

Observed Local and Remote Influences of Vegetation on the Atmosphere across North America Using a Model-Validated Statistical Technique That First Excludes Oceanic Forcings*

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ABSTRACT

The observed local and nonlocal influences of vegetation on the atmosphere across North America are quantified after first removing the oceanic impact. The interaction between vegetation and the atmosphere is dominated by forcing from the atmosphere, making it difficult to extract the forcing from vegetation. Furthermore, the atmosphere is not only influenced by vegetation but also the oceans, so in order to extract the vegetation impact, the oceanic forcing must first be excluded. This study identified significant vegetation impact in two climatically and ecologically unique regions: the North American monsoon region (NAMR) and the North American boreal forest (NABF). A multivariate statistical method, a generalized equilibrium feedback assessment, is applied to extract vegetation influence on the atmosphere. The statistical method is validated using a dynamical experiment for the NAMR in a fully coupled climate model, the Community Climate System Model, version 3.5 (CCSM3.5).

The observed influence of NAMR vegetation on the atmosphere peaks in June–August and is primarily attributed to both roughness and hydrological feedbacks. Elevated vegetation amount increases evapotranspiration and surface roughness, which leads to a local decline in sea level pressure and generates an atmospheric teleconnection response. This atmospheric response leads to moister and cooler (drier and warmer) conditions over the western and central United States (Gulf states). The observed influence of the NABF on the atmosphere peaks in March–May, related to a thermal feedback. Enhanced vegetation greenness increases the air temperature locally. The atmosphere tends to form a positive Pacific–North American (PNA)-like pattern, and this anomalous atmospheric circulation and associated moisture advection lead to moister (drier) conditions in the western (eastern) United States.

1. Introduction

The atmosphere and vegetation interact in a complex way. The atmosphere exerts a dominant control

on vegetation through variations in air temperature, precipitation, solar radiation, wind, and CO₂ concentration (Budyko 1974; Woodward 1987; Nemani et al. 2003; Woodward et al. 2004). As a result, the spatial distribution of major vegetation types is consistent with climate zones on a global scale (Bryson 1966). Although this two-way interaction is dominated by the atmosphere, vegetation does induce feedbacks on the atmosphere. Generally, vegetation can affect the atmosphere through either biogeophysical or biogeochemical processes (Pielke et al. 1998; Brovkin 2002; Bonan 2008a). Biogeophysical processes refer to vegetation forcing on the atmosphere

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directly through altered surface albedo, roughness, and plant transpiration, which affect the exchange of energy, momentum, and moisture with the atmosphere. Biogeochemical processes refer to vegetation influence on the atmosphere indirectly through altered atmospheric concentrations of CO₂, CH₄, and biogenic volatile organic compounds (BVOC) (Laothawornkitkul et al. 2009). This paper focuses on biogeophysical feedbacks. In the subsequent text, previous studies on vegetation feedbacks from the boreal (related to land surface albedo and plant transpiration) and tropical forests (related to roughness and plant transpiration) will be reviewed. In this paper, the two primary study regions are the Canadian boreal forest and the subtropical North American monsoon region, the latter of which potentially behaves similarly to a tropical forest in terms of vegetation feedbacks (Notaro et al. 2011).

The boreal forests extend in broad bands across North America and Eurasia, accounting for about 33% of global forests. It is generally accepted that the boreal forests increase the surface air temperature by lowering the surface albedo particularly during spring, but their impact on precipitation is seldom discussed. The boreal forests significantly reduce the surface albedo, based on both field measurements and satellite data. The typical albedo of a conifer forest is 0.08 in summer and slightly higher, 0.13, in winter as the canopy can mask underlying snow. In contrast, the surface albedo across grassland is 0.20 in summer and substantially higher, 0.75 in winter, as the snow covers the grass (Betts and Ball 1997). The huge difference in albedo between grasslands and forests in winter can be attributed to snow covering the grass but not persisting long on the forest canopy, especially when solar radiation or wind is strong (Betts and Ball 1997). It is noteworthy that not only evergreen forests, but also deciduous forests, can significantly reduce the surface albedo, even though during winter only their branches exist (Swann et al. 2010). The boreal forest induces a positive feedback on surface air temperature. An increase in tree fraction lowers the surface albedo, especially during the snow season, with the surface receiving more solar radiation, which increases the surface air temperature, producing a further increase in tree fraction (Brovkin 2002). Many pure modeling studies (Otterman et al. 1984; Harvey 1988; Bonan et al. 1992; Thomas and Rowntree 1992; Snyder et al. 2004; Jeong et al. 2012) have demonstrated this positive feedback in boreal forests. For example, Bonan et al. (1992) found that boreal forests can increase both winter and summer air temperatures based on experiments that either included or excluded the boreal forests. The summertime warming is mainly caused by the thermal lag of the oceans and sea ice. Snyder et al. (2004) performed a series of experiments to study the individual

global impacts of six vegetation biomes on climate by completely removing a particular biome each time and then comparing with the control run. They concluded that boreal deforestation produces the largest global temperature signal due to a vegetation–snow albedo feedback.

The influence of tropical forests on climate is still debated, although most studies argue that the tropical forests generate an increase in precipitation and decrease in temperature. Tropical forests act as a conduit, transferring moisture from the soil to the air through their stomata. A single well-watered tree can easily consume 100–150 L of water per day (Bonan 2008a). The rate of evapotranspiration depends on available energy at the surface. Both net radiation surplus and evapotranspiration peak in the tropical regions (Bonan 2008a). Owing to human activity, tropical forests are rapidly disappearing. Numerous modeling studies have assessed the potential effects of tropical deforestation (Shukla et al. 1990; Dickinson and Kennedy 1992; Dirmeyer and Shukla 1994; Costa and Foley 2000; Voltaire and Royer 2004). D’Almeida et al. (2007) reviewed previous modeling and observational studies, considering a range of the spatial extent of deforestation and model resolutions. In response to tropical deforestation, the majority of models produced an increase in surface air temperature due to reduced vegetation evapotranspiration (Dickinson and Henderson-Sellers 1988; Lean and Warrilow 1989; Shukla et al. 1990; Dickinson and Kennedy 1992). The effects of tropical deforestation on precipitation varied by study, with most models producing a decrease in precipitation. If tropical deforestation occurs on a small scale and in a heterogeneous manner, some models suggest that precipitation may increase owing to resulting mesoscale circulations (Bonan 2008b). The tropical deforestation studies also disagree about whether the impacts on climate are purely local or also remote (Hasler et al. 2009; Nobre et al. 2009).

The models applied in the aforementioned studies range in complexity from simple energy balance models (Otterman et al. 1984; Harvey 1988) to coupled atmosphere–biosphere models (Snyder et al. 2004; Xue et al. 2010) to complex GCMs (Bonan et al. 1992; Thomas and Rowntree 1992). These modeling studies are primarily limited by four factors. First, their results are model dependent, given that models differ in terms of their dynamical cores, numerical schemes, parameterizations, resolution, and simulation length. Second, nearly all modeling studies involve extreme sensitivity experiments, such as completely replacing a specific vegetation type with bare ground or another vegetation type, either locally or globally. Such extreme experiments are likely to be unrealistic since vegetation changes usually are heterogeneous and occur over time. Third, these studies

are limited by model biases. Finally, most studies focus on long-term climatic impacts, not monthly/seasonal prediction. Therefore, owing to limitations in modeling studies, observational studies are critically needed (O'Brien 1996).

In contrast to the plethora of modeling studies on vegetation feedbacks, studies that examine vegetation feedbacks through the use of observational data have been rare (Gentry and Lopezparodi 1980; Kaufmann et al. 2003; Liu et al. 2006; Notaro et al. 2006; Wang et al. 2006). Such observational studies must address certain challenges. First, the observational record is short in duration and contains measurement errors. Second, it is difficult to distinguish the modest vegetation forcing to the atmosphere from the large atmospheric internal noise. Third, besides vegetation, the atmosphere is also affected by sea surface temperature (SST), soil moisture, and snow cover. Since there is only one realization in the observations, only statistical methods can be applied. Wang et al. (2006), using a statistical technique known as Granger causality, studied observed vegetation forcing on the atmosphere. Liu et al. (2006) and Notaro et al. (2006) used a different statistical method, equilibrium feedback assessment (EFA), to quantify vegetation influence on the atmosphere, globally and across the United States, respectively. They concluded that in the northern mid to high latitudes, vegetation exerts a strong positive feedback on temperature during spring, while in the tropical and subtropical regions, vegetation only weakly affects precipitation. While these studies made critical strides in understanding vegetation feedbacks using observations, the use of EFA limited the results to local feedbacks and did not remove other forcings, such as SST. Using EFA, Sun and Wang (2012) studied the impact of soil moisture on precipitation and concluded that, because of synchronous oceanic influences on precipitation, EFA cannot separate the influences of soil moisture from that of the oceans.

The present study focuses on North America (Fig. 1). Across North America, the boreal forest extends from Alaska to Newfoundland, with tundra to the north. Across the western United States, shrublands and grasslands dominate, with a fractional vegetation cover of about 50% (Fig. 1); vegetation is sparse across regional deserts. According to prior observational and modeling studies, the North American boreal forest (NABF; 45°–60°N, 120°–85°W) and North American monsoon region (NAMR; 22°–37°N, 115°–102.5°W) (Fig. 1) are characterized by thermal (Liu et al. 2006; Notaro and Liu 2008) and hydrological feedbacks from vegetation (Notaro et al. 2011; Notaro and Gutzler 2012), respectively. These two regions, with contrasting feedbacks, will be the focus of the current study.

The purpose of this paper is to assess and quantify the observed impacts of monthly vegetation variations on atmosphere conditions across North America. In particular, this vegetation impact is obtained after excluding the influences from SST variability. The latter has been studied in an accompanying paper (Wang et al. 2013). The current paper represents the first attempt to systematically isolate vegetation impact from oceanic forcings and to quantify both local and nonlocal feedbacks from vegetation to the atmosphere. The data and model are introduced in section 2. The statistical and dynamical methods and their relationship are described in section 3. The generalized equilibrium feedback assessment (GEFA) method is validated in a fully coupled model for the NAMR in section 4. Observational vegetation influences on the North American climate from both NAMR and NABF regions are then assessed using GEFA in section 5. The conclusions and further discussions are presented in section 6.

2. Data and model

a. Data

Monthly-mean remotely sensed normalized differential vegetation index (NDVI) (Pinzón et al. 2005; Tucker et al. 2004, 2005) from the Global Inventory Modeling and Mapping Studies (GIMMS) is used to represent vegetation greenness. Given that chlorophyll in plant leaves strongly absorbs visible light (VIS) and strongly reflects near-infrared light (NIR), NDVI is defined as $NDVI = (NIR - VIS)/(NIR + VIS)^{-1}$. The data are on a $0.5^\circ \times 0.5^\circ$ grid and covers July 1981–December 2006. GIMMS NDVI applies radiometric calibration, atmospheric correction, cloud screening, and solar zenith angle correction to eliminate the effect not related to vegetation change (Holben and Fraser 1984; Holben 1986; Tucker et al. 2005). It should be noted that, although corrections and calibrations have been made to GIMMS NDVI, it still has some limitations. For example, NDVI tends to saturate over forests (Huete 1997); can be contaminated by snow, since snow has a high visible reflectance and a low near-infrared reflectance (Julien and Sobrino 2009); and can be affected by soil background conditions. The value of NDVI of bare soil in deserts is similar to that of sparse vegetation (Huete 1988).

