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Regional modeling of vegetation and long term runoff for Mesoamerica

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Abstract

Regional runoff, evapotranspiration, leaf area index (LAI) and potential vegetation were modeled for Mesoamerica using the SVAT model MAPSS. We calibrated and validated the model after building a comprehensive database of regional runoff, climate, soils and LAI. The performance of several gridded precipitation forcings (CRU, FCLIM, WorldClim, TRMM, WindPPT and TCMF) was evaluated and FCLIM produced the most realistic runoff. Annual runoff was successfully predicted (R^2=0.84) for a set of 138 catchments with a regression slope of 0.88 and an intercept close to zero. This low runoff bias might originate from MAPSS assumption of potential vegetation cover and to underestimation of the precipitation over cloud forests. The residues were found to be larger in small catchments but to remain homogeneous across elevation, precipitation and land use gradients. Based on the assumption of uniform distribution of parameters around literature values, and using a Monte Carlo-type approach, we estimated an average model uncertainty of 42% of the annual runoff. The MAPSS model was found to be most sensitive to the parameterization of stomatal conductance. Monthly runoff seasonality was fairly mimicked (Kendal tau correlation coefficient higher than 0.5) in 78% of the catchments. Predicted LAI was consistent with EOS-TERRA-MODIS collection 5 and ATSR-VEGETATION-GLOBCARBON remotely sensed global products. The simulated evapotranspiration:runoff ratio increased exponentially for low precipitation areas, stressing the importance of accurately modeling evapotranspiration below 1500 mm of annual rainfall with the help of SVAT models such as MAPSS. We propose the first high resolution (1 km^2 pixel) maps combining runoff, evapotranspiration, leaf area index and potential vegetation types for Mesoamerica.

1 Introduction

Mesoamerica has a population of around 60 million people living in its 1 million square kilometers. The region comprises 8 countries (Southern Mexico, Guatemala, Belize, El Salvador, Honduras, Nicaragua, Costa Rica and Panama) with a high diversity of human development and environmental conditions. It is also an integrated region due to shared economic development plans (Puebla-Panama Plan[1]), conservation goals (the Mesoamerican Biological Corridor[2]) and international catchments, some of them with potential usage conflicts (Wolf et al., 2003). Water issues drive many aspects of human well-being and national development. For instance, most Central American countries rely heavily on hydroelectric energy and on irrigated agriculture (Siebert and Döll, 2001; Kaimowitz, 2005).

Given the importance of understanding hydrological regimes and river runoff for better water management and hydro-power planning, there is a demand for quantitative knowledge on regional hydrological resources and water budgets (Griesinger and Gladwell, 1993; Nijssen et al., 2001). Many studies have analyzed runoff (Zadroga, 1981; Abbot, 1917; Niedzialek and Ogden, 2005; Thattai et al., 2003) and groundwater (Calderon Palma and Bentley, 2007; Genereux and Jordan, 2006) at the local scale in Mesoamerica. Cloud forests have received special attention (Cavelier et al., 1996, 1997; Clark et al., 1998; Holder, 2003, 2004). Nevertheless, there is a need to develop predictions of hydrological regimes with a regional scope and sufficiently fine resolution (typically 1 km^2) to be relevant for local and national decision makers. Global runoff simulations (Fekete et al., 2002) poorly represent the Mesoamerican region. Continental scale simulations conducted for other regions (Gordon et al., 2004, Vörösmarty et al., 1989) have an unsuitable spatial resolution (30 min) for the complex topography and climate of Mesoamerica.

Stochastic hydrological modeling has been the preferred approach for its high precision simulation of water budgets within catchments. However, this empirical approach requires long term series of climate and runoff data for calibration and it is not generic. Alternatively, choosing a process-based modeling approach allows for scaling-up from catchments to regions even in areas where runoff data are missing. Process models

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[1] http://www.planpuebla-panama.org/

[2] http://www.sica.int/

can also be forced by climate or land use change scenarios to assess future impacts of climate change on water availability.

