Title
Evaluation of hydrologic components of community land model 4 and bias identification

Authors
Du, Enhao
Di Vittorio, Alan
Collins, William D

Publication Date
2016-06-01

DOI
10.1016/j.jag.2015.03.013

Peer reviewed

Evaluation of Hydrologic Components of Community Land Model4 and Bias Identification

Enhao Du[1*], Alan Di Vittorio[1], William D. Collins[1,2]

1. Climate Science Department, Lawrence Berkeley National Laboratory
2. Department of Earth and Planetary Science, University of California, Berkeley

*Corresponding author:

Enhao Du
Earth Sciences Division
Lawrence Berkeley National Laboratory
One Cyclotron Road - M/S 74R316C
Berkeley, California 94720-8268
Phone: +1 805-205-7437
Email: enhaodu@gmail.com

Abstract

Runoff and soil moisture are two key components of the global hydrologic cycle that should be validated at local to global scales in Earth System Models (ESMs) used for climate projection. We have evaluated the runoff and surface soil moisture output by the Community Climate System Model (CCSM) along with 8 other models from the Coupled Model Intercomparison Project (CMIP5) repository using satellite soil moisture observations and stream gauge corrected runoff products. A series of Community Land Model (CLM) runs forced by reanalysis and coupled model outputs was also performed to identify atmospheric drivers of biases and uncertainties in the CCSM. Results indicate that surface soil moisture simulations tend to be positively biased in high latitude areas by most selected CMIP5 models except CCSM, FGOALS, and BCC, which share similar land surface model code. With the exception of GISS, runoff simulations by all selected CMIP5 models were overestimated in mountain ranges and in most of the Arctic region. In general, positive biases in CCSM soil moisture and runoff due to precipitation input error were offset by negative biases induced by temperature input error. Excluding the impact from atmosphere modeling, the global mean of seasonal surface moisture oscillation was out of phase compared to observations in many years during 1985-2004. The CLM also underestimated runoff in the Amazon, central Africa, and south Asia, where soils all have high clay content. We hypothesize that lack of a macropore flow mechanism is partially responsible for this underestimation. However, runoff was overestimated in the areas covered by volcanic ash soils (i.e. Andisols), which might be associated with poor soil porosity representation in CLM. Our results indicate that CCSM predictability of hydrology could be improved by addressing the compensating errors associated with precipitation and temperature and updating the CLM soil representation.

Highlights

- We evaluated gridded soil moisture and runoff of nine CMIP5 models
- We isolated biases from the atmosphere model
- We identified areas with anomalies generated by CLM4
- We proposed modifications to improve hydrologic simulations in CLM

Key words

CLM4, surface soil moisture, runoff, historical evaluation, bias test

1. Introduction

The Community Land Model (CLM) serves as the land model for the Community Climate System Model (CCSM) [*Collins et al.*, 2006] and includes land biogeophysics, hydrology, and biogeochemistry. Hydrology comprises key processes that link and integrate atmosphere, ocean, vegetation, and human systems. Increasing greenhouse gas concentrations and potential global warming may affect water cycle dynamics, which in turn provide feedbacks to the atmosphere and land surface. As a tool for predicting future states of ecosystems and climate, land surface model development requires rigorous calibration and validation against observations.

The growing demand for assessing the potential impacts of projected climate change on human systems [*Field et al.*, 2014] highlights the importance of understanding surface hydrological responses within fully coupled Earth System Models (ESMs), in addition to evaluating the accuracy of standalone land surface models. While the IPCC AR5 has implemented a new framework for assessing these impacts [*Field et al.*, 2014] a recent study with the newly developed integrated Earth System Model (iESM), which directly couples the Global Change Assessment Model (GCAM) with the Community Earth System Model (CESM) [*Collins et al.*, 2014], has quantified the unintended consequences of not implementing complete consistency among land use and land cover components of the economic Integrated Assessment Models (IAMs) and the biophysical ESMs [*Di Vittorio et al.*, 2014]. The next steps for assessing climate impacts include implementing and examining feedbacks between ESM water supply and IAM water demand and management. In the context of the iESM, closer examination of the surface hydrology of the fully coupled CCSM/CESM will enable development of a more consistent framework for incorporating human-earth water cycle feedbacks into projections of water availability and use.

Runoff is an important component of the hydrological cycle, but runoff trend detection at the global scale is a difficult task. Even the sign of the trends are uncertain, as recent estimates of global runoff trends in the twentieth century from various modeling studies are both positive [*Gedney et al.*, 2006; *Labat et al.*, 2004; *Piao et al.*, 2007] and negative [*Dai et al.*, 2009; *Shi et al.*, 2011]. Positive trends may be a result of increased continental precipitation, stomatal closure due to rising CO_2 concentration, land use changes, or decline of land ice content [*Alkama et al.*, 2013]. Decreasing trends in global runoff could be a consequence of climate forcing changes with minor effects from nitrogen deposition and land use change [*Shi et al.*, 2011]. These uncertainties in runoff simulations are largely due to different model implementations of atmosphere-plant-soil system interactions and the range in responses from these parameterizations to model-specific climate forcings.

Soil moisture has been demonstrated to affect regional climate via evaporation and evaporative cooling [*Seneviratne et al.*, 2013]. For example, atmospheric circulation over the land surface is largely affected by soil moisture during summer [*Owe et al.*, 2008]. In particular, surface soil moisture controls partitioning between sensible and latent heat, and affects partitioning between overland flow and infiltration [*Hou et al.*, 2012]. However, surface soil moisture is among the most complex hydrologic variables to simulate as it interacts with the atmosphere, plant canopy and roots, and vadose zone. This complexity is likely evidenced by studies showing that peak variability in soil moisture occurs at the surface [*Decker and Zeng*, 2009].

Our evaluation procedures comply with the benchmarking framework proposed by *Luo et al.* [2012]. We focus on runoff and soil moisture because observation-based, gridded, global datasets have recently become available for these two key hydrologic variables[*Fekete and Vorosmarty*, 2002; *Liu et al.*, 2012]. Other variables such as river discharge and soil water storage of CLM4 [*Lawrence et al.*, 2011] and earlier versions (3-3.5) were reported to match observations of major basins globally, although the accuracy of timing for simulated hydrologic quantities varied among rivers and areas [*Lawrence et al.*, 2011; *Oleson et al.*, 2008; *Qian et al.*, 2006]. However, CLM4 hydrologic simulations have not been fully assessed at the level of a global grid. Thus, we define a set of metrics including absolute and normalized biases, temporal correlation, and seasonal dynamics to identify model strengths and deficiencies at the grid level. Using these metrics, we identify the contributions of uncertainty from both the atmosphere and the land components of the earth system model to soil moisture and runoff. Based on our evaluation, we propose improvements to the land model hydrology. Our results not only meet evaluation objectives that are coincident with CMIP5 goals [*Taylor et al.*, 2012], they also provide insights toward coupling ESM and IAM water cycles to examine human-earth feedbacks affecting water supply, demand, and management.

2. Datasets and methods

The study was designed as two parts to answer following questions:

1. How well do the fully coupled models, particularly CCSM/CLM, represent the surface soil moisture and runoff? What atmospheric forcings have the greatest influence on these two variables?

The hydrologic simulations of the CMIP5 models are largely dependent on the forcings of various atmosphere models, but the ensemble comparison may still help to reveal areas where hydrology is frequently underrepresented by the earth system models and areas where observations/satellite products have biases.

2. What are the contributions of these dominant forcings to hydrologic biases? How do these biases relate to biases generated by land component? What are the potential modifications for addressing land component – driven biases?

By applying alternate atmospheric forcings, offline CLM simulations help to determine contributions of biases in the coupled model from those driven by the land model component.

2.1 Fully coupled global model outputs

The CCSM version 4.0 (CCSM4) is a coupled climate model for simulating the earth system. The historical model outputs are available from the Climate Model Intercomparison Project Phase 5 (CMIP5) repository. We use outputs from the CCSM4 MOther of All Runs (MOAR) for several reasons. First, MOAR is the historical control run with fixed satellite phenology and hence more realistic interactions between vegetation and hydrological processes than the unconstrained model. This constraint helps us focus on the physical rather than vegetative hydrologic components of version 4 of the land model (CLM4) in CCSM4. The MOAR run is the only century-long ensemble member with sub-daily atmosphere variables, making it possible to perform subsequent offline runs driven by the same set of forcing. Also, the MOAR outputs cover the time period of 1850-2005 that is overlapped with observations.

In CLM4, soil moisture dynamics is controlled by infiltration, runoff (surface and subsurface), gradient diffusion, gravity, and root extraction in a ten-layer model (3.8 m) plus an underlying five-layer aquifer (5 m). The runoff is parameterized as exponential functions of groundwater level [*Oleson et al.*, 2010]. The model has been calibrated and validated against major river discharge and terrestrial water storage observations [*Oleson et al.*, 2008]. Using uncertainty quantification framework, *Huang et al.* [2013] found that subsurface runoff generation and soil texture-related parameters are the most significant to runoff simulations. Details of hydrologic parameterizations in CLM4 can be found in [*Huang et al.*, 2013; *Niu et al.*, 2005; *Niu et al.*, 2007; *Oleson et al.*, 2008]. The choice of CLM4 hydrologic parameters may have considerable impact on the results of runoff and soil moisture, but is not the scope of the study.