Land cover type is obtained from the Earth Resources Observation and Science (EROS) global land cover characterization (GLCC) dataset, which is based primarily on 1-km Advanced Very High-Resolution Radiometer (AVHRR) 10-day NDVI composites from April 1992 through March 1993. The fraction of different land cover types (evergreen forest, deciduous forest, and

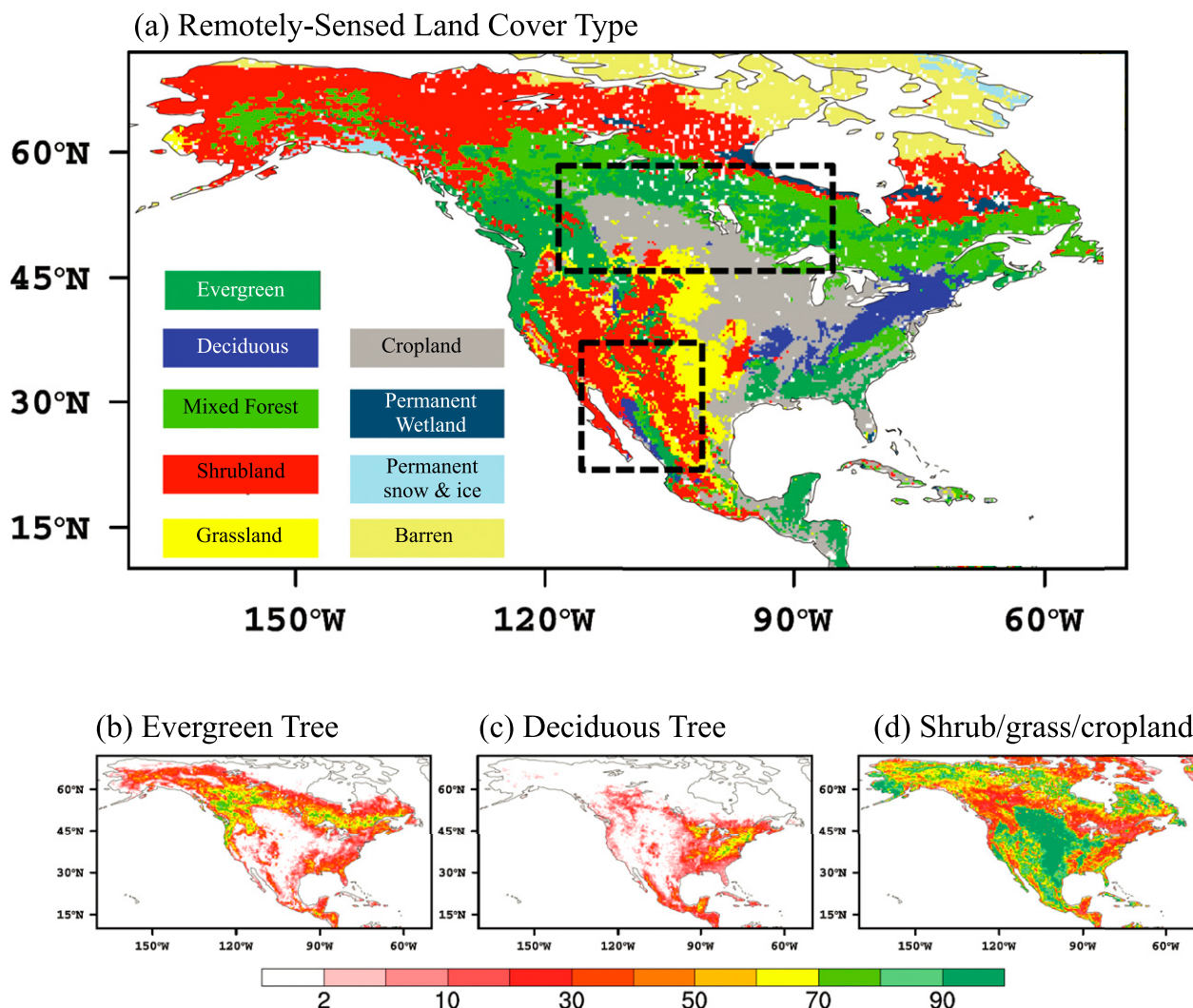


FIG. 1. (a) Remotely sensed land cover type from the EROS GLCC dataset and the percent cover of (b) evergreen tree, (c) deciduous tree, and (d) shrub/grass/cropland from the ISLSCP II Global Continuous Fields of Vegetation Cover dataset. Dashed boxes indicate the NABF and NAMR regions.

herbaceous/shrubs) is retrieved from the International Satellite Land Surface Climatology Project, Initiative II (ISLSCP II) Global Continuous Fields of Vegetation Cover dataset (DeFries et al. 1999, 2000). Monthly SSTs, which represent the oceanic forcing, are obtained from the Hadley Center Sea Ice and Sea Surface Temperature dataset (HadISST) (Rayner et al. 2003).

To check the robustness of the atmospheric response to the vegetation forcing, three different observed surface air temperature and precipitation datasets are used. They are from the University of Delaware (UDEL) ($0.5^\circ \times 0.5^\circ$ for 1901–2009) (Willmott and Matsuura 1995), the Climate Research Unit (CRU) ($0.5^\circ \times 0.5^\circ$ for 1901–2009) (Mitchell and Jones 2005), and the Parameter–Elevation Regressions on Independent Slopes

Model Climate Group (PRISM) ($4 \text{ km} \times 4 \text{ km}$ for 1895–2010, only over the contiguous United States) (Daly et al. 2008), respectively. Upward and downward shortwave radiation fluxes at the surface used to compute surface albedo, and cloud fractional cover, are obtained from the National Aeronautics and Space Administration (NASA) Langley Research Center Atmospheric Science Data Center Surface Radiation Budget (SRB) project ($1^\circ \times 1^\circ$ for 1984–2006) (Gupta et al. 1999). A global terrestrial evapotranspiration (ET) from 1983 to 2006, with $1^\circ \times 1^\circ$ resolution, is assessed using a satellite-based ET algorithm (Zhang et al. 2010). The algorithm quantifies canopy transpiration, soil evaporation, and open water evaporation. Other atmospheric variables, such as geopotential height and wind, are retrieved for 1979–present from the

North American Regional Reanalysis (NARR) (Mesinger et al. 2006), with a spatial resolution of $32 \text{ km} \times 32 \text{ km}$.

All data for this study are extracted for January 1982–December 2006 (except the upward/downward shortwave flux at surface, cloud cover fraction, and ET) and remapped to a $2^\circ \times 2^\circ$ grid, except the land cover type and land cover fraction. The seasonal cycle and third-order polynomial trend are removed to compute the anomaly field.

b. CCSM3.5

The National Center for Atmospheric Research Community Climate System Model, version 3.5 (CCSM3.5) (Gent et al. 2010), an interim version of CCSM, is used in this study. The atmospheric, land, oceanic, and ice components are the Community Atmosphere Model (CAM3), Community Land Model–Dynamic Global Vegetation Model (CLM–DGVM), Parallel Ocean Program, version 2 (POP2), and Community Sea Ice Model, version 5 (CSIM5), respectively, with no use of flux adjustment. The dynamic core of the atmosphere component is finite volume discretization, and the horizontal resolution is 2.5° longitude $\times$ 1.9° latitude. The vertical coordinate of CAM3 is the hybrid sigma pressure coordinate with 26 levels. There are 10 soil layers in CLM. To study the vegetation impact on the atmosphere, the DGVM is coupled to the CLM. CLM–DGVM (Levis et al. 2004; Bonan and Levis 2006) simulates the potential vegetation type, so no land use is included. There are a total of 10 plant function types simulated by the model, including 7 types of trees and 3 types of grasses.

A multicentury, modern-day simulation (CTL) in equilibrium is produced, and the last 100 years are analyzed. From the CTL run, two statistical methods, the univariate EFA and multivariate GEFA, are used to evaluate the impacts of fluctuations in vegetation amount on North American climate. Oceanic forcings are still present with EFA, while with GEFA they are first extracted before vegetation forcings are assessed. The model is only applied to validate the GEFA methodology through dynamical experiments. If the statistical assessment from the CTL run agrees with the dynamical experiments in the same model in terms of spatial pattern and magnitude of response, then GEFA is shown to be reliable and can be applied to observations with some confidence. Therefore, it is unnecessary to compare the simulated and observed results or to validate the simulated climatology against observational data.

3. Method

a. Statistical method

The statistical method, GEFA, is applied in this study to assess vegetation forcing on the atmosphere across

North America, primarily in the observations. Since this method has been discussed in detail in previous studies (Liu et al. 2008; Liu and Wen 2008) and has been successfully applied to estimate the influence of global SST patterns on global geopotential height (Wen et al. 2010), U.S. precipitation (Zhong et al. 2011), North Atlantic heat flux (Wen et al. 2013), and U.S. surface air temperature and precipitation (Wang et al. 2013), it is only briefly described here. GEFA is a multivariate method, making it possible to extract the vegetation influence on the atmosphere after removing oceanic forcings. At the time scale considered in this study, which is monthly, the atmospheric response to vegetation and oceanic forcing has reached quasi equilibrium. The memory of the atmosphere is only one to two weeks, while that of the ocean and vegetation exceeds one month. Therefore, at the monthly time scale, the atmosphere has already reached equilibrium and atmospheric internal variability can be considered as white noise. Based on stochastic climate theory (Frankignoul and Hasselmann 1977), the atmospheric variable $\mathbf{A}$ at time t can be decomposed into two terms: one is the feedback response to vegetation and oceanic forcings $\mathbf{VO}$ and the other is atmospheric internal variability $\mathbf{N}$. Therefore,

$$\mathbf{A}(t) = \mathbf{B} \times \mathbf{VO}(t) + \mathbf{N}(t), \quad (1)$$

where $\mathbf{B}$ is the feedback matrix. Application of the covariance of $\mathbf{VO}(t - \tau)$ to both sides of Eq. (1) results in

$$\mathbf{B} = \frac{\langle \mathbf{A}(t), \mathbf{VO}(t - \tau) \rangle}{\langle \mathbf{VO}(t), \mathbf{VO}(t - \tau) \rangle} - \frac{\langle \mathbf{N}(t), \mathbf{VO}(t - \tau) \rangle}{\langle \mathbf{VO}(t), \mathbf{VO}(t - \tau) \rangle}, \quad (2)$$

where $\langle a, b \rangle$ indicates the covariance between variables a and b , and the second term is the sampling error. Since variability in either SSTs or vegetation amount at a previous time, $\mathbf{VO}(t - \tau)$, does not correlate with atmospheric internal variability at time t , $\mathbf{N}(t)$, it is concluded that $\langle \mathbf{VO}(t - \tau), \mathbf{N}(t) \rangle = 0$. Therefore,

$$\mathbf{B} = \frac{\langle \mathbf{A}(t), \mathbf{VO}(t - \tau) \rangle}{\langle \mathbf{VO}(t), \mathbf{VO}(t - \tau) \rangle}, \quad \tau > 0, \quad (3)$$

where τ is the time lag, which should be longer than the atmospheric persistence time: $\mathbf{B}$ represents the instantaneous atmospheric response to a slowly evolving forcing term. The unit of $\mathbf{B}$ is (unit of the atmospheric variable) (standard deviation of vegetation) $^{-1}$, and by multiplying $\mathbf{B}$ by the standard deviation of vegetation the feedback strength can be quantified. Theoretically, $\mathbf{B}$ does not change with lag τ but for a finite sample size, the sampling error, $\langle \mathbf{N}(t), \mathbf{VO}(t - \tau) \rangle \langle \mathbf{VO}(t), \mathbf{VO}(t - \tau) \rangle^{-1}$ is not zero. When the lag time τ increases, the autocovariance of $\mathbf{VO}$,

$\langle \mathbf{VO}(t), \mathbf{VO}(t - \tau) \rangle$ will decrease, and then the sampling error increases (Liu et al. 2006). Therefore, the first lag is usually preferred. In this paper, τ is assigned to 1 month. The feedback response at $\tau = 2$ is also checked for robustness, but not shown. In the GEFA Eqs. (1)–(3), if the forcing $\mathbf{VO}$ consists of a single forcing, it degenerates to the equilibrium feedback assessment. Therefore, if one wants to analyze the influence of vegetation in NAMR on the atmosphere using EFA, just let $\mathbf{VO} = \text{NAMR}$. Clearly, if the atmosphere $\mathbf{A}(t)$ is truly affected by multiple forcings, the EFA will mix the assessed response to other forcings not included.