Neilson (1995) developed a soil-vegetation-atmosphere transfer (SVAT) model with outputs such as water balance partition, runoff, evapotranspiration, leaf area index, and potential vegetation cover. This model, called MAPSS (Mapped Atmosphere Plant Soil System), has been validated at the continental scale for the United States (Neilson, 1995; Bishop et al., 1998). The main assumptions of MAPSS are: (i) potential vegetation cover can be simulated based solely on climate and soils data and does not need to be forced into the model, which is of considerable advantage in areas where detailed land use maps are missing, (ii) the resulting water balance partitioning is a fairly good proxy for the actual runoff for most basins, (iii) water storage can be neglected on an annual basis and (iv) evapotranspiration, which is estimated through explicit ecophysiological modeling, is a key component of the water balance partitioning, particularly for dry areas.

To our knowledge, a high-resolution (1 km^2) model to map runoff, evapotranspiration and vegetation in Mesoamerica does not exist. Thus, the goals of this study were:

i) To calibrate and validate the MAPSS model runoff outputs using a set of representative Mesoamerican catchments,

ii) To evaluate the uncertainty of simulated runoff, the model sensitivity to its parameters, and the model-data misfit (residuals) distribution

iii) To validate the modeled leaf area index and potential vegetation distribution using remotely sensed data (MODIS and GLOBCARBON)

iv) To map regional runoff, evapotranspiration, leaf area index and potential vegetation for Mesoamerica at a working resolution of 1 km^2.

2 Materials and methods

2.1 Region description

The study area spans continental land within 6.5 and 22 degrees latitude and −76.5 and −99 degrees longitude. This one million square kilometer area covers Southern Mexico in the north and the 7 Central American countries down to Panama in the south. This region has a highly complex biophysical environment; Hastenrath (1967) describes it as structurally rich in coast lines and plains, with high mountains and plateaus exerting a large influence on climate. The main topographic feature is a mountain range that reaches over 4000 m. a.s.l. and runs close to the Pacific coast with few interruptions (Fig. 1a).

Mean annual surface temperature has small fluctuations over the year. By contrast, precipitation is highly variable. Precipitation seasonality is determined by the Inter-Tropical Convergence Zone (ITCZ), which brings convective rains. Winds coming from the Caribbean interact with mountains and coastlines further increasing seasonality (Nieuwolt, 1977). The result is a high variability of precipitation over short distances, with humid windward mountains and coastal areas, and dry leeward valleys (Fig. 1b). Therefore, convective rains dominate the Atlantic watersheds and orographic rains have a higher contribution in the Pacific watersheds (Shultz, 2002; Guswa et al., 2007).

The rainy season lasts from May to October (Hastenrath, 1967). The distribution of precipitation is bimodal, with two maxima during June and September–October, and a distinctive relative minimum in between called the mid-summer drought (Magaña et al., 1999). Runoff follows precipitation inputs because most rivers in the region are rainfed. The longest and largest rivers are on the Atlantic side (Griesinger and Gladwell, 1993).

Vegetation of the Pacific watersheds and northern part of the Yucatán Peninsula is tropical with summer rain (Schultz, 2002). The vegetation of the Atlantic watersheds is tropical with year-round rain. In pristine Pacific areas, there are savanna grasslands of variable tree density depending on available moisture. In the Atlantic areas, evergreen forests dominate. Anthropogenic influence has reduced natural vegetation to 58% of the total area. Rainfall, vegetation and high radiation, much of it being diffuse due to high cloud cover, leads to high annual evapotranspiration rates over 1000 mm (Shultz, 2002).

2.2 MAPSS model description

MAPSS simulates potential vegetation cover and leaf area given light and water constraints. A monthly time step water balance is calculated based on the vegetation leaf area and stomatal conductance for canopy transpiration and soil hydrology (Neilson, 1995). Interception is a function of the number of rain events and leaf area index (LAI). Water reaching the soil layer is divided into fast runoff and infiltration. The latter is regulated by saturated and unsaturated percolation processes according to Darcy's Law (Hillel, 1982). The soil is divided in three layers with grasses having access to water from the top layer, woody vegetation from the top and intermediate layers and the deepest layer is used for base-flow. Before percolation, transpiration by grasses and woody plants occurs. The ratio of actual to potential evapotranspiration (PET) increases exponentially with LAI. PET is calculated using climate and an aerodynamic turbulent transfer model (Marks, 1990). Stomatal conductance decreases with decreasing soil water potential and with increasing PET.

The calculation of LAI involves competition for both water and light between woody and herbaceous vegetation. Water is provided to grasses from the first soil layer whereas woody vegetation has access to the two top soil layers. The third and deepest soil layer is used for base flow. The final equilibrium LAI is calculated iteratively for grasses and woody vegetation, so that LAI consumes most of the available water in a single month of the growing period and never drops below the wilting point.