We included eight other models from the CMIP5 repository in our comparison with observations: HadCM3, MIROC5, GFDL-CM3, CSIRO-Mk3, BCC-csm1, MRI-ESM1, FGOALS-g2, and GISS-E2-R. The models were selected to meet two criteria: they must have both runoff and surface soil moisture monthly outputs and they must have historical runs. Brief descriptions of each model and institution can be found in CMIP5 website (http://cmip-pcmdi.llnl.gov/cmip5/availability.html). Outputs were extracted from a single historical run (1850-2005) by each model.

Two types of coupled model output were involved in this evaluation: the hydrologic outputs (i.e. runoff and surface soil moisture) for comparison against observations, and the atmosphere outputs from CCSM4 MOAR simulations for driving the CLM4 offline runs. We extracted monthly surface soil moisture in the top 10 cm and runoff from the CMIP5 archive via the Earth System Grid (http://pcmdi9.llnl.gov) for the CCSM4 and the eight other models. Coupled model monthly land outputs were extracted from ensemble member r6i1p1 for CCSM4 and from r1i1p1 for the eight other models. Atmosphere outputs from the coupled CCSM MOAR run were acquired from the National Center for Atmosphere Research (NCAR) via the Earth System Grid (https://www.earthsystemgrid.org) and used to force the offline CLM4 runs. The forcing data include 3-hourly solar radiation, specific humidity, temperature, surface pressure, and wind together with 6-hourly fields of precipitation.

2.2 Observational data

2.2.1 Surface soil moisture

Soil moisture products have been estimated from an individual remote sensing satellite in various studies (e.g., *Al-Yaari et al.* [2014] and *Loew et al.* [2013]), but a multi-sensor approach has improved global soil moisture estimates. *Liu et al.* [2012] have merged four passive microwave soil moisture retrievals from the Scanning Multichannel Microwave Radiometer, the Special Sensor Microwave Imager, the Tropical Rainfall Measuring Mission microwave imager, and the Advanced Microwave Scanning Radiometer – Earth Observing System with two active microwave soil moisture estimates from the European Remote Sensing satellite and the Advanced Scatterometer into the new European Space Agency (ESA) global soil moisture product. The product's temporal domain ranges from 1978 to 2010 with daily values at 0.25° spatial resolution. The detection depth of the microwave signal ranges from 2 to 5 cm depending on the type of sensor and soil condition [*Liu et al.*, 2012]. We use Volumetric Water Content (VWC, vol vol^{-1}) as the basis for our comparisons.

The ESA data product has no coverage in densely vegetated regions such as the Amazon and central Africa where dense canopy masks out both passive and active microwave signals. The soil moisture retrievals are also absent under frozen or snow conditions. Whenever data are available, the areas are included in the calculation as well as the model simulations. Intercomparison and validation of the microwave satellite data have been conducted at regional and continental scales against in-situ observations [*Albergel et al.*, 2012; *Brocca et al.*, 2011; *Gruhier et al.*, 2010; *Loew et al.*, 2013]. In general the satellite product accurately reproduces the seasonal cycle as well as short-term variability.

2.2.2 Monthly runoff

The University of New Hampshire (UNH) Global Runoff Data Center (GRDC hereafter) composite runoff field V10 is a gridded runoff dataset at 0.5 degree [*Fekete and Vorosmarty*, 2002]. The dataset was constructed by first calculating basin-scale runoff based on a water balance model developed by UNH. The water balance model (WBM) simulation at each cell was corrected by runoff estimates for the corresponding interstation area. The interstation areas were defined by a river routing model, the Global Simulated Topological model, to which the GRDC stations were geo-registered. A total of 663 GRDC stations were included and represented 72% of actively discharging areas. The majority of discharge records were from the 1970s and the final product is a composite annual runoff. The WBM-modeled runoff from 1971 to 1980 was averaged to approximate the time period.

The runoff dataset has more complete global coverage than the soil moisture dataset, enabling evaluation of densely forested areas such as the Amazon and central Africa and permafrost areas such the Himalayas and Arctic Circle. We compared the runoff differences divided by Global Precipitation Climatology Centre (GPCC) precipitation reanalysis, which gives the normalized runoff difference (NRD):

$$NRD = \frac{Q_{model} - Q_{obs}}{P}$$

where Q_{model} and Q_{obs} denote the modeled and observed runoff and P the GPCC precipitation. NRD was used instead of percent change because the long-term runoff is zero or close to zero in arid areas, making any percent difference either very large or infinite. We applied GPCC precipitation instead of precipitation from each corresponding model because our aim was to reduce the range of runoff difference induced by variations in modeled precipitation. Dividing runoff by precipitation within each model generates a runoff ratio that describes the portion of runoff relative to precipitation, which is not the intention of this comparison. Furthermore, applying precipitation from each individual model also introduces uncertainties from atmospheric simulation that we wanted to minimize in our comparison. The GPCC monthly precipitation 1-degree data [*Schneider et al.*, 2011] were provided by the NOAA/OAR/ESRL Physical Science Division from the website at http://www.esrl.noaa.gov/psd.

2.2.3 Qian's reanalysis data and GPCC

Qian et al. [2006] adjusted NCEP-NCAR (National Centers for Environmental Prediction-National Center for Atmospheric Research) reanalysis forcing dataset by combining it with station records and satellite observations of temperature, precipitation, and cloud cover. Qian's reanalysis dataset covers the global land areas with 3-hourly and T62 (~1.875°) resolution and serves as the offline CLM model forcing data from 1948 to 2004.

The GPCC full data reanalysis version 6.0 comprises globally gridded gauge-analysis precipitation products over land areas derived from quality controlled station data [*Becker et al.*, 2013]. The monthly precipitation data were used to normalize the runoff discrepancies between CMIP5 models and observations.

2.3 Offline experiments to assess sources of error

We extracted climate variables from the MOAR run to construct the forcings for offline CLM4 runs. The MOAR climate variables are available in 3-hourly, 6-hourly, and monthly time steps. All our processing was based on 3-hourly data. The standard climate forcings for a CLM4 historical run with satellite phenology include three NetCDF files: 3-hourly solar radiation, 6-hourly precipitation (converted by averaging from 3-hourly), and 3-hourly surface temperature, specific humidity, pressure, wind speed. The MOAR climate variables were combined with Qian's reanalysis data [*Qian et al.*, 2006] to construct offline runs

with four sources of climate forcings (Table 1):

Table 1. List of offline experiments and forcings

	QIAN	MOAR	MOAR_PRECIP	MOAR_TEMP
Precipitation	reanalysis[1]	coupled run[2]	reanalysis	coupled run
Temperature/humidity	reanalysis	coupled run	coupled run	reanalysis
Other forcings[3]	reanalysis	coupled run	coupled run	coupled run

1. Qian's 2006 reanalysis dataset (see section 2.2.3)
2. atmosphere forcings from MOAR coupled run
3. other forcings include solar radiation, wind, and surface pressure

a. Qian's 2006 reanalysis dataset (QIAN hereafter)
b. Atmosphere outputs from the MOAR coupled run (MOAR hereafter)
c. Qian's reanalysis, but with precipitation data from the MOAR run (MOAR_PRECIP hereafter)
d. Qian's reanalysis, but with surface temperature and specific humidity from MOAR run (MOAR_TEMP hereafter).

In the offline experiments, soil moisture is extracted from top 4.5 cm soils and excludes ice content. This soil moisture output matches the satellite product closely both in scale and phase, and therefore provides the most appropriate comparison with observation datasets. Monthly global mean values were compared between simulations and observations to reveal the dynamics of runoff and soil moisture. Differences between MOAR_TEMP and MOAR_PRECIP relative to QIAN determine what fractions of the total variance between MOAR and QIAN are due to temperature/humidity and precipitation, respectively.

2.4 Correlation analyses

Temporal correlation analysis between model simulations and observations used Pearson's correlation coefficient *r*. The Pearson correlation coefficient was calculated between simulations and observations, and between the hydrologic variables (runoff and surface soil moisture) and atmosphere forcings (precipitation and surface temperature).

3. Results and discussions

3.1 Surface soil moisture

The soil volumetric water content differences between CCSM4 and the ESA dataset indicate that soil moisture discrepancies are within 5% in the majority of the area covered by the ESA dataset. The inclusion of wetland areas in the surface soil moisture data in the CCSM4 CMIP5-archived outputs contributes to the apparent, but incorrect, signal of permanently saturated soils in high latitude areas between 50 to 70° N including the Hudson Bay in Canada and parts of Siberia (Figure 1). For this reason, the wetland areas have been omitted from the calculation of surface soil moisture in the remainder of our analyses. Outside of the wetland areas, CCSM4's soil moisture exceeded ESA's observation by 0.05-0.20 VWC in predominantly mountainous regions covering the Rocky Mountains, central Europe and the Alps, central Africa, areas immediately south of Himalayas including India, Bangladesh, Burma etc., northern and central China, and western Australia. CCSM4 underestimated surface soil moisture by up to 0.20 in high latitude areas of North America and Eurasia, central Asia, and southern China.

