GISS (Fig. 6 and

Figs. S4–S6g). This is consistent with previous research that found that future aridity was not strongly controlled by changes in net radiation and cloud cover (Seneviratne et al. 2013).

Herein, the annual cycle of vegetation phenology (LAI) is prescribed to be stationary. To test the sensitivity of future ET trends to changes in vegetation, the CMIP-PM-ET are recomputed with LAI linearly increasing 30% between 2006 and 2100 (greening ET), which is consistent with historical trends in satellite-based measurements of LAI (Zeng et al. 2018). As expected in response to the increasing trend in LAI, trends in ET increased ~ 2 – 4 times relative to CMIP-PM-ET (Fig. 6). This increasing trend is predominantly in the forested southeast portion of the domain (Figs. S4–S6h). Consistent with the greatest ET trends in MIROC, this model also had the greatest increase in the trend in the greening experiment relative to CMIP-PM-ET (increase of 1.0 – $1.1 \text{ mm yr}^{-1} \text{yr}^{-1}$ cf. 0.7 – $0.8 \text{ mm yr}^{-1} \text{yr}^{-1}$ from GFDL and GISS). The ET trend response to LAI is also dependent on emissions trends, with the increase in trend between greening ET and CMIP-PM-ET ~ 0.05 – $0.08 \text{ mm yr}^{-1} \text{yr}^{-1}$ greater in RCP8.5 than in RCP4.5, indicating compounding influence of temperature and carbon dioxide trends. LAI has changed in the past and will likely continue to change into the future. These changes impact terrestrial ET (Y. Zhang et al. 2016; Zeng et al. 2016; Zhang et al. 2015), but are poorly constrained in current models (Piao et al. 2015). For example, the domain mean $\pm$ standard deviation peak LAI from the first decade of the simulations was $5.2 \pm 1.9 \text{ m}^2 \text{m}^{-2}$ from GFDL and $2.2 \pm 0.9 \text{ m}^2 \text{m}^{-2}$ from MIROC compared to $2.4 \pm 1.2 \text{ m}^2 \text{m}^{-2}$ from MODIS (LAI output is not available from GISS). While the domain mean peak LAI from MIROC is comparable to MODIS, there is a large underestimation in LAI over the eastern North America forests (~ 2 – $3 \text{ m}^2 \text{m}^{-2}$ from MIROC cf. $>4 \text{ m}^2 \text{m}^{-2}$ from MODIS), where the sensitivity of ET trends to vegetation greening is greatest. Further, while MIROC LAI is relatively stationary 2006–2100, some grid cells exhibit substantial trends in GFDL. Thus, LAI is clearly a major uncertainty in ET trends estimated herein and from climate models.

4. Discussion

The Penman–Monteith equation with dynamic but constrained canopy surface resistance (Mu et al. 2011; Sullivan et al. 2019) is used along with in situ measurements of meteorological and radiative properties to quantify the response of mean annual ET to perturbations in meteorological, radiative, and vegetation state variables (T , e , R , and LAI). Over North America, ET

is more sensitive to atmospheric demand (i.e., VPD) than energy limitation. Annual ET increases and decreases $\sim 1\%$ per percent increase in T and e , respectively, but only increases $\sim 0.5\%$ per percent change in net radiation. Even though ET is strongly controlled by transpiration, annual ET was less sensitive to changes in LAI, with an estimated increase in ET of $\sim 0.2\%$ per percent increase in LAI. Spatially, the strongest sensitivities coincide with regions of the highest ET rates, indicating strong potential feedback mechanisms that, if poorly represented in climate models, could propagate to considerable bias in simulated meteorological fields.

Relative to in situ turbulent heat flux measurements, ET from CMIP5 land surface models exhibit substantial bias in annual ET rates of 38%–73% depending on the model. Nevertheless, the information content contained in the simulations permit reconstructing ET from the meteorological and surface radiation fields. ET recomputed from CMIP5 output and the PM equation reduces the annual ET bias to -8% to $+14\%$. When recomputed for the simulation period 2006–2100, CMIP-PM-ET alludes that the magnitude of ET trends in CMIP-ET are also overestimated. These biases are particularly notable in the Midwest and Great Plains where agricultural land is prevalent and in the western United States where water resources are limited and wildfires are common. Thus, poorly constrained ET in the CMIP5 simulations can inhibit their utility for understanding climate change impacts on agricultural, water resource, and wildfire management.

Trends in CMIP5 land surface model ET exhibit extensive model to model discrepancy in not only the magnitude, but also the sign of the trend. When recomputed using the PM equation, the models are in improved agreement with regards to the sign and spatial gradients in the ET trends, reinforcing further confidence in CMIP-PM-ET. Averaged over the entire domain, ET is projected to increase $0.26\text{--}0.87\text{ mm yr}^{-1}\text{ yr}^{-1}$ through 2100. Consistent with the strong atmospheric demand control on ET, the trends are $0.17\text{--}0.34\text{ mm yr}^{-1}\text{ yr}^{-1}$ greater in RCP8.5 relative to RCP4.5. Thus, uncertainty in anthropogenic emissions contributes considerably to uncertainty in future trends in ET.