MAPSS assumes the annual soil and aquifers water storage term (Δs) in Eq. (1) is close to zero, which is mostly true on an annual basis or in catchments characterized by a high superficial runoff to infiltration ratio:

$$R = P - E - I - \Delta s \tag{1}$$

Where, R is runoff, P is precipitation, E is evapotranspiration, I is interception and Δs is the water storage in soils and aquifers.

2.3 Model set up and input data

We implemented MAPSS at the resolution of climate forcing data (1 km^2) unless otherwise stated.

2.3.1 Precipitation

Meteorological forcing data have a strong influence on the model's performance and uncertainty (Linde et al., 2008). This is particularly true in the topographically complex Mesoamerican region. Uncertainties in the climate input dataset could thus have a larger influence on model output in the context of our fine scale application, as compared to uncertainties of model parameters which are known to impact modeling hydrology at a macro-scale (Arnell, 1999). To assess climate uncertainties, we tested 6 different precipitation data sources, 4 with monthly averages of at least 30 years, and 2 covering a 10 year average (Table 1). These precipitation datasets were:

- CRU CL 2.0: the coarsest dataset used, based on interpolation of weather stations data using latitude, longitude and elevation as co-predictors (New et al., 2002)
- WorldClim: developed from weather stations data, interpolated at high resolution, and accounting for elevation (Hijmans et al., 2005)
- FCLIM: developed specifically for Central America by interpolation of weather stations, distance to southern coastline, elevation, and precipitation data from remote

sensing sources by the Climate Hazard Group at the University of California in Santa Barbara[3]

- Wind PPT (modeling wind driven precipitation): modeled with the TRMM dataset using wind-speed and direction as well as terrain conditions (slope, aspect and topographic exposure) (Mulligan, 2006)
- TRMM: developed from two remote sensing sources (a passive microwave radiometer and a scanning radar) to estimate rainfall (Mulligan, 2006)
- TCMF: developed by calculating a 10% increase in precipitation in the FCLIM dataset, over areas covered by cloud forests (from a map developed by Mulligan and Burke, 2005). As clouds go through forests in these areas, water is intercepted by the vegetation and adds to the total amount of water available for runoff production. This intercepted water is not regularly captured by rain gauges. The increase in value was arbitrarily selected from a range of interception values ranging 6 to 35% of total rainfall (Bruijnzell, 2005).

2.3.2 Sensitivity tests

We performed three sensitivity tests. The first test uses FCLIM precipitation with MAPSS original parameters. The second test is based upon FCLIM with a calibrated MAPSS version (see section on calibration method). The third is based upon FCLIM with a compilation of national soils maps (NS) to evaluate the effect of high resolution soils data (no data was available for Nicaragua and Belize).The NS soil parameters (texture and soil depth) compilation was made by digitizing country-wide soils maps and analyzing their technical documentation to estimate soil texture and depths to bedrock (see Table 1 for references). Gaps in information were filled with data from a global soils map (FAO, 2003).

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[3] data available at http://www.geog.ucsb.edu/~diego/projects/rainfall/climatologia.html

2.3.3 Runoff observation at catchment scale

A new runoff dataset was created from data with different levels of temporal resolution (daily, monthly, and annual) and different series length collected from several institutions across the Mesoamerican region (see Table 1). The catchment boundaries of each runoff station were delineated using the SRTM (Shuttle Radar Topography Mission) 90 m digital elevation model (Jarvis et al., 2008). Stream flow data in cubic meters per second was converted to depth values in mm by normalizing the flow with the catchment area above the measurement point.

We selected 135 catchments (out of a total of 466 available) across the region (Fig. 1a and b) using the following criteria:

i) Retain only catchments with an annual-runoff-precipitation ratio smaller than unity, thus excluding catchments where either precipitation interpolation or runoff data are miscalculated,

ii) Exclude water bodies bigger than 1% of the catchment area as this could represent regulated catchments,

iii) Retain catchments with available runoff data from data series >15 years (Gerten et al., 2004) to minimize the effects of inter-annual variability (Hartshorn, 2002; Aguilar et al., 2005).