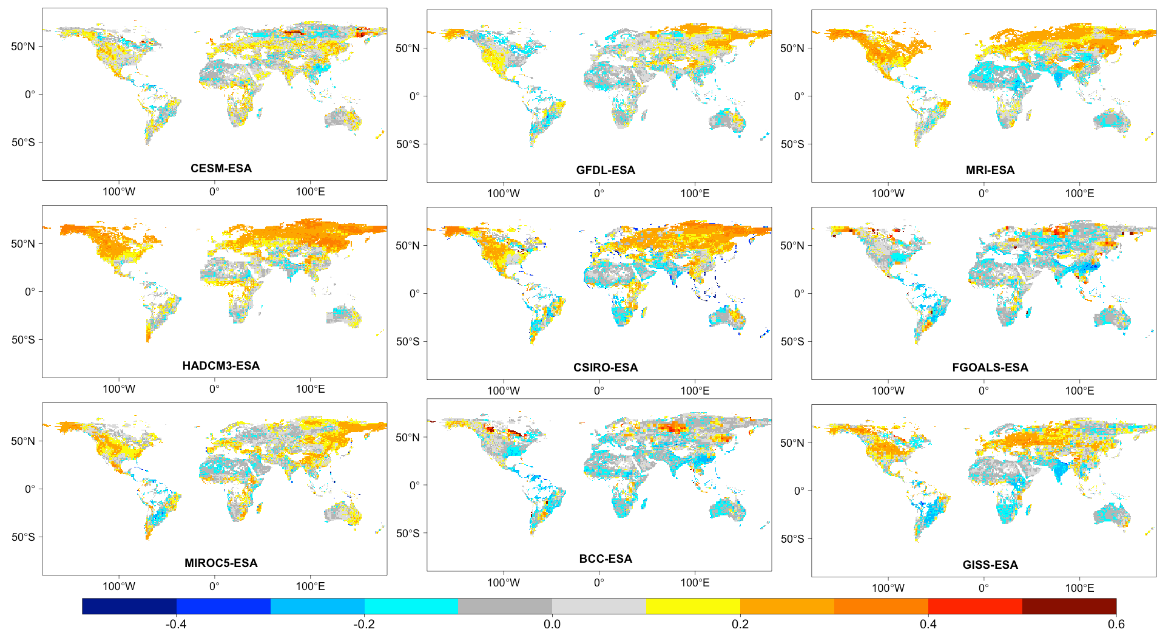

Figure 1. Absolute surface soil moisture difference indicates CCSM4's soil moisture exceeds ESA's observation by up 0.05-0.20 (vol vol^{-1}) in the Rocky Mountains, central Europe, central Africa, south of Himalayas, most of China, and west Australia. CCSM4 underestimated surface soil moisture by up to 0.20 in high latitude areas. Most other CMIP5 models had positive biases in high latitude areas and United States except FGOALS and BCC.

In contrast, with the exception of FGOALS and BCC, most other CMIP5 models had positive biases in high latitude areas and in the United States. Both FGOALS and BCC models suffered from the inclusion of wetland in the soil moisture calculation and thus displayed oversaturation. This is not surprising because FGOALS used an earlier version of the CCSM land surface model (CLM3). FGOALS and BCC were the only models with an overall negative bias compared to ESA dataset. An extremely dry bias followed the edge of continents and small islands in CSIRO.

Two types of mismatch between these simulation outputs and satellite observations cause models to overestimate soil moisture. The first possible cause is a depth mismatch between the archived top 10 cm layer and the 2-5 cm layer measured by the instruments in the ESA data set. Although *Wagner et al.*

[1999] has demonstrated that surface soil moisture can act as a predictor of deeper soil profile, the surface soil is inherently drier than the underlying layers at long time scales (e.g. monthly) because of loss by surface evaporation. The archived outputs include more than double the depth of the satellite observation, which potentially introduces a positive bias in water content in many areas with respect to the ESA product. The second possible cause is a phase mismatch between the modeled and observed VWC. The archived surface soil water content includes the mass of water in all phases, whereas the satellite data includes only the liquid phase of soil water. The satellite data as a rule excludes areas with snow cover or land surface temperature below zero, but it may not exclude all areas with ice content below the surface that would not be detected as water content. Therefore the satellite product is potentially ‘drier’ than the modeled soil, especially in high latitude areas.

Therefore both thicker depth and the inclusion of ice content in the CCSM4 simulation tend to give higher water content values than the ESA observations. In general the two types of mismatch would artificially shift the systematical bias in modeled surface soil moisture toward small positive values. For the purposes of this comparison, areas with a negative difference or a positive difference greater than 0.2 exhibit significant surface soil moisture biases. Fortunately, we were able to remove these mismatches from our offline analyses because we ran our own simulations and were not restricted to archived data. On the other hand, under certain extreme circumstances, the modeled and satellite-derived estimates of a given soil could differ by the total soil pore volume. This situation would occur only where the surface temperature is above freezing so that the measurement is included in the data set but the ground remains partially to completely frozen, thereby resulting in a spurious satellite retrieval of low VWC while the model output may contain a frozen, saturated soil column.

The evaluation of soil moisture estimation may be limited by the quality of the observational dataset. ESA soil moisture products were found to have poor correlations at high latitude of north hemisphere against the reanalysis of the European Centre for Medium-Range Weather Forecasts Interim [*Albergel et al.*, 2013], partly owing to the low average observation densities in northern latitudes due to snow and ice [*Dorigo et al.*, 2014]. Also, the quality of ESA soil moisture dataset is affected by surface soil moisture simulation of GLDAS-1 Noah, a land surface model that was used to rescale the microwave products [*Liu et al.*, 2012].

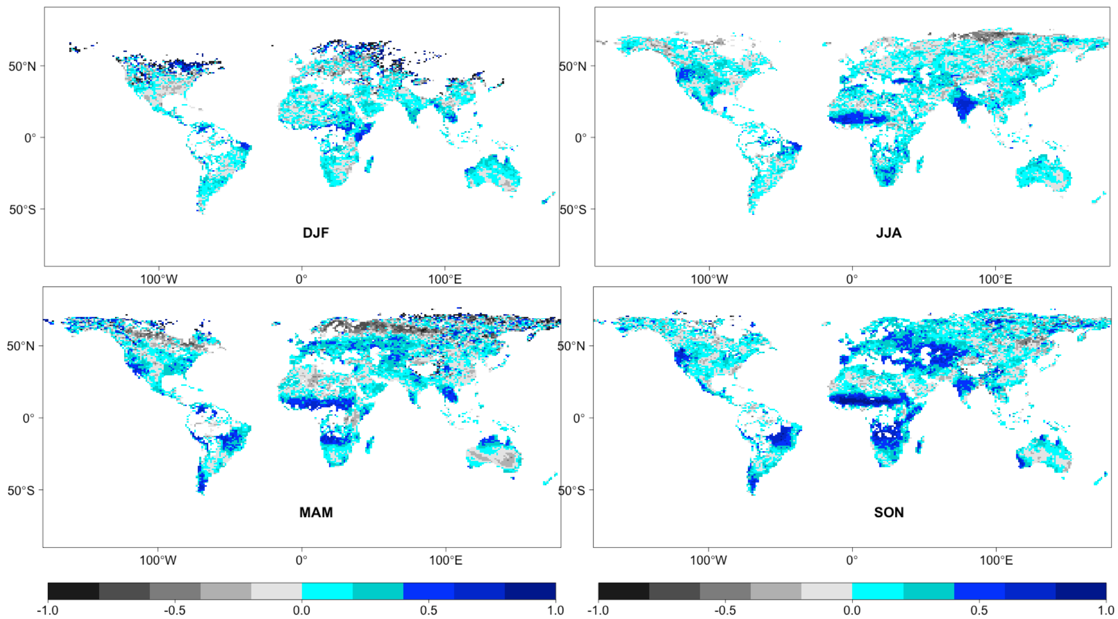

Figure 2. Temporal correlation of CCSM4's surface soil moisture in four seasons indicates monthly soil moisture dynamics are better correlated with observations in low- to mid-latitude areas.

The temporal dynamics of soil moisture, however, are more consistent than the magnitudes between the models and observations (Figure 2). Monthly CCSM4 soil moisture dynamics are better correlated with observation in tropical areas, but have decreased coefficients in high latitude areas, especially in northern hemisphere winter (DJF) and spring (MAM). Similar to CCSM4, most CMIP5 models displayed similar annual spatial patterns with decreased correlation coefficient in permafrost areas such as Canada and Siberia and in arid zones such as the Sahara and central Australia (not shown). The high latitude areas with the least correlation generally have the largest absolute biases. Overall, soil moisture is better correlated in northern hemisphere summer and fall, but has more negative coefficients in spring (MAM), implying model deficiency in snowmelt simulation.