The projected positive trend in ET is strongly linked to temperature trends. When T trends are removed from the computed ET the magnitude of the trends is greatly reduced and/or becomes increasingly negative over the majority of central and southwest North America. While this is expected in response to changing VPD, the dependency is relatively nonlinear. For example, when trends in water vapor pressure are removed the magnitude of the increasing ET trend over central

North America increases, and negative trends emerge in the east and northwest. In contrast, removing trends in net radiation has negligible impact on the ET trends. Consistent with the analysis of present-day ET (USCRN-ET), ET trends (CMIP-PM-ET) are more dependent on atmospheric demand than energy limitation.

There is substantial intermodel spread in CMIP5 LAI and model LAI differs drastically from satellite-based remote sensing estimates. Further, future trends in LAI are highly uncertain and will be dependent on changes in meteorology, greenhouse gas and nutrient concentrations, and land use changes (Biederman et al. 2017; Milly and Dunne 2016; Kumar et al. 2013). When a linear trend in LAI greening of 30% between 2006 and 2100 is introduced, ET trends increased an additional $0.7\text{--}1.1\text{ mm yr}^{-1}\text{ yr}^{-1}$. This response is greater in RCP8.5 than RCP4.5 indicating additional feedbacks from temperature and carbon dioxide trends. Thus, changes in vegetation and land cover can be a large uncertainty in projecting ET trends, and should be addressed in future research.

Increasing ET has been projected to increase global aridity (Teuling et al. 2013), and consistent with analysis herein, these trends are muted when temperature trends are suppressed (Dai 2013). Further, photosynthetic rates of different vegetation types respond differently to increased aridity and drought conditions (Teuling et al. 2010; Konings et al. 2017) and may have significant impacts on the magnitude and sign of terrestrial carbon sinks and sources (Biederman et al. 2017). Similarly, changes in carbon dioxide concentrations modify stomatal conductance, and thus transpiration rates (Milly and Dunne 2016). These strongly coupled, bidirectional feedbacks highlight the importance and uncertainty in predicting future changes in the terrestrial water and carbon cycles (Berg et al. 2016; Huntzinger et al. 2017; Ukkola et al. 2016). Thus, while ET estimated herein improves on CMIP5 ET relative to in situ measurements, and therefore can be used to study future ET trends with greater confidence, future work is warranted to fully understand how these findings are sensitive to these complex, nonlinear feedback systems.

5. Conclusions

Evapotranspiration modeled in select CMIP5 simulations is substantially biased relative to in situ measurements across North America (bias in annual ET of 38%–73%; 2006–15), hindering confidence in the models' fidelity in simulating future ET trends. However, forcing a Penman–Monteith model with CMIP5 meteorological outputs results in a greatly reduced bias in annual

ET estimates (-8% to $+14\%$). Using the improved ET estimates, it is shown that present-day North American ET is more sensitive to changes in atmospheric demand for ET (temperature and water vapor pressure) than energy limitation (net radiation), and to a lesser extent vegetation properties (leaf area index). Further, projected increases of ET over North America through 2100 are driven primarily by trends in temperature.

While the methods outlined herein are demonstrated to improve ET estimates relative to in situ measurements, the trends in ET must be interpreted with caution. ET depends on complex interactions between the ET drivers, feedback mechanisms, teleconnections, response of vegetation water use efficiency to changes in carbon dioxide concentrations, changes in vegetation density, and changes in land use. Further, the validity of the PM model is based on the assumption that in situ measurements can be treated as ground truth, and that future projections of the forcing variables are robust. In light of these large uncertainties, the trends in ET discussed herein are not intended to be interpreted as deterministic projections of future ET. However, from these results it is evident that parameterization of surface processes (such as terrestrial evapotranspiration) in the climate models analyzed here require improvement.

The current study focuses on recovering terrestrial evapotranspiration from imperfect climate model outputs under the postulate that while the land surface models poorly parameterize ET, the climate models can sufficiently simulate the drivers of ET variability and thus contain the information content necessitated to recover ET estimates to an extent. In addition, the framework could also readily be applied for other climate variables with large uncertainties. For example, while a physically based model (i.e., Penman–Monteith) is used here to derive the improved estimates of ET, a range of statistical techniques, such as artificial neural networks, could be used in similar “parameter downscaling” exercises to reconstruct other climate variables that are poorly represented in the current generation of climate models. Thus, future efforts should focus on heightened exploitation of the complete information content of current climate model output in addition to developing higher fidelity climate models.

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