Forcing fields of vegetation are represented by the regional-mean time series of vegetation index [NDVI in

the observations and leaf area index (LAI) in the model, since the model only outputs LAI, and the length of available remotely sensed NDVI exceeds that of LAI] for NAMR and NABF. The oceanic forcing fields are represented by principal components (PCs) through empirical orthogonal function (EOF) analysis. The global ocean north of 20°S is divided into five ocean basins: the tropical Pacific (TP; 20°S–20°N, 120°E–60°W), the North Pacific (NP; 20°–60°N, 120°E–60°W), the tropical Indian (TI; 20°S–20°N, 35°–120°E), the tropical Atlantic (TA; 20°S–20°N, 65°W–15°E), and the North Atlantic (NA; 20°–60°N, 100°W–20°E). The vegetation time series and SST PCs are combined into a single forcing matrix for $\mathbf{VO}$:

$$\mathbf{VO} = [\text{NABF} \quad \text{NAMR} \quad \text{TP1} \quad \text{TP2} \quad \text{NP1} \quad \text{NP2} \quad \text{TI1} \quad \text{TI2} \quad \text{TA1} \quad \text{TA2} \quad \text{NA1} \quad \text{NA2}]. \quad (4)$$

The numbers 1 and 2 after each ocean basin indicate the first and second PC, respectively. For example, TP1 represents the first PC of tropical Pacific SST, and NABF and NAMR represent the vegetation time series for the two study regions. The forcing matrix used here is the same as applied by Wang et al. (2013), except here it also includes two vegetation forcings and the time series is shorter in duration, which is limited by the duration of the vegetation time series. The influence of global SST modes on the atmosphere does not change significantly with or without the inclusion of these vegetation forcings.

In this paper, the results of vegetation forcing to the atmosphere are discussed by season. Seasonal GEFA feedback coefficients are obtained by averaging the corresponding 3-monthly GEFA feedback coefficients. For example, the March GEFA feedback matrix is computed using data from February and March as follows:

$$\mathbf{B}(\text{Mar}) = \frac{\langle \mathbf{A}(\text{Mar}), \mathbf{VO}(\text{Feb}) \rangle}{\langle \mathbf{VO}(\text{Mar}), \mathbf{VO}(\text{Feb}) \rangle}. \quad (5)$$

Then, the springtime [March–May (MAM)] atmospheric response is calculated as

$$\mathbf{B}(\text{MAM}) = \frac{\mathbf{B}(\text{Mar}) + \mathbf{B}(\text{Apr}) + \mathbf{B}(\text{May})}{3}. \quad (6)$$

The statistical significance of $\mathbf{B}$ is tested using the Monte Carlo bootstrap approach (Czaja and Frankignoul 2002). The atmospheric variable is randomly scrambled 1000 times, $\mathbf{B}$ is computed each time, and the accumulative probability is then used to judge the significance, with 90% chosen as the significant level. The results are found to be robust if we modify either the latitude/longitude range of

the ocean basins and vegetation regions or the spatial resolution of the analyzed data.

b. Dynamical method

In a climate model, the feedback coefficient μ can be estimated through a dynamical assessment using ensemble sensitivity experiments in which the forcing field $\mathbf{V}(t)$ is prescribed. Here μ , instead of $\mathbf{B}$, is used to represent the feedback coefficient because μ from the dynamical assessment represents the feedback from a single forcing, while $\mathbf{B}$ from the statistical assessment represents feedbacks from all forcings. Therefore,

$$\mathbf{A}(t) = \mu \mathbf{V}(t) + \mathbf{N}(t). \quad (7)$$

Theoretically, the ensemble mean of the atmospheric internal variability should be zero, or $\langle \mathbf{N}(t) \rangle = 0$, where the braces represent the ensemble mean. Therefore, the ensemble mean of the atmospheric response is

$$\langle \mathbf{A}(t) \rangle = \mu \langle \mathbf{V}(t) \rangle, \quad (8)$$

and the feedback coefficient μ is computed as the ratio of the ensemble mean of the atmospheric response to the ensemble mean of the forcing:

$$\mu = \frac{\langle \mathbf{A}(t) \rangle}{\langle \mathbf{V}(t) \rangle}. \quad (9)$$

To eliminate the oceanic impacts on the atmosphere completely and to minimize computation time, a fixed SST experiment (CLM_SST) is first conducted. In this 50-yr simulation, the atmosphere and land are dynamically active, and the boundary conditions for the ocean and sea ice are held fixed to the climatology from the

CTL run. Monthly restart files are saved so as to perform the dynamic experiments.

A set of 50 ensemble experiments (CAP_LAI) is conducted with CCSM3.5. Beginning on 1 July of each model year in the CLM_SST run, LAI in the NAMR is capped at or below $2 \text{ m}^2 \text{ m}^{-2}$ during the whole month. This experiment design is further explained in section 4b. NAMR rather than NABF is chosen to do the dynamical experiment, first, because of the large simulated LAI interannual variability there (it is very small in NABF) and, second, because the atmosphere is influenced by both vegetation and SST (Wang et al. 2013).

c. Relationship between statistical and dynamical assessments

Statistical and dynamical methods have their own advantages and disadvantages and are complementary to each other. The statistical method can be used on both observational and model data, while the dynamical method is limited to models. Compared with conducting dynamical experiments, the statistical method is easily applied and computationally inexpensive. Unlike with assumptions made in the GEFA statistical method, such as the linear relationship between the forcing and response fields, almost no assumptions are made with the dynamical method. In this study, these two methods are applied as follows. First, the statistical method is applied to the CTL run to analyze the vegetation influence on the atmosphere. Second, in the same model, dynamical experiments are performed to analyze vegetation influence on the atmosphere. The results from both statistical and dynamical approaches in the model are compared: if they are found to be consistent, then it demonstrates that the statistical method, GEFA, is valid. Finally, GEFA is applied with confidence to the observations in order to understand the observed influence of vegetation anomalies on North American climate.

4. Validation of GEFA in CCSM3.5

Although GEFA was previously validated using the fully coupled model, CCSM3.5, by Wang et al. (2013), the current study represents its first application to vegetation feedbacks. Therefore, it is necessary to first validate the method in a model before applying it to observations. The validation will be performed for the NAMR in a two-step process. First, the ability of GEFA to separate the vegetation influence from that of the ocean is demonstrated by examining the influences of NAMR vegetation on the atmosphere in the CTL run using statistical methods, GEFA and EFA. The discrepancy between GEFA and EFA indicates the oceanic influence. Second, statistical GEFA results from the

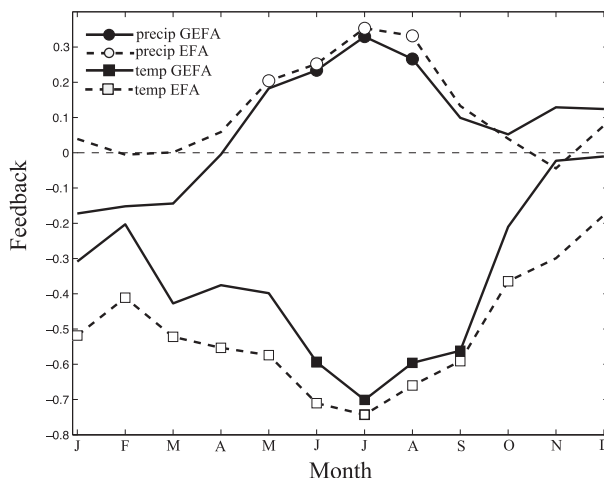


FIG. 2. Simulated monthly response of regional-mean local surface air temperature (lines with squares, $^{\circ}\text{C}$) and precipitation (lines with circles, mm day^{-1}) to the NAMR forcing in the CTL run using both GEFA (solid lines) and EFA (dashed lines). The markers indicate 90% statistical significance, based on Monte Carlo tests. Values in this figure indicate the simulated atmospheric response to a one standard deviation increase in LAI across the NAMR.

CTL run are compared with results from the dynamical experiments.

a. Statistical assessment

In this part, the influence of NAMR vegetation on the atmosphere in the CTL run is studied using statistical methods, GEFA and EFA. The EFA assessment is used for comparison and highlighting the impacts of oceanic forcings. This is because EFA is a univariate method, so the computed atmospheric response to the vegetation forcing is corrupted by oceanic forcings. GEFA is a multivariate method, allowing for the elimination of oceanic forcings prior to calculating vegetation forcings on the atmosphere. The simulated regional-mean time series of NAMR LAI is used to represent the forcing field of NAMR vegetation (Fig. 4a). In this section, the feedback coefficient is multiplied by the standard deviation of simulated monthly LAI anomaly, which is $1.26 \text{ m}^2 \text{ m}^{-2}$.

The monthly atmospheric response to the NAMR vegetation forcing is analyzed in the model and presented as a regional mean since the simulated atmospheric response is mainly local. To the first order, both EFA and GEFA results indicate NAMR vegetation has the strongest simulated impacts on surface air temperature and precipitation during summer [June–September (JJAS)], with peaks in July (Fig. 2). A study by Xue et al. (2010) also concluded that the impact of NAMR vegetation biophysical process on precipitation is strongest in June–August