3.2 Runoff

Canada and Siberia and the major mountain ranges, including the Rocky Mountains, Andes, and Himalayas are the areas where most models overestimate runoff by more than the magnitude of the Global Precipitation Climatology Centre (GPCC) precipitation reanalysis (Figure 3). FGOALS and BCC both produce unrealistically high amounts of runoff in the Saharan region. GISS is the exception in that it generally underestimates runoff. The Amazon is the only region where all models underestimate runoff, and these results are consistent with a negative precipitation bias reported for CMIP5 models [*Mehran* *et al.*, 2014]. Similar to soil moisture, the runoff comparison has a mismatch between the simulation and observations: the CMIP5 models define runoff as the total liquid water leaving the grid cell, which accounts for both surface and subsurface terms, while the GRDC runoff product assumes all water leaving a grid cell emerges as river discharge at a given stream gauge. Thus, the GRDC product may underestimate total runoff in headwater and upstream basins if subsurface water does not discharge within a grid cell and/or discharges to a stream outside a measurement basin.

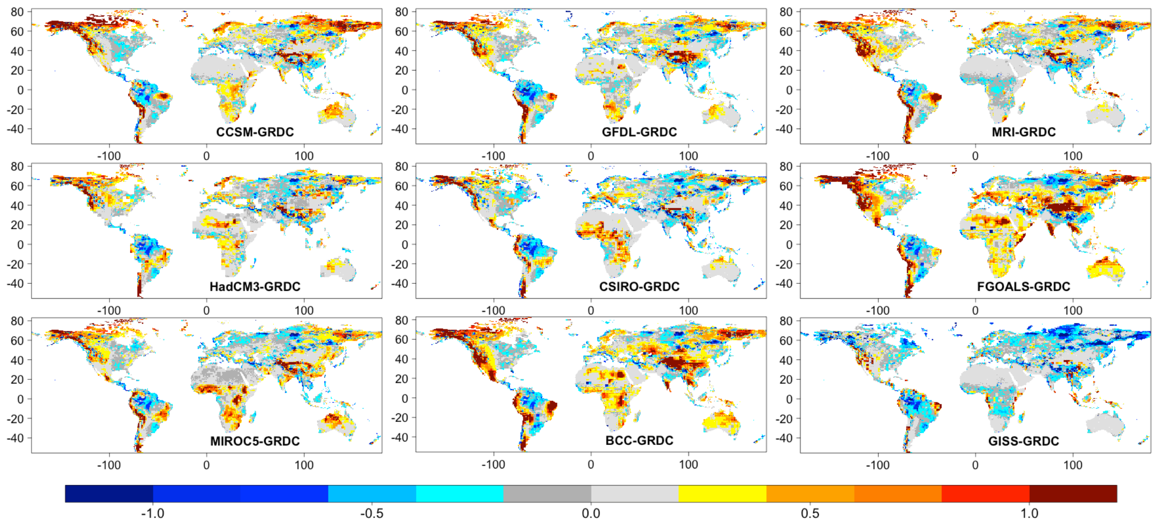

Figure 3. Precipitation normalized runoff difference between CMIP5 models and GRDC dataset. Most CMIP5 models, except GISS, produced higher runoff than GRDC in mountain ranges. All models underestimated runoff in the Amazon.

Our evaluations of both surface soil moisture and runoff indicated that the largest discrepancies between model outputs and observations occur in mountainous and high latitude areas. *Mehran et al.* [2014] found that CMIP5 models generally overestimate precipitation in steep terrain. Their bias map for CESM1_BGC_es, a version close to CCSM4, shows a very similar pattern to the runoff bias in this study except in Canada and Siberia. We speculate that that the runoff biases in mountainous regions are caused by precipitation biases in the atmosphere model, while biases in high latitude areas may be caused by other atmosphere forcings or by the land surface model algorithms.

Another potential reason for most CMIP5 models having large biases in mountainous areas may be tracked to deficiencies in the GRDC dataset. The gridded GRDC runoff was generated by linking discharge gauging station data with a digital river network and distributing runoff across interstation regions using a water balance model. The WBM itself could be biased due to meteorological forcings (e.g. precipitation) and physical (e.g. soil properties) or biophysical attributes (e.g. land cover). Inconsistencies also exist between the GRDC station data and the river network due to resolution discrepancies and data quality [*Fekete and Vorosmarty*, 2002], but the GRDC dataset is still the only gridded runoff field available for global scale evaluation. The GRDC composite runoff dataset provides only a monthly mean runoff field, which limits our analysis to bias evaluation.

3.3 Atmosphere-land hydrology correlations in the coupled CCSM4

Four potential sources of bias are 1) the error from observational data, 2) structural deficiencies of CLM4, 3) forcing errors from the atmosphere, and 4) model parameterization. Many researchers are currently working to improve CLM and its parameters, and here we attempt to identify the effects of atmospheric forcing on land hydrology to better understand CLM deficiencies.

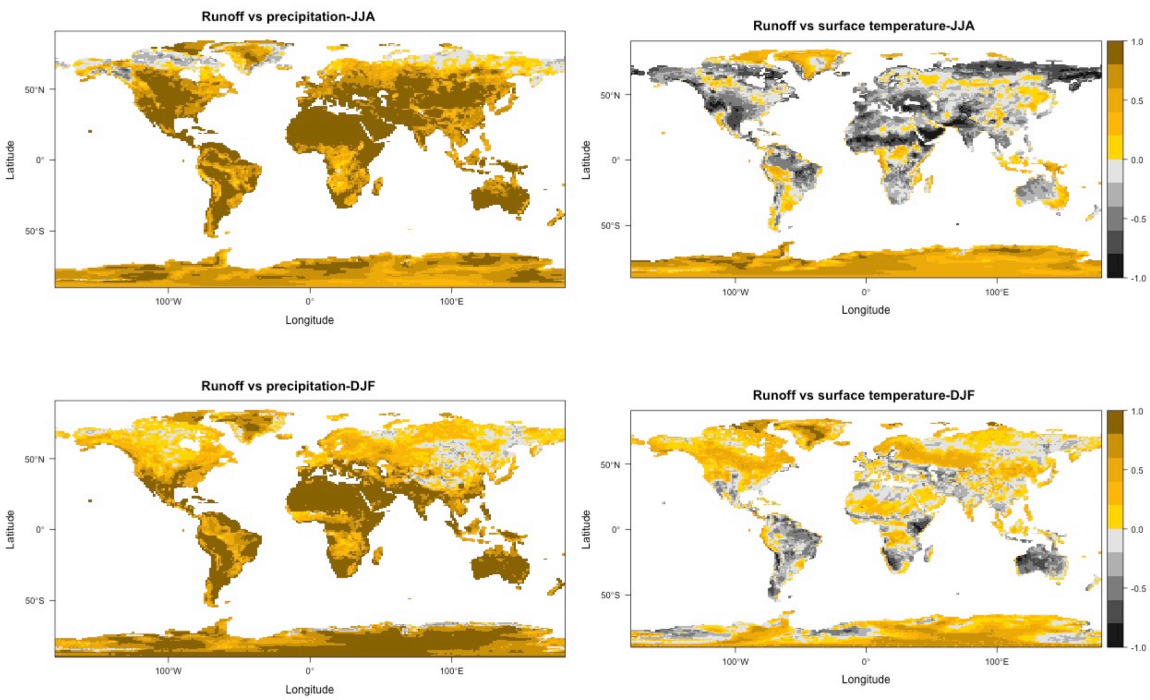

Figure 4. Correlation between runoff and precipitation, and runoff and surface temperature in winter and summer, respectively. Precipitation is positively correlated to runoff in northern hemisphere summer (JJA) except for the areas above Arctic Circle. In northern hemisphere winter (DJF), the correlation is weakened in the high elevation areas where freeze and thaw dominate the hydrology. Surface temperature is negatively correlated to runoff in JJA but more positively correlated in DJF. Correlations with soil moisture follow similar patterns.

Atmospheric forcings are expected to be one of the major sources of bias in land surface hydrology when hydrologic cycles are driven by climate model outputs. Precipitation has been found to largely affect runoff trends while temperature has relatively weaker influences [*Gerten et al.*, 2008; *McCabe and Wolock*, 2011]. CLM4 imports six atmospheric variables from the Community Atmosphere Model 4.0 (CAM4) including solar radiation, precipitation, surface temperature, pressure, wind, and specific humidity. Monthly correlation analysis reveals that precipitation and surface temperature are the major predictors for soil moisture and runoff. The correlations for each hydrologic variable exhibit similar geographic and temporal patterns. In northern hemisphere summer (JJA), precipitation is positively correlated to both runoff (Figure 4) and soil moisture (not shown), except for areas above Arctic Circle. In northern hemisphere winter (DJF), precipitation is not as strongly correlated to runoff and soil moisture, especially in the northern hemisphere and in high elevation areas when freeze and thaw are the main drivers for hydrology. Surface temperature, on the other hand, is negatively correlated to soil moisture and runoff in JJA as high temperature dries up soil via evaporation and transpiration. Areas where temperature correlation coefficients are positive are either within the Arctic Circle or affected by summer monsoon. In DJF high temperatures induce snow thaws that consequently moisten the soil, therefore surface temperature is more positively correlated to the two hydrologic components. The rest of the atmospheric forcings indicate much weaker correlations with the two hydrologic variables.

As the precipitation shows strong correlation to the runoff and surface soil moisture in mid- to low-latitude areas and temperature shows stronger (positive and negative) correlation in high latitude zones, understanding the geographic differences in atmosphere-driven biases can help evaluation of hydrological processes in the land surface model. For example, the CMIP5 archived models often have larger biases in high latitude areas where snow and permafrost freeze-and-thaw mechanism may be underrepresented due to deficiency from temperature or land model. Similarly, runoff simulation of CMIP5 models in high latitude areas may be more biased by temperature forcing, but more affected by precipitation in mountainous areas. The correlations between climate forcings and hydrologic variables open the possibility of isolating the biases from atmospheric forcings therefore revealing respective sources of uncertainty from the atmosphere and land models.

3.4 Atmospheric drivers of soil moisture and runoff errors in CLM4

The offline MOAR simulation demonstrates that our offline runs can be used to diagnose the coupled model simulations (i.e. CMIP5). The offline MOAR simulation generates almost identical 10-cm soil moisture (comparisons not shown here) and surface runoff as the coupled simulation, except where the wetland area has been removed from the soil moisture calculations in the offline outputs. See section 3.1 for discussion of improperly inclusion of wetland in soil moisture outputs in CMIP5 simulations. This confirms that offline runs can be used to determine the error sources of the land model hydrology in the coupled model.

To better evaluate the contributions of atmospheric forcing error to hydrologic uncertainty, the following analyses reduce the effects of soil depth and ice content mismatch present in the CMIP5 analysis of soil moisture. For the offline analyses, we used the modeled soil moisture in the top 4.5 cm layers, which matches closely with the satellite detecting depth, and included only liquid water in the modeled water content. These procedures were not possible for the CMIP5 evaluations as the CMIP5 repository provides limited output variables. The difference between the two outputs is mostly within 0.04 except the CMIP5 soil (10 cm with ice content) contains 0.1-0.2 more water content in high latitude areas. This explains the discrepancies in high latitude areas between two comparisons of coupled and offline runs (Figure 1, CCSM-ESA vs Figure 5, MOAR-ESA).

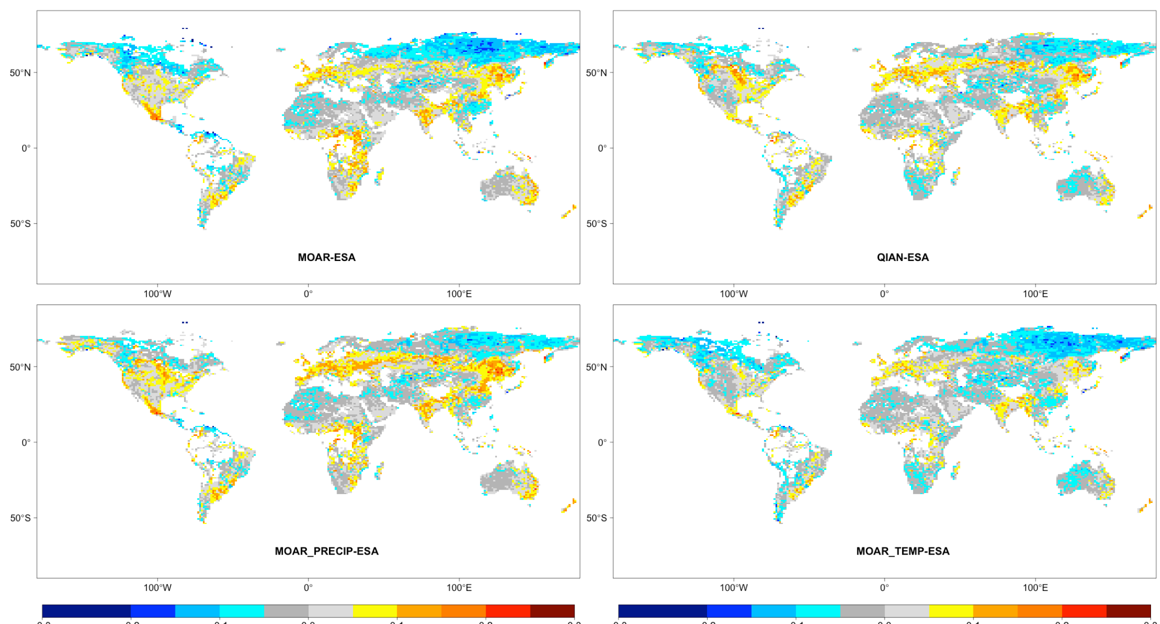

Figure 5. Absolute biases between offline runs and ESA surface soil moisture observations. a). the offline MOAR run resembled the CCSM4 coupled run. b). Qian's reanalysis forced run served as the reference that alleviated the underestimation of soil moisture in high latitude areas and Central America. c). offline run forced by reanalysis and modeled precipitation increased soil moisture compared to MOAR and QIAN runs, especially in the band of north 40 to 70. d) offline run forced by modeled temperature and relatively humidity reduce surface soil moisture compared to other offline runs.

Qian's reanalysis dataset is the closest atmosphere forcings to the observations and was therefore intended to isolate the biases to the land surface model only. Using reanalysis forcings improved soil moisture and runoff outputs with respect to the offline MOAR simulation. Underestimation of soil moisture in the MOAR simulation was alleviated in the QIAN simulation in high latitude areas and Central America (Figure 5). Additionally, positive differences from ESA data in Europe and Africa were reduced in the QIAN simulation. Runoff output was even more drastically improved in the QIAN simulation. The overestimation of runoff in mountains was mostly alleviated (Figure 6a and b), including the Rocky Mountains, Andes, Himalayas, and Northern Oceania. The QIAN simulation also improved runoff in the eastern Amazon, central Africa, and high latitude areas, although it increased overestimation in Eastern Europe. East of the Amazon and Central Africa changed from positive biases to neutral or negative. Overall, the biases in mountainous and tropical areas have been improved by using reanalysis data in place of the MOAR atmosphere model outputs.

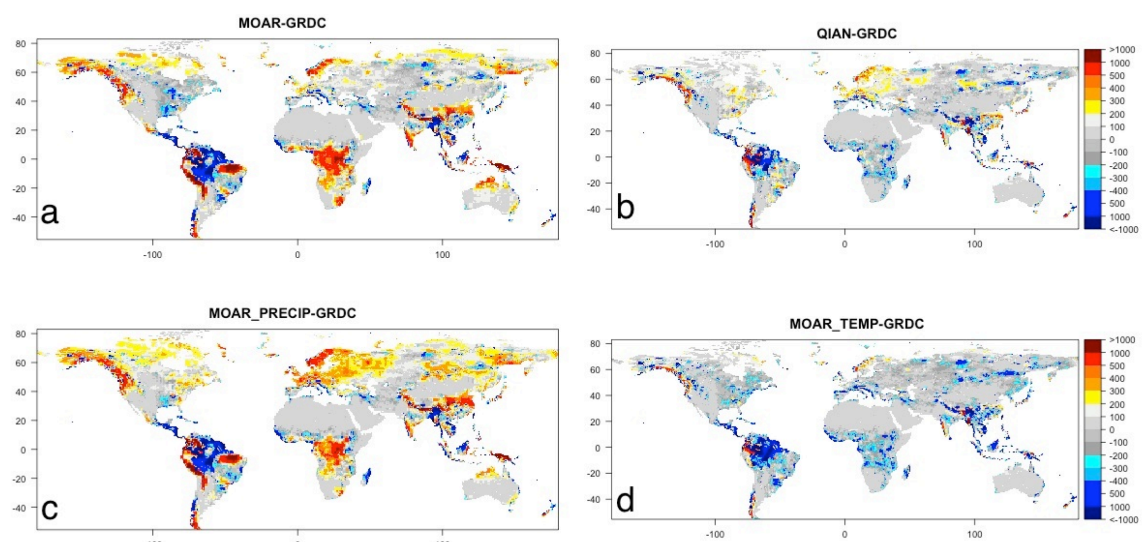

Figure 6. Absolute biases between offline runs and GRDC runoff dataset. Similar as surface soil moisture, a) offline run driven by modeled forcings; b) offline run driven by reanalysis eliminated most of positive biased in mountainous areas; c) offline run driven by MOAR precipitation produced more positive biases than the reference; d) offline run driven by modeled temperature and relative humidity changed the overall positive biases into negative.