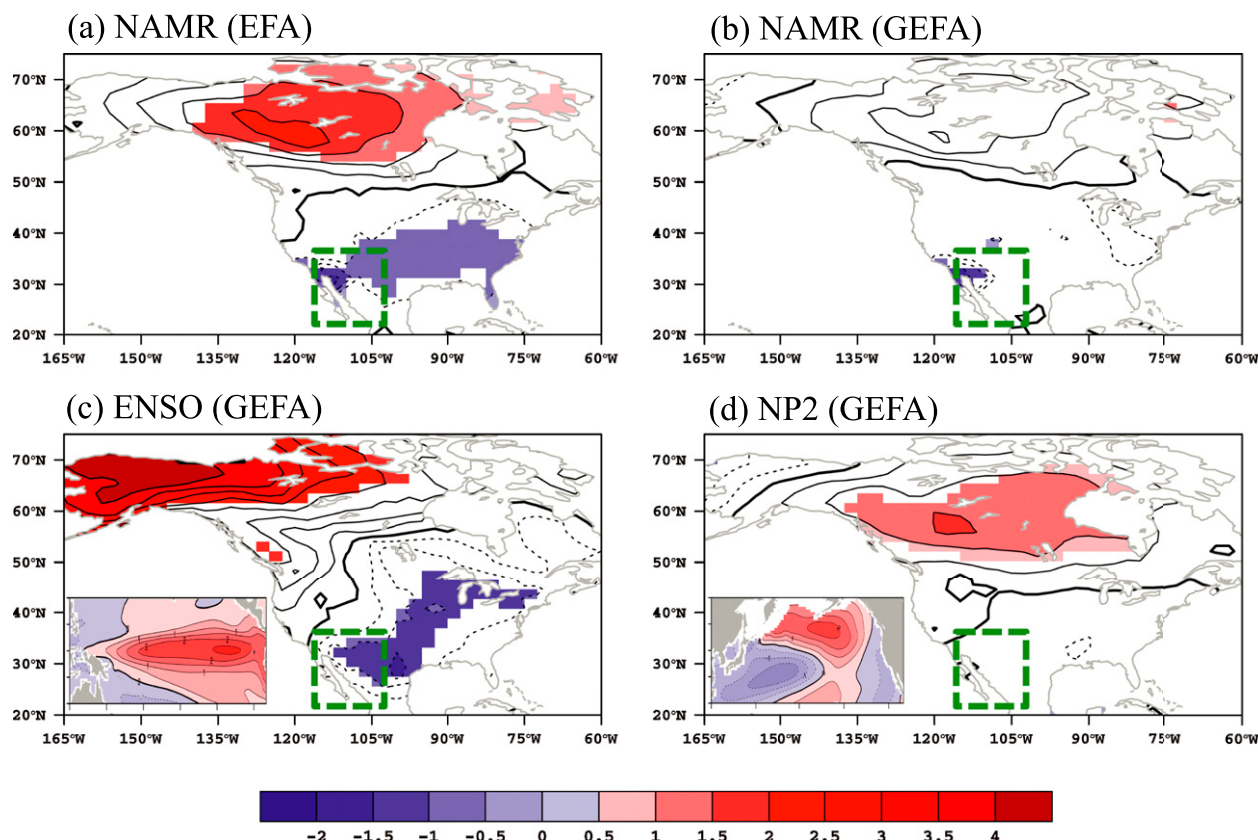


FIG. 3. Simulated response of surface air temperature ($^{\circ}\text{C}$) to the NAMR vegetation forcing in the CTL run using (a) EFA and (b) GEFA in January. Simulated response of surface air temperature ($^{\circ}\text{C}$) to (c) TP1 (ENSO) and (d) NP2 forcing in the CTL run using GEFA. Shading indicates 90% statistical significance, based on Monte Carlo tests. Spatial patterns of SST anomalies for TP1 and NP2 are shown in inset maps in (c) and (d), respectively. Dashed boxes indicate the NAMR.

(JJA) and weakest in December–February (DJF) (Fig. 3 in Xue et al. 2010). An increased vegetation amount results in local cooling and an increase in precipitation during summer. However, there are also significant differences between GEFA and EFA for both temperature and precipitation, with the greatest difference during winter. During winter, the nearly zero temperature response in GEFA suggests that NAMR vegetation does not significantly affect surface air temperature, while the modestly negative temperature response in EFA suggests that NAMR vegetation has a significantly negative impact on temperature. The discrepancies between GEFA and EFA imply a significant impact from forcings other than the NAMR vegetation, most likely the oceanic forcings. The discrepancies also suggest the limited accuracy of the univariate EFA approach, as applied by Notaro et al. (2006) and Liu et al. (2006).

Since the discrepancies are largest in January, we will focus on that month to understand the oceanic impact on the atmosphere. According to EFA, an increase in LAI over the NAMR supports an increase in temperature to

the north of 50°N and a decrease over the southern United States (Fig. 3a). However, the GEFA result suggests that the NAMR vegetation only exerts a significant local impact on surface air temperature (Fig. 3b). Most likely, the ENSO mode can explain the decrease in surface air temperature over the southern United States (Fig. 3c) (Wang et al. 2013), and the North Pacific second EOF mode (NP2) can explain the increase in surface air temperature north of 50°N (Fig. 3d), rather than a non-local vegetation feedback. Through comparing GEFA and EFA results, it is shown that the GEFA method can separate the vegetation impact from that of the ocean. The response of surface air temperature to the ocean forcing has been demonstrated in an accompanying paper (Wang et al. 2013).

Now, we shift the focus to summer when NAMR vegetation has the strongest impact on both air temperature and precipitation in the model. The response spatial patterns for June, July, and August are very similar (figure not shown) except that the response strengths are different (Fig. 2). Here, we focus on July. According to GEFA,

Statistical assessment (July)

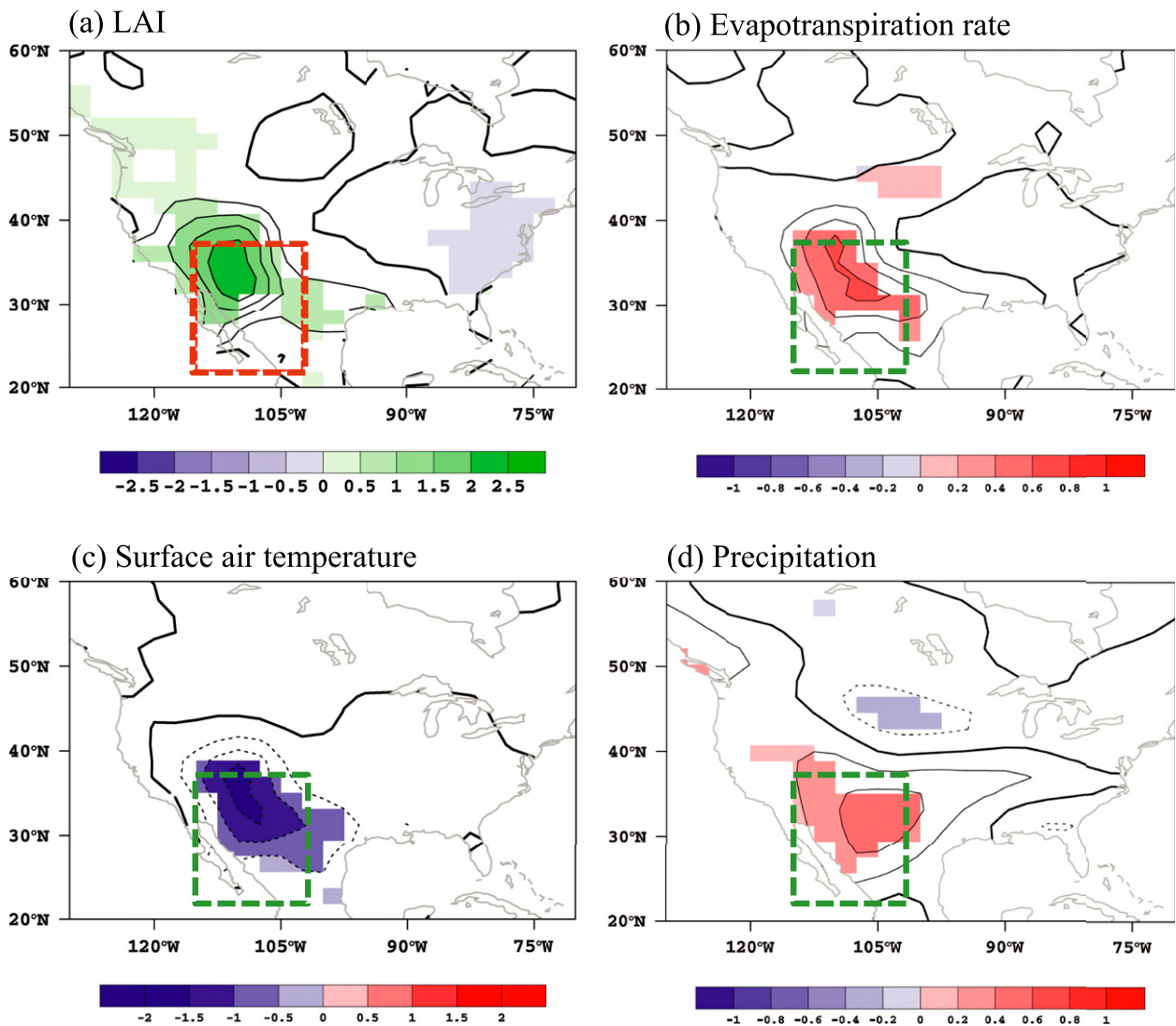


FIG. 4. Results from the CTL run using the GEFA statistical assessment for July. (a) Spatial pattern of NAMR forcing, which is the regression pattern of regional-mean LAI to itself (unitless). Response pattern of (b) evapotranspiration rate (mm day^{-1}), (c) surface air temperature ($^{\circ}\text{C}$), and (d) precipitation (mm day^{-1}). Shading indicates 90% statistical significance, based on a t test in (a) and Monte Carlo tests in (b)–(d). Dashed boxes indicate the NAMR.

the enhanced vegetation amount over the NAMR increases local and downstream simulated precipitation up to 0.70 mm day^{-1} (Fig. 4d) and reduces the surface air temperature locally up to -1.88°C (Fig. 4c). To elucidate the responsible mechanism for these feedbacks in CCSM3.5, the regional-mean response of each component of the surface energy budget is analyzed using GEFA. According to the surface energy budget (Fig. 5), the negative surface air temperature anomaly is caused by both an increase in net latent heat flux (LH) [primarily canopy transpiration (FCTR)] and decrease in net shortwave

radiation (SW) [primarily downward solar radiation ($\text{SW}\downarrow$)]. The lowered surface air temperature corresponds to decreased net sensible heat flux (SH) [from both the canopy (SH_V) and ground (SH_G)] and decreased net longwave radiation (LW) [mainly emitted longwave radiation ($\text{LW}\uparrow$)].

The statistical GEFA results suggest the following mechanism for the NAMR in CCSM3.5. When LAI is increased, canopy transpiration and evaporation are enhanced (Fig. 4b), given that the expanded leaf area can intercept more precipitation. This cools the surface air and

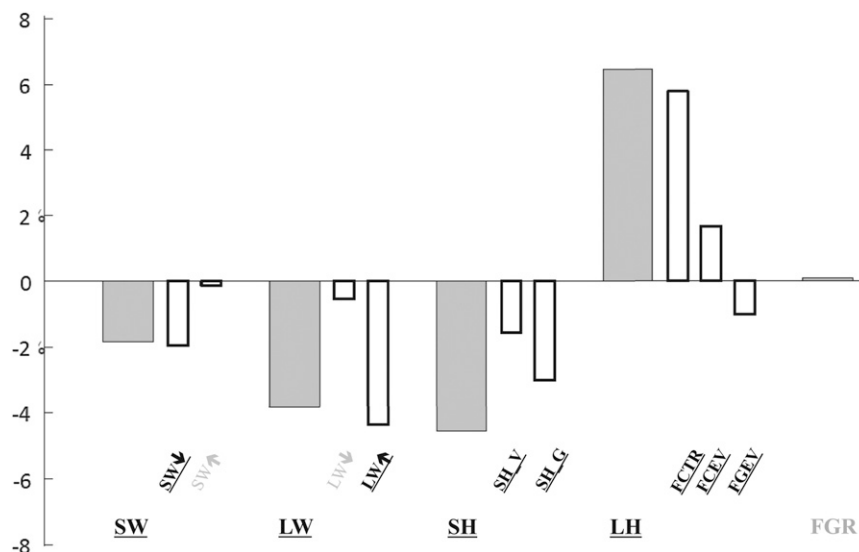


FIG. 5. Results from the CTL run using the GEFA statistical assessment. Regional-mean response of surface energy fluxes (W m^{-2}) to the NAMR forcing in July. Gray bars indicate the main terms of the surface energy budget, and blank bars are the components of the gray bar to their left. From left to right are net downward shortwave (SW), incident shortwave ($\text{SW}\downarrow$), reflected shortwave ($\text{SW}\uparrow$), net downward longwave (LW), downward longwave ($\text{LW}\downarrow$), emitted longwave ($\text{LW}\uparrow$), sensible heat flux from surface (SH), sensible heat flux from vegetation (SH_V), sensible heat flux from ground (SH_G), latent heat flux to the atmosphere (LH), canopy transpiration (FCTR), canopy evaporation (FCEV), ground evaporation (FGEV), and heat flux into soil (FGR). The underscored terms indicate 90% statistical significance based on Monte Carlo tests. Values in this figure represent surface energy flux changes due to a one standard deviation increase in LAI across the NAMR.

increases atmospheric moisture content and relative humidity. The moistened atmosphere helps the formation of low-level clouds (not shown) and precipitation, which diminish downward solar radiation and further cool the surface air. To detect whether the change in precipitation is primarily caused by local moisture recycling or remote moisture fluxes, the response in total evapotranspiration rate is compared to that of precipitation. The total evapotranspiration rate is increased locally (Fig. 4b, regional mean: 0.34 mm day^{-1}) at a greater rate than precipitation (Fig. 4d, regional mean: 0.25 mm day^{-1}), suggesting that an inefficient moisture recycling dominates instead of remote moisture resources. The resulting moisture divergence (not shown) is further evidence that local moisture recycling is more important than remote moisture fluxes into the region during July, in response to elevated vegetation amount. In CCSM3.5, the North American monsoon onsets in July but does not peak until September. It is found that vegetation has more influence on the atmosphere during the onset of the North American monsoon, which is consistent with Notaro et al. (2011) and Notaro and Gutzler (2012). The strong evapotranspiration–precipitation response is likely caused by the wet bias and excess vegetation amount simulated in the model (Notaro and Gutzler 2012).