Independent use of modeled precipitation and temperature forcings for offline simulations indicates that these atmospheric inputs have opposing effects on land surface hydrology with respect to their respective reanalysis forcings. The MOAR_PRECIP simulation increases soil moisture compared to the QIAN simulation, especially within the latitude band of north 40° to 70°, but otherwise has limited effects across the rest of the land surface (Figure 5b and c). The MOAR_PRECIP simulation has a greater impact on runoff through increases in area and magnitude of positive biases (Figure 6b and c). Furthermore, the soil moisture and runoff in the MOAR_PRECIP simulation are greater than in the MOAR simulation (Figures 5a and c, and 6a and c). The MOAR_TEMP simulation shows that modeled temperature and humidity reduced the surface moisture and runoff with respect to the QIAN simulation (Figures 5b and d, and 6b and d). The runoff bias maps in particular show the distinct contrast between runs driven by modeled precipitation and temperature (Figure 6c and d). In the original coupled CCSM4 and offline MOAR simulations the positive bias introduced by precipitation input is canceled out to varying degrees around the globe by the negative bias from temperature input.

Monthly global 10-year mean runoff (1971-1980) shows a similar pattern of opposing hydrological effects of modeled precipitation and temperature inputs. The CMIP5 fully coupled CCSM4 simulation matches observations well in April to September when hydrologic cycles are active (Figure 7). The QIAN simulation matches observations even better at low flow months, but underestimates runoff in June and July. This indicates that either the Qian dataset has low precipitation or high temperature bias in these two months, or the CLM has deficiency in simulating the drying limb of the spring peakflow. The offline MOAR simulation follows the coupled run well with subtle discrepancies in spring and summer. These discrepancies are likely induced by lack of land-atmosphere feedbacks (e.g. evapotranspiration effects on temperature and humidity). The MOAR_PRECIP simulation has high positive bias in spring and early summer (February to June in northern hemisphere, September to December in the southern hemisphere) when snow melts and high flows occur. These are the months when MOAR precipitation is more positively biased than QIAN, implying precipitation is the main driver of runoff bias. In contrast, the MOAR_TEMP simulation has the greatest negative bias compared to the other three simulations throughout the year. Peakflow timings were advanced from June to May in the QIAN and MOAR_PRECIP simulations. These monthly global results are consistent with the spatial results in that opposite hydrological effects of modeled precipitation and temperature inputs cancel each other out.

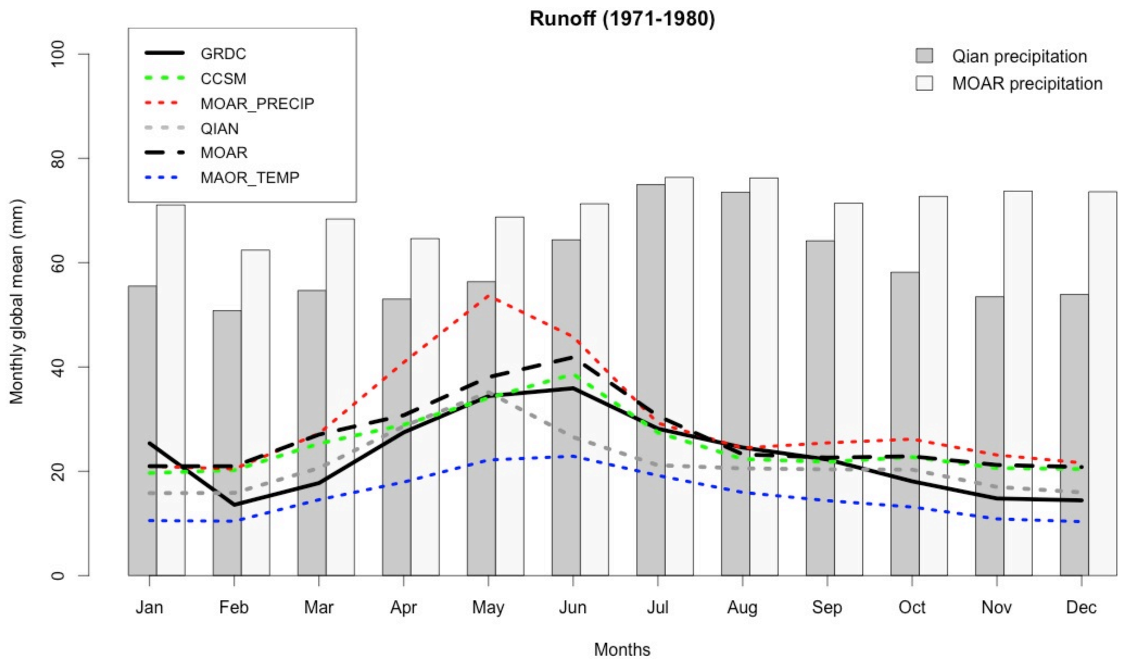

Figure 7. Global mean monthly runoff (10-year average) of model simulations and GRDC data indicates that CCSM simulation matched GRDC well April to September. QIAN simulation matched GRDC in all months but June and July. MOAR_PRECIP run has high positive biases in the months when MOAR precipitation is more positively biased than the Qian's reanalysis. MOAR_TEMP run simulation has greater negative biases throughout the year.

The annual cycle of global mean surface soil moisture also demonstrates hydrological compensation in simulations due to opposing effects of modeled precipitation and temperature inputs (Figure 8). The 1991 trough is related to a global precipitation deficiency associated with a warm El Niño Southern Oscillation (http://www.isse.ucar.edu/sadc/chptr5.html). The trough starting in 2001 are the results of the millennium drought in many areas (e.g., [*van Dijk et al.*, 2013; *Wandel et al.*, 2009]). The ESA data generally have troughs in January and peaks in the middle of the year (i.e. June and July). The MOAR simulation tends to have two peaks in the first and second half of a year (e.g., year 1995) and has more intra-annual variability than the observations. The QIAN simulation follows the observations more closely in both phase and magnitude, except for the years after 2002, indicating that sources of uncertainty are more likely from the atmospheric forcings. Similar as surface runoff, the surface soil moisture simulations were shifted upwards by MOAR_PRECIP and downwards by MOAR_TEMP relative to the MOAR run.

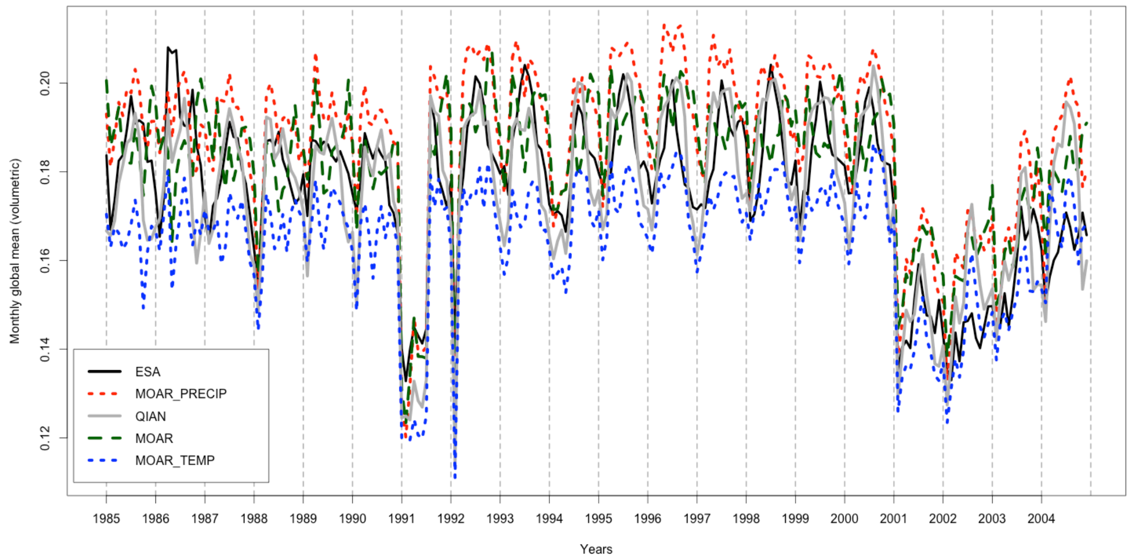

Figure 8. Global mean monthly soil moisture (1985-2004) of model simulations and observations shows that seasonal moisture dynamics are out of phase in some years (i.e. opposite wet and dry extremes). Basically all runs except MOAR_TEMP overestimated runoff globally, implying the deficiency is more likely from land surface model rather than forcing data.

3.5 Potential sources of bias from CLM4

If we assume the CLM4 offline run driven by Qian's reanalysis data eliminates most of the uncertainty generated by atmospheric forcing, the rest of the QIAN simulation bias is most likely induced by CLM4 itself. The QIAN simulation has negative runoff bias in the Amazon, central Africa, southwest China, and south Asia. Comparing with soil texture maps generated by National Aeronautics and Space Administration Land Data Assimilation Systems (http://ldas.gsfc.nasa.gov/gldas/GLDASsoils.php) and by Global Soil Wetness Project-Phase 3 (http://hydro.iis.u-tokyo.ac.jp/~sujan/research/gswp3/soil-texture-map.html), the areas with runoff underestimation are mostly associated with high clay content soils including sandy clay loam, clay loam, and clay. The bias may be propagated from the mischaracterization of clayey soils though pedo-transfer functions or parameterizations. For example, clayey soils tend to exhibit aggregation structure, which is one of most important characteristics of macropore formation. Macropores enable water to flow through unsaturated soil more rapidly than it would in a soil matrix defined by Darcy's law [*Beven and Germann*, 1982]. The existence of macropores increases effective hydraulic conductivity, thus decreases water content in surface soils. Without this mechanism, CLM4 may overestimate evapotranspiration and in turn underestimate runoff by retaining too much plant available water. Comparing to

FLUXNET-MTE global land estimates, *Tang and Riley* [In review] found that CLM4.5 overestimated evapotranspiration in the same areas where runoff was underestimated in this study. We propose that macropore flow is an essential mechanism that is lacking in the CLM and may be responsible for the mis-partitioning of water among evapotranspiration, groundwater, and runoff in tropical and other high clay content areas.

Another important process often associated with clayey soils is the shallow subsurface lateral drainage (i.e. interflow) [*McDaniel et al.*, 2008]. The restricting layers formed by argillic and fragipan horizons intercept percolating water and contribute to river discharge directly thus contribute much more rapidly than groundwater [*Jackson et al.*, 2014]. Hillslope with restricting layers may therefore produce considerably more runoff than those without argillic/fragipan layers [*Needelman et al.*, 2004]. The CLM hydrology contains no lateral drainage except in frozen soils. We therefore argue that adding lateral drainage in the high clay content soils with high contrast hydraulic conductivity may potentially change the water balance in the areas currently with large runoff biases. The lateral drainage from restricting layer may be directly added to the surface runoff depending on the topography and river channel network.

The areas where runoff simulation is overestimated overlap with the global distribution of Andisols [*Takahashi and Shoji*, 2002]. Defined by United States Department of Agriculture soil taxonomy (http://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcs142p2_051232.pdf), Andisols are soils formed in volcanic ash with very high porosity (often >0. 60 cm^3 cm^{-3}) and therefore high water holding capacity. The mineral soil porosity θ is defined by sand content in CLM as $\theta = 0.489 - 0.00126(\%sand)$. Increasing porosity has been shown to be among the most sensitive parameters for decreasing runoff yield in a physically-based hydrologic model [*Du et al.*, 2013]. With low porosity, CLM4 may retain insufficient plant available water and underestimate evapotranspiration, therefore partitioning too much to runoff. Sensitivity of surface hydrology to saturated hydraulic conductivity and porosity needs to be evaluated before future modifications are taken, as the two parameters were identified as secondarily significant to runoff and sensible/latent heat flux after subsurface runoff parameters [*Hou et al.*, 2012; *Huang et al.*, 2013]. The proposed modifications are speculated by overlapping the biases with the CLM soil texture map and need further test and proof.

4. Summary

Comparisons of surface soil moisture between fully coupled model simulations and observations reveal large positive biases, mostly in mid- to high-latitude areas, except for CCSM4, FGOALS, and BCC. Runoff is overestimated in mountain ranges and in most of the arctic by all CMIP5 models except GISS. All models underestimated runoff in Amazon areas. Terrestrial water storage and dynamics at high northern latitudes are critical to the global water balance. Hydrological fluxes have been poorly monitored in these areas [*Kane*, 2005], and hydrologic models have difficulties obtaining high quality data for calibration and validation. Current model deficiencies, like those presented above, urge the land modeling community to better understand hydrologic cycles in high latitudes and to help improve overall performance of the models.

When assessing runoff and soil moisture, one should not seek an exact match between model simulations and observations due to the mismatch and uncertainty derived from both ends. The validation of soil moisture from land surface modeling should focus mainly on relative changes and dynamics, but we do need to pay attention to the areas consistently having large biases. For example, the CIMP5 archived CLM simulated 10-cm soil moisture was up to 10% different from the observed moisture in 2-5 cm in many areas such as southern China and central/ southern Africa over the long term. The discrepancies were expectedly reduced in the offline tests with 4.5-cm soil moisture and ice content excluded, however the overall spatial pattern was retained. The simulated runoff had the same sign of bias in the same area and implied precipitation might be responsible for the dry or wet in both variables. There were also areas where the biases are opposite sign from soil moisture and runoff such as east half of the United States. It indicates that the land model may not correctly partition the water into surface runoff and infiltration.

CCSM4 produces reasonable soil moisture estimates (except where wetlands are included) and positive runoff bias in mountain ranges and central Africa. Negative runoff biases are found mainly in the Amazon, Southeast Asia, and the Middle East. Positive bias of global mean runoff occurred mainly in February-April and October-December. CCSM4 globally averaged surface soil moisture follows observed seasonal cycles but is out of phase compared to ESA data in some years. Overall, CCSM4 produces less bias in surface soil moisture prediction compared to eight other CMIP5 models, but has similar runoff over-predictions in high altitude and high latitude areas as most of the other models.

Modeled precipitation and temperature errors generate compensating biases in CCSM4 soil moisture and runoff. Offline CLM4 runs driven by simulated and reanalysis atmospheric inputs reveal that simulated precipitation causes overestimation of runoff in the mountainous areas, east Amazon, and central

Africa, and a general increase in overestimation of soil moisture. CLM4 tends to compensate for these overestimations when provided with simulated temperature and humidity, but at the cost of exacerbating surface soil moisture underestimates in high latitudes.

Bias from atmosphere forcings is not sufficient to explain all the deviation of simulated runoff and soil moisture from observation. Driven by Qian's reanalysis data, the CLM4 underestimates runoff in Amazon, central Africa, and other areas with high soil clay content. We hypothesize that the lack of fast path water infiltration is partially responsible for erroneous partitioning between evapotranspiration and runoff. CLM does not include preferential fast flow through macropore structure, and implementing this structure into global scale climate model is a challenging task involving extra parameterization and computational demand. Adding lateral drainage within the shallow soil layers is however relatively straightforward, but the model sensitivity needs to be tested first. We also hypothesize that low soil porosity causes overestimation of runoff in mountainous areas with volcanic soils. Improving these processes and data in CLM might help correct the compensating sensitivities of soil moisture and runoff to errors in precipitation and temperature inputs.

Acknowledgement: This material is based upon work supported by the U.S. Department of Energy, Office of Science, Climate and Environmental Sciences Division, BER Program, under Contract Number DE-AC02-05CH11231.

References:

Al-Yaari, A., et al. (2014), Global-scale evaluation of two satellite-based passive microwave soil moisture datasets (SMOS and AMSR-E) with respect to Land Data Assimilation System estimates, *Remote Sensing of Environment*, *149*, 181-195.

Albergel, C., P. de Rosnay, C. Gruhier, J. Munoz-Sabater, S. Hasenauer, L. Isaksen, Y. Kerr, and W. Wagner (2012), Evaluation of remotely sensed and modelled soil moisture products using global ground-based in situ observations, *Remote Sensing of Environment*, *118*, 215-256.

Albergel, C., W. A. Dorigo, G. Balsamo, J. Munoz-Sabater, P. de Rosnay, L. Isaksen, L. Brocca, R. de Jeu, and W. Wagner (2013), Monitoring multi-decadal satellite earth observation of soil moisture products through land surface reanalyses, *Remote Sensing of Environment*, *138*, 77-89, doi:10.1016/j.rse.2013.07.009.

Alkama, R., L. Marchand, A. RIbes, and B. Decharme (2013), Detection of global runoff changes: results from observations and CMIP5 experiments, *Hydrology and Earth System Science*, *10*, 2117-2140, doi:10.5194/hessd-10-2117-2013.

Becker, A., P. Finger, A. Meyer-Christoffer, B. Rudolf, K. Schamm, U. Schneider, and M. Ziese (2013), A description of the global land-surface precipitation data products of the Global Precipitation Climatoloty Centre with sample applications including centennial (trend) analysis from 1901-present, *Earth System Science Data*, *5*, 71-99, doi:10.5194/essd-5-71-2013.

Beven, K., and P. Germann (1982), Macropores and water flow in soils, *Water Resources Research*, *18*(5), 1311-1325.

Brocca, L., et al. (2011), Soil moisture estimation through ASCAT and AMSR-E sensors: an intercomparison and validation study across Europe, *Remote Sensing of Environment*, *115*, 3390-3408.

Collins, W. D., et al. (2006), The Community Climate System Model Version 3 (CCSM3), *Journal of Climate*, *19*, 2122-2143.

Collins, W. D., et al. (2014), The integrated Earth System Model (iESM): Formulation and functionality, *GeoSi. Model Dev. Discuss*, *in review*.

Dai, A., T. Qian, and K. E. Trenberth (2009), Changes in continental freshwater discharge from 1948 to 2004, *Journal of Climate*, *22*, 2773-2791.

Decker, M., and X. Zeng (2009), Impact of modified Richards equation on global soil moisture simulation in the Commnity Land Model (CLM3.5), *Jounral of Advances in Modeling Earth Systems*, *1*, 22, doi:10.3894/JAMES.2009.1.5.