The statistical assessment demonstrates the GEFA's ability to separate the vegetation impact from that of the ocean in the CTL run, but this validation approach is not as direct as dynamical experiments. Therefore, in section 4b, dynamical experiments are conducted, and in section 4c, the results from the statistical and dynamical assessments are compared.

b. Dynamical assessment

According to the statistical assessment, vegetation in the NAMR has the strongest impact on the atmosphere during summer, so the dynamical assessment focuses on July. In the CAP_LAI ensemble experiments, LAI is capped at or below $2 \text{ m}^2 \text{ m}^{-2}$ across the NAMR throughout the entire month since the simulated interannual standard deviation of LAI is about $2 \text{ m}^2 \text{ m}^{-2}$. An upper limit, rather than a lower limit, is assigned since the model generally simulates excessive LAI. It should be noted that since LAI of forests is larger than that of grass, CAP_LAI by 2 will have more effect on forest. By comparing the climate in Clim_SST and CAP_LAI, both of which use fixed SST, the simulated impact of a change in LAI across the NAMR can be dynamically assessed.

In comparing Clim_SST with CAP_LAI, LAI increases significantly in the NAMR, with no significant

Dynamical assessment (July)

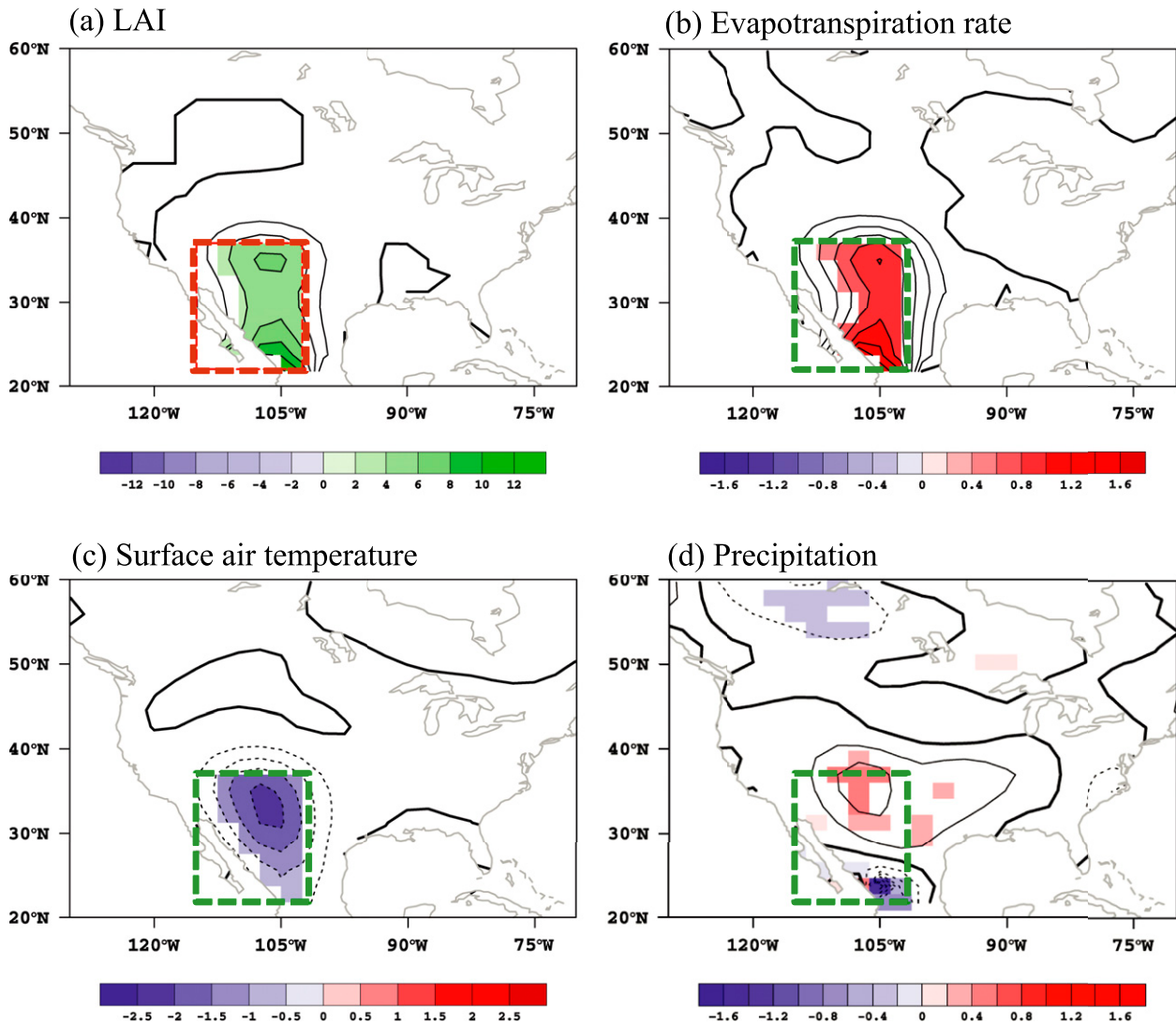


FIG. 6. Results of dynamical assessment, based on CLM_SST – CAP_LAI: changes in (a) LAI ($\text{m}^2 \text{m}^{-2}$), (b) evapotranspiration rate (mm day^{-1}), (c) surface air temperature ($^{\circ}\text{C}$), and (d) precipitation (mm day^{-1}) in July. Shading indicates 90% statistical significance, based on t tests. Dashed boxes indicate the NAMR.

change outside of the NAMR (Fig. 6a). One of the advantages of dynamic experiments is that one may modify vegetation in a specific region and isolate the climatic response. When LAI increases, the surface air temperature decreases locally (Fig. 6c) and precipitation increases both locally and downstream (Fig. 6d). The dynamical response patterns in surface air temperature and precipitation are qualitatively consistent with the statistical GEFA results (cf. Figs. 6c,d and Figs. 4c,d). By comparing the change in regional-mean surface energy budget (Fig. 7) and moisture divergence (not shown) between both methods, it is evident that the proposed

mechanism is consistent, with the reduction in surface air temperature mainly caused by increased net latent heat flux (primarily FCTR) and the increased precipitation mainly due to local moisture recycling. The comparison of the response strengths between the statistical and dynamical assessments is discussed in section 4c.

c. Comparison of statistical and dynamical assessments

In sections 4a and 4b, the influence of vegetation in the NAMR on the atmosphere is assessed in CCSM3.5 using two independent methods: the statistical method

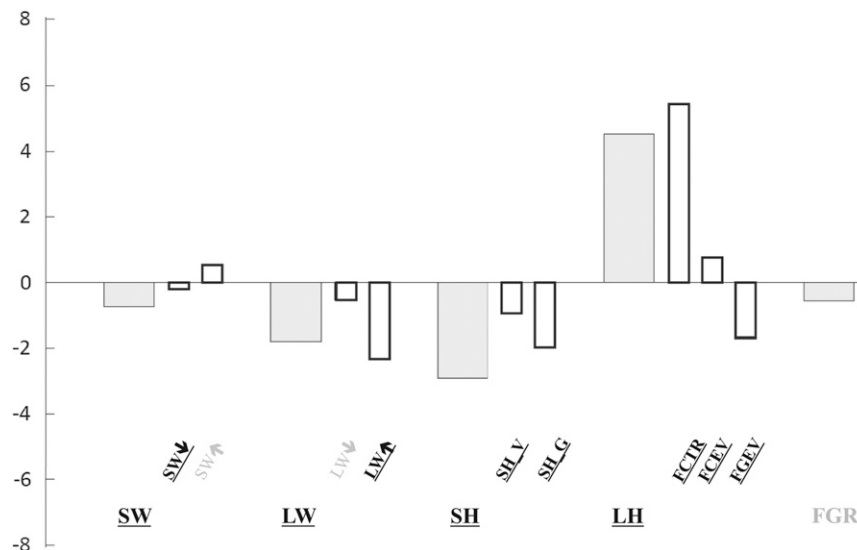


FIG. 7. As in Fig. 5, but for the results of dynamical assessment: CLM_SST – CAP_LAI and significance is checked with t tests. Values in this figure represent surface energy flux changes due to the increase one standard deviation of LAI.

(GEFA) and the dynamical method (ensemble experiment). The two assessments qualitatively agree with each other (cf. Fig. 4 versus Fig. 6 and Fig. 5 versus Fig. 7). The results of the statistical assessment (Figs. 4b–d and 5) are based on the multiplication of the feedback coefficient with the standard deviation of LAI, thereby quantifying the atmospheric response to a one standard deviation increase in LAI. The results of the dynamical assessment (Figs. 6b–d) are computed as the difference between Clim_SST and the CAP_LAI experiments, thereby indicating the atmospheric response to the LAI anomaly in Fig. 6a. To directly compare the two assessments, the dynamical results must be divided by the LAI change and multiplied by the standard deviation of LAI. Since the simulated climatic response to NAMR vegetation is mainly local, the regional-mean responses in surface air temperature, precipitation, and total evapotranspiration are summarized in Table 1. The statistical feedback assessments are always larger than that of the dynamical assessments, although they are of the same order of magnitude and direction. The discrepancy in magnitude between the two assessments can likely be explained by the indirect vegetation–soil moisture feedback (Notaro et al. 2008; Liu et al. 2010). In the NAMR, LAI and soil moisture are positively correlated. The influence of vegetation on the atmosphere from the CTL run is the sum of that of vegetation and soil moisture, while from the CAP_LAI run, it is the pure vegetation influence. Since LAI and soil moisture are so closely correlated, the GEFA method cannot separate the impact of LAI from that of soil moisture. A dynamic experiment in which

LAI and soil moisture decrease together may match GEFA results closer.

Overall, by applying two independent methods in the model it is shown that GEFA can determine the atmospheric response pattern to a specific vegetation forcing in agreement with dynamical experiments. In the next section, we will apply GEFA to the observational data.

5. Observational assessment of vegetation influences

In the previous section, the vegetation impact on the atmosphere in the NAMR was systematically assessed using both statistical and dynamical methods in CCSM3.5 and found to be in agreement, thereby validating the statistical approach GEFA. In this section, the observed influence of vegetation on the atmosphere is examined using this statistical approach for both the NAMR and NABF.

It is more difficult to explore the mechanism for the atmospheric response to vegetation forcing using

TABLE 1. Regional-mean response of surface air temperature, precipitation, and total evapotranspiration to the NAMR vegetation forcing according to the statistical and dynamical methods in CCSM-DGVM for July.