Di Vittorio, A. V., et al. (2014), From land use to land cover: restoring the afforestation signal in a coupled integrated assessment–earth system model and the implications for CMIP5 RCP simulations, *Biogeosciences*, *11*, 6435-6450, doi:10.5194/bg-11-6435-2014.

Dorigo, W. A., et al. (2014), Evaluation of the ESA CCI soil moisture product using ground-based observations, *Remote Sensing of Environment*, doi:http://dx.doi.org/10.1016/j.rse.2014.07.023.

Du, E., T. E. Link, J. A. Gravelle, and J. A. Hubbart (2013), Validation and sensitivity test of the distributed hydrology soil-vegetation model (DHSVM) in a forested mountain watershed, *Hydrological Processes*, doi:10.1002/hyp.10110.

Fekete, B. M., and C. J. Vorosmarty (2002), High-resolution fields of global runoff combining observed river discharge and simulated water balances, *Global Biogeochemical Cycles*, *16*(3), doi:10.1029/1999GB001254.

Field, C. B., et al. (2014), IPCC, 2014: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*Rep.*, 1132 pp pp, Cambridge, United Kingdom and New York, NY, USA.

Gedney, N., P. M. Cox, R. A. Betts, O. Boucher, O. Huntingford, and P. A. Stott (2006), Detection of a direct carbon dioxide effect in continental river runoff records, *Nature*, *439*, 835-838.

Gerten, D., S. Rost, W. von Bloh, and W. Lucht (2008), Causes of change in 20th century global river discharge, *Geophysical Research Letters*, *35*, doi:1029/2008GL035258.

Gruhier, C., et al. (2010), Soil moisture active and passive microwave products: intercomparison and evaluation over a Sahelian site, *Hydrology and Earth System Science*, *14*, 141-156.

Hou, Z., M. Huang, L. R. Leung, G. Lin, and D. M. Ricciuto (2012), Sensitivity of surface flux simulations to hydrologic parameters based on an uncertainty quantification framework applied to the Community Land Model, *Journal of Geophysical Research*, *117*, D15108, doi:10.1029/2012JD017521, 2012.

Huang, M., Z. Hou, L. R. Leung, Y. Ke, Y. Liu, Z. Fang, and Y. Sun (2013), Uncertainty of runoff simulaitons and parameter identifiability in the Community Land Model: evidence from MOPEX basins, *Jounral of Hydrometeorology*, *14*, 1754, doi:10.1175/JHM-D-12-0138.1.

Jackson, C. R., M. Bitew, and E. Du (2014), When interflow also percolates: downslope travel distances and hillslope process zones, *Hydrological Processes*, *28*, 3195-3200, doi:10.1002/hyp.10158.

Kane, D. L. (2005), High-latitude hydrology, what do we know?, *Hydrological Processes*, *19*, 2453-2454, doi:10.1002/hyp.5929.

Labat, D., Y. G. Aeris, and J. L. Guyot (2004), Evidence for global runoff increase related to climate warming, *Advances in Water Resources*, *27*, 631–642.

Lawrence, D. M., et al. (2011), Parameterization improvements and functional and structural advances in Version 4 of the Community Land Model, *Journal of Advances in Modeling Earth System*, *3*, 27, doi:10.1029/2011MS000045.

Liu, Y. Y., W. A. Dorigo, R. M. Parinussa, R. A. M. de Jeu, W. Wagner, M. F. McCabe, J. P. Evans, and A. I. J. M. van Dijk (2012), Trend-preserving blending of passive and active microwave soil moisture retrievals, *Remote Sensing of Environment*, *123*, 280-297, doi:10.1016/j.rse.2012.03.014.

Loew, A., T. Stacke, W. A. Dorigo, R. A. M. de Jeu, and S. Hagemann (2013), Potential and limitations of multidecadal satellite soil moisture observations for selected climate model evaluation studies, *Hydrology and Earth System Science*, *17*, 3523-3542, doi:10.5194/hess-17-3523-2013.

Luo, Y. Q., et al. (2012), A framework for bencharking land models, *Biogeosciences*, *9*, 3857-3874, doi:10.5194/bg-9-3857-2012.

McCabe, G. J., and D. M. Wolock (2011), Century-scale variability in global annual runoff examined using a water balance model, *International Journal of Climatology*, *31*, 1739-1748, doi:10.1002/joc.2198.

McDaniel, P. A., M. P. Regan, E. Brooks, J. Boll, S. Barndt, A. Falen, S. K. Young, and J. E. Hammel (2008), Linking fragipans, perched water tables, and catchment-scale hydrological processes, *Catena*, *73*, 166-173, doi:10.1016/j.catena.2007.05.011.

Mehran, A., A. AghaKouchak, and T. J. Philips (2014), Evaluation of CMIP5 continental precipitation simulations relative to satellite-based gauge-adusted observations, *Jounral of Geophysical Research*, 35, doi:doi: 10.1002/2013JD021152.

Needelman, B. A., W. J. Gburek, G. W. Petersen, A. N. Sharpley, and P. J. Kleinman (2004), Surface runoff along two agricultural hillslopes with contrasting soils, *Soil Science Soceity of America*, *68*, 914-923.

Niu, G. Y., R. E. Dickinson, and L. E. Gulden (2005), A simple TOPMODEL-based runoff parameterization (SIMTOP) for use in global climate models, *Journal of Geophysical Research*, *110*(D21106), doi:10.1029/2005JD006111.

Niu, G. Y., Z. L. Yang, R. E. Dickinson, L. E. Gulden, and H. Su (2007), Developement of a simple groundwater model for use in climate models and evaluation with Gravity Recovery and Climate Experiment data, *Journal of Geophysical Research*, *112*, doi:10.1029/2006JD007522.

Oleson, K. W., et al. (2010), Technical description of version 4.0 of the Community Land Model (CLM).*Rep.*, 257 pp, NCAR Tech. Note NCAR/TN-4781STR.

Oleson, K. W., et al. (2008), Improvements to the Cummunity Land Model and their impact on the hydrological cycle, *Jounral of Geophysical Research*, *113*, doi:10.1029/2007JG000563.

Owe, M., R. de Jeu, and T. Holmes (2008), Multisensor historical climatology of satellite-derived global land surface moisture, *Jounral of Geophysical Research*, *113*, doi:10.1029/2007JF000769, 2008.

Piao, S., P. Friedlingstein, P. Ciais, N. de Noblet-Ducoudre, D. Labat, and S. Zaehle (2007), Changes in climate and land use have a larger direct impact than rising CO_2 on global river runoff trends, *Proceedings of the National Academy of Sciences*, *104*, 15242-15247.

Qian, T., A. Dai, K. E. Trenberth, and K. W. Oleson (2006), Simulation of global land surface conditions from 1948 to 2004. Part I: forcing data and evaluations, *Journal of Hydrometeorology*, *7*, 23.

Schneider, U., A. Becker, P. Finger, A. Meyer-Christoffer, B. Rudolf, and M. Ziese (2011), GPCC full data reanalysis version 6.0 at 1.0°: monthly land-surface precipitation from rain-gauges built on GTS-based and historic data, edited by G. P. C. Centre, Boulder, Colorado USA, doi:10.5676/DWD_GPCC/FD_M_V6_100.

Seneviratne, S. I., et al. (2013), Imapct of soil-climate feedbacks on CMIP5 projections: first results from the GLACE-CMIP5 experiment, *Geophysical Research Letters*, *40*, 5212-5217, doi:10.1002/grl.50956, 2013.

Shi, X., J. Mao, P. E. Thornton, F. M. Hoffman, and W. M. Post (2011), The impact of climate, CO_2, nitrogen deposistion and land use change on simulated contemporary blobal river flow, *Geophysical Research Letters*, *38*, doi:10.1029/2011GL046773.

Takahashi, T., and S. Shoji (2002), Distribution and classification of volcanic ash soils, *Global Environmental Research*, *6*(2), 83-97.

Tang, J., and W. J. Riley (In review), Impacts of incorporating root hydraulic redistribution on global evapotranspiration, edited.

Taylor, K. E., R. J. Stouffer, and G. A. Meehl (2012), An overview of CMIP5 and the experiment desigh, *American Meteorological Society*, 485-498, doi:10.1175/BAMS-D-11-00094.1.

van Dijk, A. I. J. M., H. E. Beck, R. S. Crosbie, R. A. M. de Jeu, Y. Y. Liu, G. M. Podger, B. Timbal, and N. R. Viney (2013), The Millennium Drought in southeast Australia (2001–2009): Natural and human causes and implications for water resources, ecosystems, economy, and society, *Water Resources Research*, *49*, 1-18, doi:01/2013; DOI: 10.1002/wrcr.20123.

Wagner, W., G. Lemoine, and H. Rott (1999), A method for estimating soil moisture from ERS scatterometer and soil data, *Remote Sensing of Environment*, *70*, 191-207.

Wandel, J., G. Young, and B. Smit (2009), The 2001-2001 drought: vulnerability and adaptation in Alberta's special areas, *Prairie Forum*, *34*(1), 211-234.