Variable	Statistical assessment	Dynamical assessment
Surface air temperature ($^{\circ}\text{C}$)	−0.66	−0.34
Precipitation (mm day^{-1})	0.25	0.10
Total evapotranspiration rate (mm day^{-1})	0.34	0.22

observational, remote sensing, and reanalysis data than with a climate model. Reanalysis data is generated using a land model whose vegetation condition is specified using an observed climatological vegetation index. For example, the daily green vegetation fraction in NARR data is derived from the National Environmental Satellite, Data, and Information Service (NESDIS) 5-yr global monthly climatological vegetation index (Mesinger et al. 2006). Therefore, there is no interannual variability in the reanalysis vegetation index. As observations are assimilated during reanalysis, model variables such as surface air temperature, precipitation, sea level pressure, geopotential height, and wind are influenced by vegetation interannual variability. Therefore, the mechanism of the atmospheric response can be deduced from these variables. Model variables such as evapotranspiration and albedo are poorly constrained since no assimilation is done during reanalysis. It is better to use satellite-derived evapotranspiration and albedo to do the mechanism analysis. The record length of the remotely sensed NDVI (25 yr) and other satellite-derived variables, such as evapotranspiration (24 yr), downward/upward solar radiation at surface, and cloud fractional cover (23 yr), is short, and such a short time series can induce large sampling errors. To increase the degree of freedom and decrease the sampling error, only the seasonal-mean response patterns are shown in this study. Also, three atmospheric datasets are used to check the robustness, and through comparing the statistical results using these different datasets, an ensemble estimate of the atmospheric response strength is formulated. Further understanding will rely on model sensitivity experiments and field experiments.

a. Influence of NAMR vegetation on the atmosphere

The observed regional-mean time series of NAMR NDVI is used to represent the forcing field of NAMR (Fig. 10a). In the following discussion, the feedback coefficient is multiplied by the standard deviation of observed NDVI, which is 0.017 (unitless). The observed vegetation types in the NAMR include shrubland and grassland in the western United States and evergreen and deciduous forests along west coast of Mexico (Fig. 1a).

The three datasets consistently show that the observed response of surface air temperature and precipitation to the NAMR vegetation forcing is strongest during JJA (Fig. 8a). During JJA, an enhanced vegetation amount leads to cooler conditions across north central North America and the western United States and warmer conditions across the Gulf states (Figs. 9a,c,e). The peak cooling ranges from -0.97°C in PRISM to -1.20°C in UDEL, while the peak warming ranges from $+0.96^{\circ}\text{C}$ in CRU to $+1.02^{\circ}\text{C}$ in UDEL. An increase in NAMR vegetation amount leads to enhanced precipitation in the

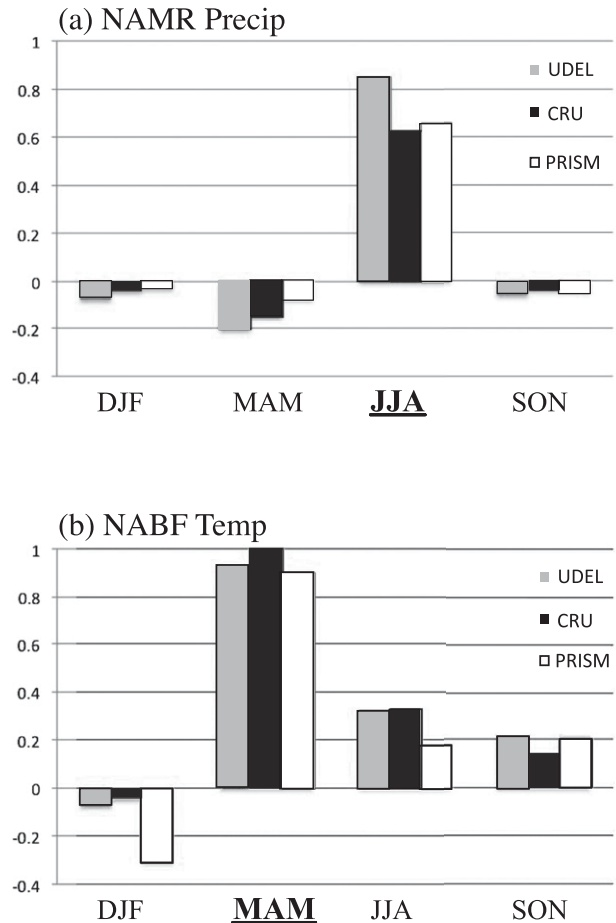


FIG. 8. (a) Regional-mean (115° – 102.5°W , 35° – 45°N) observed seasonal precipitation response (mm day^{-1}) to the NAMR vegetation forcing. (b) Regional-mean (115° – 100°W , 40° – 60°N) observed seasonal surface air temperature response ($^{\circ}\text{C}$) to the NABF vegetation forcing. Gray, black, and blank bars represent results from UDEL, CRU, and PRISM, respectively. Underscored seasons indicate 90% statistical significance, based on Monte Carlo tests. Values in this figure indicate the observed atmospheric response to a one standard deviation increase in NDVI.

north central United States and a precipitation deficit over the Gulf states (Figs. 9b,d,f). The strongest precipitation surplus ranges from $+0.43 \text{ mm day}^{-1}$ in UDEL to $+0.58 \text{ mm day}^{-1}$ in CRU over the western United States, while the most severe precipitation deficit ranges from $-1.06 \text{ mm day}^{-1}$ in PRISM to $-1.23 \text{ mm day}^{-1}$ in CRU over the Gulf states.

The NAMR vegetation influences the atmosphere mainly through both hydrological and roughness feedbacks during JJA. Enhanced vegetation amount in NAMR slightly increases local evapotranspiration (Fig. 10b), mainly across the southwestern United States, which favors more precipitation there. The main determinant of the change of land surface roughness is vegetation height (Sud et al. 1988). Increased vegetation amount in the

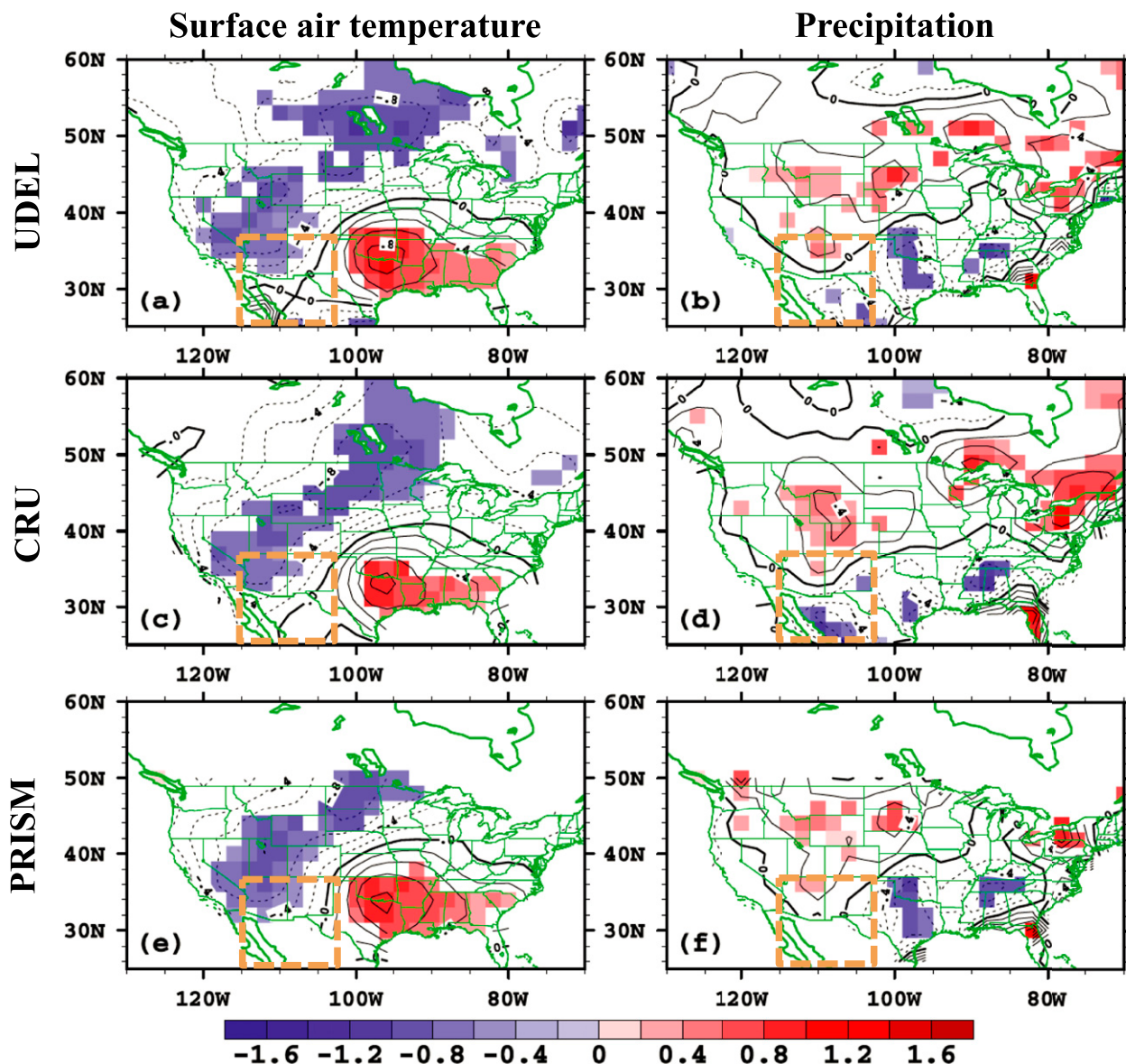


FIG. 9. Observed response of (left) surface air temperature ($^{\circ}\text{C}$) and (right) precipitation (mm day^{-1}) to the NAMR vegetation forcing during JJA using (a),(b) UDEL, (c),(d) CRU, and (e),(f) PRISM. Shading indicates 90% statistical significance, based on Monte Carlo tests. Dashed boxes indicate the NAMR. Spatial correlations between the UDEL and CRU, UDEL and PRISM, and CRU and PRISM response patterns are 0.95, 0.95, and 0.97, respectively, for surface air temperature and 0.75, 0.78, and 0.79 for precipitation.

NAMR leads to greater surface roughness, which favors a local low pressure anomaly (Fig. 10d) and air convergence near the surface. At 700 hPa, the low pressure anomaly is further generated over the southwestern and north central United States (Fig. 11a), which is associated with ascending motion (not shown) and more cloud cover (Fig. 11b), supporting an increase in precipitation. The local low pressure anomaly further generates an atmospheric teleconnection response, consisting of a high pressure anomaly over the southeastern United States, corresponding to descending motion, less cloud cover (Fig.

11b), and a precipitation deficit. The southwesterly wind anomaly (Fig. 11b, green arrow) brings Pacific moisture to the southwestern United States, leading to a precipitation surplus. The northerly wind anomaly (Fig. 11b, red arrow) advects dry continent air and also blocks moisture flow from the Gulf of Mexico, thereby drying the southeastern United States.

Generally, the observed response pattern of surface air temperature is opposite of the precipitation response (Fig. 9). Enhanced (diminished) precipitation is associated with more (less) cloud cover (Fig. 11b), which

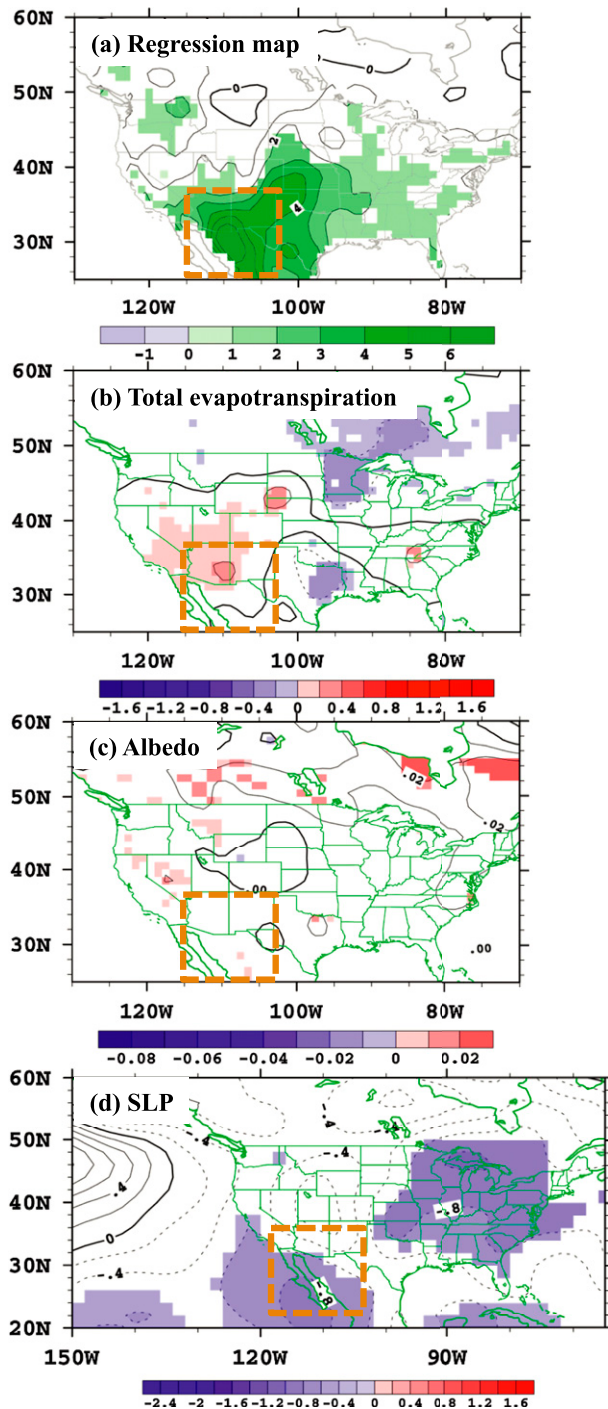


FIG. 10. (a) Spatial pattern of NABF vegetation forcing, which is the regression pattern of observed regional-mean NDVI to itself (unitless). Observed response pattern of (b) satellite-derived total evapotranspiration (mm day^{-1}), (c) albedo from NASA SRB, and (d) sea level pressure (hPa) from NARR to the NABF vegetation forcing during JJA. Shading indicates 90% statistical significance, based on Monte Carlo tests. Dashed boxes indicate the NAMR.

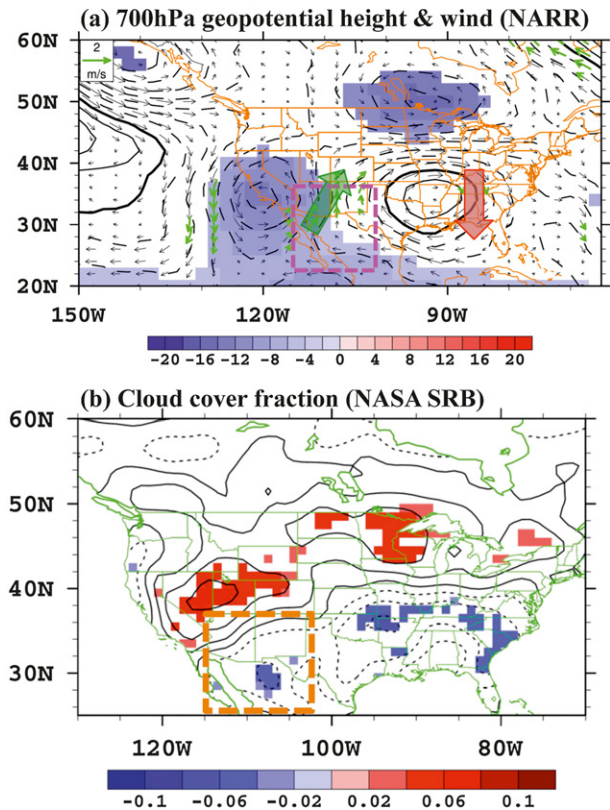


FIG. 11. Observed response pattern of (a) 700-hPa geopotential height (m) and corresponding wind (m s^{-1}) from NARR and (b) cloud cover fraction from NASA SRB to the NABF vegetation forcing during JJA. Shading and thick green arrows indicate 90% statistical significance, based on Monte Carlo tests. Dashed boxes indicate the NAMR. Red and green arrows in (a) indicate negative and positive anomalies of moisture flux, respectively.

decreases (increases) the downward solar radiation (not shown) and cools (warms) the air.

b. Influence of NABF vegetation on the atmosphere

The regional-mean time series of observed NABF NDVI is used to represent the forcing field of the NABF (Fig. 13a). In the subsequent discussion, the feedback coefficient is multiplied by the standard deviation of this time series, which is 0.023 (unitless). This forcing field is highly correlated with the entire boreal forest belt across North America (Fig. 1a).

All three datasets indicate that the observed influence of NABF vegetation on both surface air temperature and precipitation is strongest during MAM (Fig. 8b). The response pattern of surface air temperature is consistent with past studies (Bonan et al. 1992; Snyder et al. 2004; Notaro et al. 2006; Notaro and Liu 2008), indicating a local positive feedback between boreal forest cover and surface air temperature. Enhanced vegetation

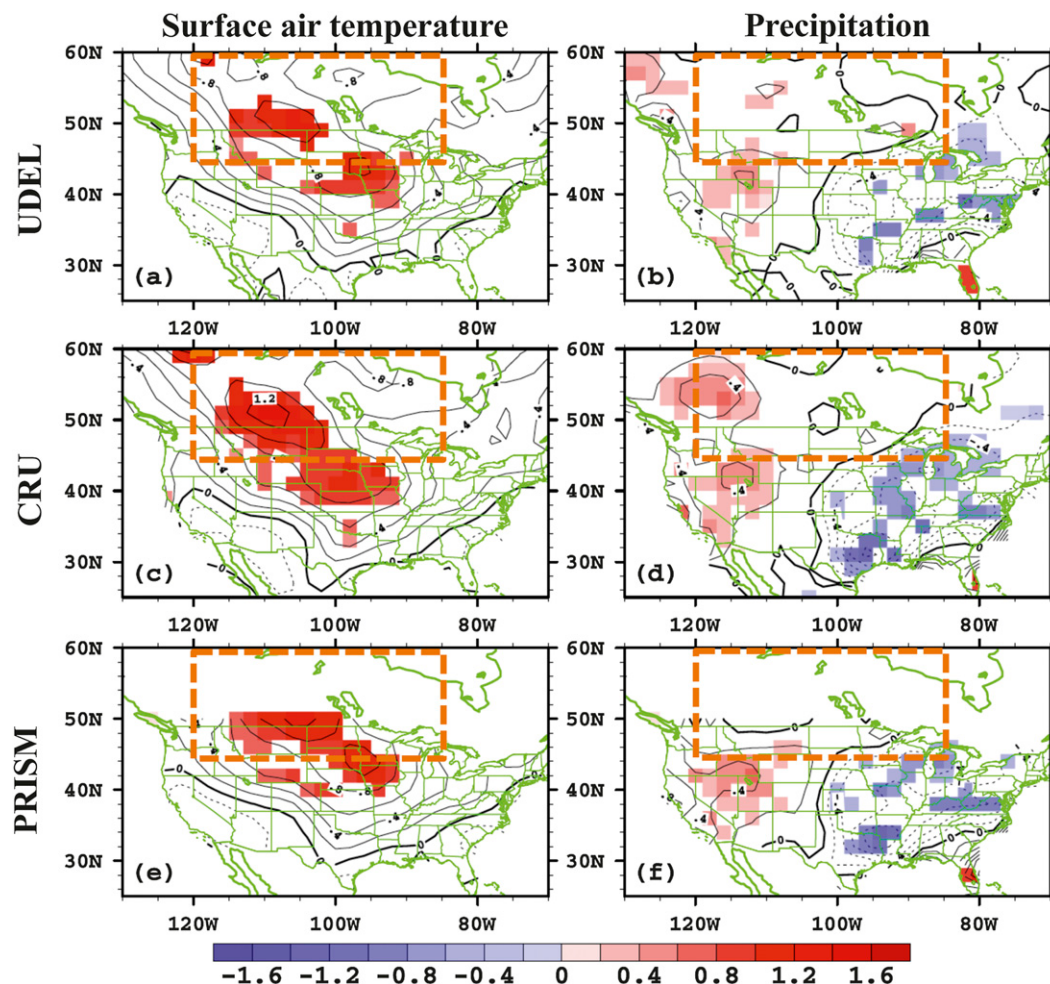


FIG. 12. As in Fig. 9, but indicating the response to the NABF vegetation forcing during MAM. Spatial correlations between the UDEL and CRU, UDEL and PRISM, and CRU and PRISM response patterns are 0.95, 0.97, and 0.95, respectively, for surface air temperature and 0.87, 0.89, and 0.92 for precipitation.

greenness leads to local warming, particularly around the central United States–Canadian border (Figs. 12a,c,e). The peak warming ranges from $+1.34^{\circ}\text{C}$ in PRISM to $+1.41^{\circ}\text{C}$ in CRU. The positive surface air temperature anomaly is mainly caused by a decrease in surface albedo (Fig. 13c, peaks at -0.088), which is consistent with the field study by Betts and Ball (1997). Although greater evapotranspiration (Fig. 13b) should contribute cooling near the surface, this response is weak compared with the warming effect of albedo during spring (Brovkin 2002).

Little is known about the feedback of NABF vegetation on precipitation. In this study, we found that NABF vegetation mainly has nonlocal impacts on precipitation. Positive anomalies in NABF vegetation lead to enhanced precipitation in the western United States, with peaks ranging from $+0.56\text{ mm day}^{-1}$ in CRU to 0.61 mm day^{-1} in PRISM, and reduced precipitation in the eastern United States, with peaks ranging from

-1.04 mm day^{-1} in UDEL to -1.33 mm day^{-1} in CRU (Figs. 12b,d,f). The nonlocal precipitation response can be explained by an anomalous atmospheric circulation. The atmospheric response to the surface warming has a nearly equivalent barotropic structure (Figs. 14a,b), with an anomalous trough over the Gulf of Alaska, anomalous ridge over the NABF, and anomalous trough over the subtropical North Atlantic, similar to a positive PNA pattern. The mechanism of this warm ridge response is likely related to the dominant atmospheric response associated with eddy–mean flow interaction in the mid- to high latitudes (Peng et al. 1995; Peng and Whitaker 1999), which is beyond the scope of this paper. A precipitation surplus is generated over the western United States due to an anomalous southwesterly wind (Fig. 14b, blue arrow) that advects moist air from the Pacific inland and more cloud cover (Fig. 14c). The northerly wind anomaly over the eastern United States

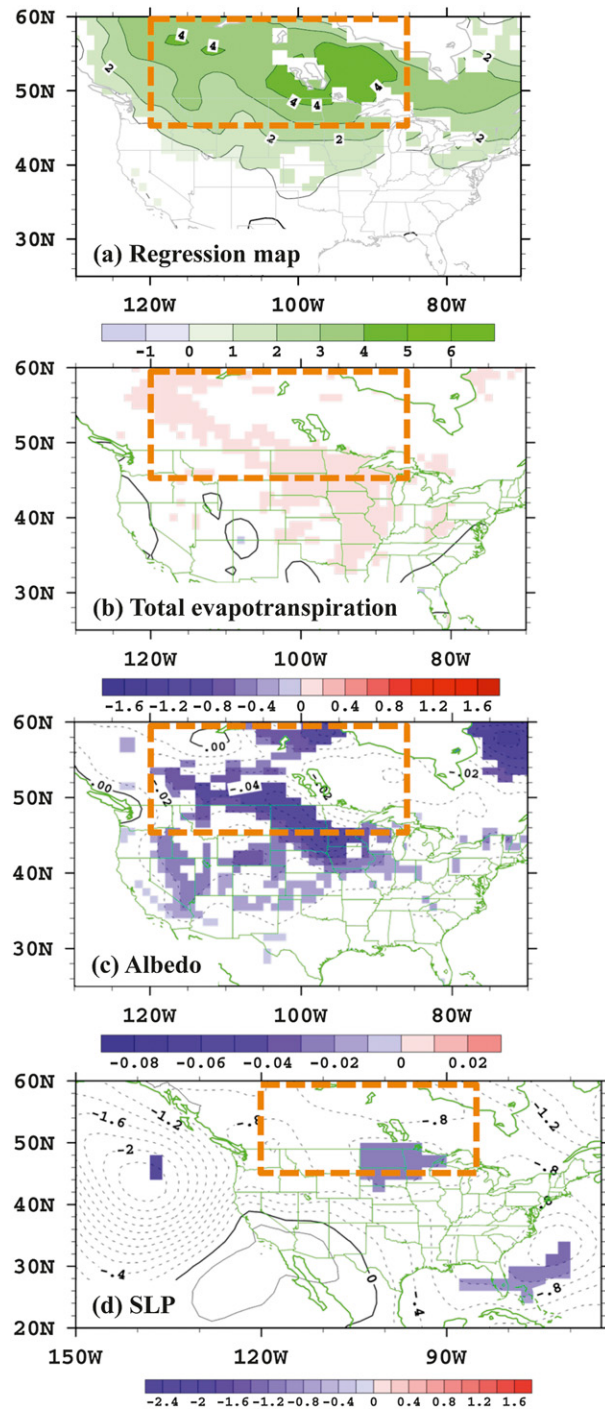


FIG. 13. As in Fig. 10, but indicating the response to the NABF vegetation forcing during MAM.

(Fig. 14b, orange arrow) brings dry continental air and less cloud cover to the eastern United States and weakens the flow from the Gulf of Mexico (Fig. 14c), leading to downstream drying. The local precipitation response is the result of competition among vegetation hydrological,

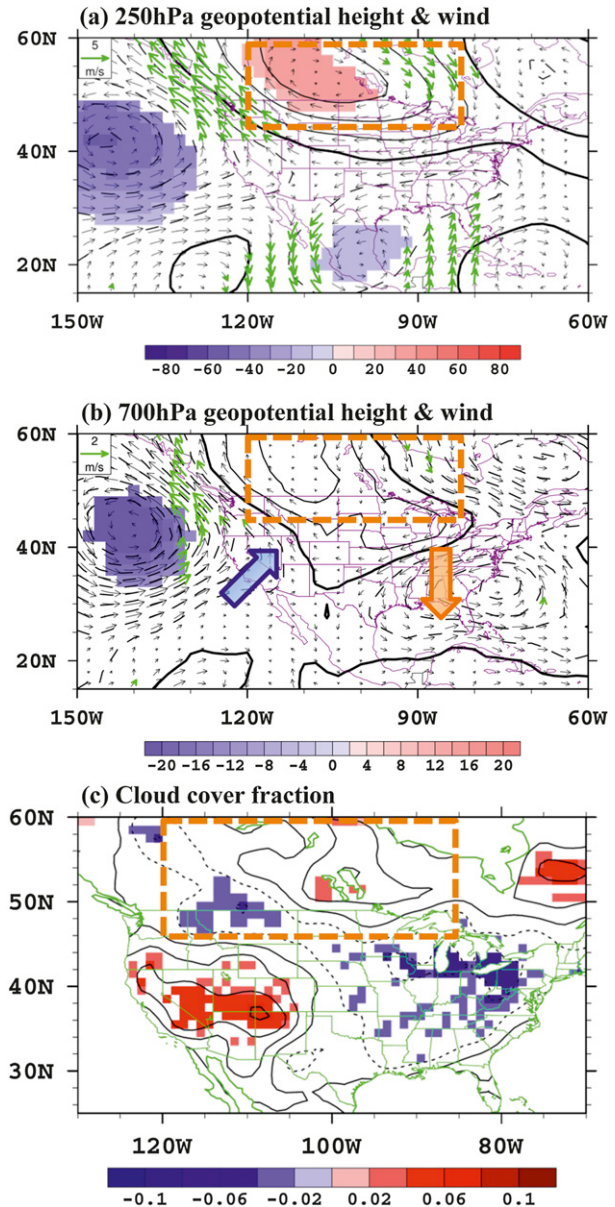


FIG. 14. Observed response pattern of (a) 250-hPa and (b) 700-hPa geopotential height (m) and corresponding wind (m s^{-1}) from NARR and (c) cloud cover fraction from NASA SRB to the NABF vegetation forcing during MAM. Shading and thick green arrows indicate 90% statistical significance, based on Monte Carlo tests. Dashed boxes indicate the NAMR. Orange and blue arrows in (b) indicate negative and positive anomalies of moisture flux, respectively.

roughness, and thermal feedback. Elevated vegetation amount increases evapotranspiration, which tends to moisten the local atmosphere and favors more local precipitation. Increased roughness caused by more vegetation induces a local low pressure anomaly, which also favors more local precipitation. However, these local

precipitation surpluses are cancelled by the anomalous descending motion of the air caused by the vegetation thermal feedback (albedo effect).

6. Conclusions and discussion

The influence of vegetation on the atmosphere across North America is assessed using the multivariate statistical method, GEFA, in three observational datasets. Isolating vegetation feedbacks is challenging not only because the influence of vegetation on the atmosphere is modest compared with that of the atmosphere on vegetation, but also because both vegetation and the oceans can influence the atmosphere. This is the first systematic study to quantify and understand vegetation local and nonlocal impacts on the atmosphere under the premise of first removing oceanic impacts. Before applying the statistical method to observational data, it is first applied to a CCSM3.5 fully coupled control run and validated against dynamical experiments in the same model. By comparing results obtained through both statistical (GEFA) and dynamical (ensemble experiments) assessments, it is demonstrated that the GEFA can exclusively distinguish the influence of vegetation on the atmosphere. We next focus on observed vegetation feedbacks in two contrasting regions: the North American monsoon region (NAMR) and North American boreal forest (NABF).

The observed influence of vegetation in the NAMR on the atmosphere, characterized by both roughness and hydrological feedbacks, peaks in JJA and includes both local and nonlocal effects. When the vegetation amount is increased in the NAMR, the vegetation evapotranspiration is enhanced, which favors local precipitation. Elevated vegetation amount also increases local surface roughness, which leads to a local low pressure anomaly and further generates an atmospheric teleconnection response downstream. This anomalous atmospheric circulation and corresponding moisture advection cause a precipitation surplus over the western and central United States and precipitation deficit over the Gulf states. The response of surface air temperature is mainly determined by the change in downward solar radiation and cloud cover fraction, which is related to the precipitation change.

The observed influence of vegetation in the NABF on the atmosphere, characterized by a thermal feedback, is greatest during MAM. The boreal forest has a local effect on temperature and both a local and nonlocal effect on precipitation. By lowering the surface albedo, an increase in vegetation across the NABF can warm the air locally. The atmospheric response to this warming consists of a local equivalent barotropic high and remote equivalent barotropic lows near Alaska and the

subtropical North Atlantic. This anomalous atmospheric circulation and associated moisture advection lead to drying in the eastern United States and greater precipitation in the western United States.

Vegetation influence on the atmosphere in NAMR and NABF is unique from each other. In NAMR, the vegetation influence is strongest during JJA at the onset of the North America monsoon since water supply is limited then, while in NABF it peaks in MAM because the large albedo difference between vegetation and snow and shortwave radiation is significant. In NAMR, the vegetation hydrological and roughness feedback is dominant in NAMR since vegetation activity is strong, while thermal feedback is dominant in NABF due to the albedo difference between boreal forest and snow. In NAMR, vegetation primarily influences both local and nonlocal precipitation and then consequently affects the surface air temperature, while in NABF vegetation first influences local surface air temperature and then the nonlocal precipitation.

The observed feedback results are found to be relatively insensitive to the size of the study region (e.g., NAMR or NABF). Although we made some progress in understanding vegetation feedbacks, it should be kept in mind that the statistical method used in this study is based on linear theory; however, in the real world, vegetation may produce nonlinear feedbacks (Zhou et al. 2003). Therefore, the results attained here should be viewed as first-order estimates. The accuracy of the statistical assessment using observation data is limited by observational errors and the short duration of the observational record. To estimate how many years of data are needed for stable GEFA results, spatial correlations of GEFA response pattern estimates using a different length of data and estimates using the full 100-yr data are computed (Fig. 15). The 35-yr data is sufficient for surface air temperature to reach a 0.9 correlation with the 100-yr result, while 60-yr data is needed for precipitation to reach a 0.9 correlation with the 100-yr result. The 0.9 correlation is chosen because the correlation coefficient, as a function of length of data, reaches an asymptote around that value. Results using only 25-yr data contain a large sampling error; however, that is the best we can achieve at this time with observations. Besides SST and vegetation, there are still other forcings that impact the atmosphere, and we will consider adding them when time and data permit.

Although the climate model is only used to validate the statistical GEFA method, a comparison of the atmospheric responses to the vegetation forcing between observations and the model can aid in understanding the model's performance. Both in the model and observations, the atmospheric response to the NAMR

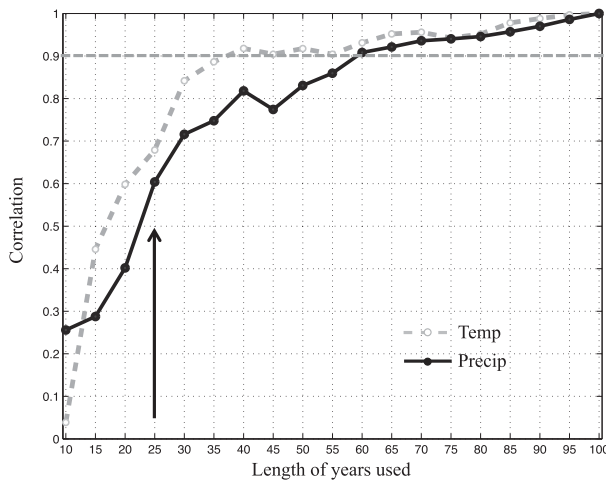


FIG. 15. Consistency of GEFA results for the NAMR in July from the model CTL run. Spatial correlation of GEFA response pattern between estimates using different lengths of data (from 10 to 100 yr) and estimates using the full 100-yr data. Gray dashed and solid black lines represent surface air temperature and precipitation, respectively.

vegetation forcing is strongest during JJA. The atmospheric response is mainly local in the model (Fig. 4) but nonlocal in the observations (Fig. 9). In the model, vegetation hydrological feedback dominates, while in the observations, both vegetation roughness and hydrological feedbacks play an important role. This is likely due to the wet bias and excessive vegetation bias simulated over the NAMR by CCSM3.5 (Notaro et al. 2011; Notaro and Gutzler 2012). Owing to the simulated gap in boreal forest, and the zero interannual variability of evergreen forest, the vegetation interannual variability in NABF is very small; the impact of the boreal forest on the atmosphere cannot be studied using this model. In short, the model still needs to be improved. Using the University of California, Los Angeles AGCM, Xue et al. (2010) found that a comprehensive vegetation biophysical process can reduce the model bias significantly. To have a better understanding of land–atmosphere interaction, a model intercomparison study of the Global Land–Atmosphere Coupling Experiment (GLACE) has been done (Koster et al. 2006). With a longer time series and improved model simulations, vegetation–atmosphere feedbacks can be better understood.

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