From now on, this dataset will be called the Long Time Series Average dataset (LTSA). Another runoff dataset was constructed without criteria iii), leaving 243 catchments. This larger dataset is called the Time Series Average dataset (TSA). TSA results are presented separately since they are based on a larger dataset for calibration and validation, but could be biased by some catchments characterized by short dry or wet periods.

The area of each LTSA catchment ranged between less than 100 km^2 to 15 378 km^2 (Fig. 2a). As the difference between potential and actual vegetation may affect model performance, we corroborated that these catchments represent the full range of natural vegetation cover (Fig. 2b). Selected catchments are representative of the study area in terms of their precipitation and mean elevation (Fig. 1a and b).

On a monthly basis, the storage term Δs of Eq. (1) can represent a substantial fraction of the total water budget in some catchments. These catchments are associated with a high coefficient of variation in their monthly R:P ratio ($CV-R$:P). Thus, we performed a monthly analysis of the model-data comparison only in catchments with a $CV-R$:P<0.5. This threshold was selected to minimize the effect of high Δs variability while keeping at least half of the catchments for analysis. Using this criterion, monthly model-data comparison is possible for 63 catchments in the LTSA dataset (94 in the TSA dataset).

2.3.4 Model calibration and validation

Calibration and validation of MAPSS was performed with annual runoff data using a split-sample test (Klemes, 1986; Xu 1999; Xu and Singh, 2004), i.e. by randomly selecting half of the catchments for calibration and the remaining half for validation. This test is a common approach for splitting data into calibration and validation sets, either spatially or temporally (Motovilov et al., 1999; Wooldridge and Kalma, 2001; Donker 2001; Guo et al., 2002; Xu and Singh, 2004; Linde et al., 2008). This calibration and validation method was selected due to the diversity of biophysical conditions present in our runoff dataset.

We calibrated the model by manually adjusting parameters controlling transpiration and soil layer thickness until modeled runoff matched the observations. First, results from the un-calibrated MAPSS parameterization were inspected for runoff under or over prediction. Then, adjustments for reducing modeled runoff in watersheds where the model overestimated runoff were made, to obtain a regression curve with a slope close to 1 and a negative intercept. The negative intercept results from MAPSS modeling the potential vegetation distribution, thus having a higher evapotranspiration rate and lower runoff than observations. The actual vegetation includes pasture and croplands which have lower transpiration rates than the potential forest vegetation (Neilson, 1995; Haddeland et al., 2007; Gordon et al., 2005). Parameters selected for manual adjustment (Table 2) included:

i) Total soil layer thickness: we increased this parameter relative to its MAPSS default value in our manual calibration procedure, to account for high rooting depths (Shenk and Jackson 2002; Ichii et al., 2007)

ii) Stomatal conductance: this parameter is also increased to reduce runoff and match the data (Ray Drapek and Ron Neilson, personal communication)

iii) The wilting points of trees and grassy vegetation: were decreased to match runoff data.

2.3.5 Model performance and efficiency

Several indices were used to compare observed against modeled annual and monthly runoff values for each catchment. Model performance was evaluated with the "linear regression" method (Bellocchi et al., 2009) where the R^2 statistic is complemented with slope and intercepts analysis to asses over or under prediction. The water balance error (WB) estimates the bias as a percentage in annual modeled runoff (Guo et al., 2002; Boone et al., 2004; Quintana Seguí et al., 2009) (Table 3). WB rating was based on Moriasi et al. (2007) and Quintana Seguí et al. (2009). The LTSA dataset contains 128 catchments with monthly data, for which model performances were estimated using the Nash-Sutcliffe efficiency coefficient (NS, Eq. 2) (Nash and Sutcliffe, 1970) and Kendall's ranked correlation coefficient (τ, Eq. 3) (Guo et al., 2002; Boone et al., 2004; Gordon et al., 2004; Quintana Seguí et al., 2009). NS and τ coefficients were rated according to Moriassi et al. (2007). The NS efficiency assesses the match between modeled and observed monthly values. A value of 1 indicates a perfect match while a value of 0 means the model is as poor of a predictor as the mean of the observed data. Negative values indicate the mean of observed values performs better than the model (Table 3). Kendall's coefficient is calculated with ranked monthly values, to assess how the seasonal variation is mimicked by the model. The coefficient ranges from 1, indicating a perfect agreement between the two rankings, to −1, indicating a perfect disagreement (one ranking is the opposite of the other).

$$\mathrm{NS} = 1 - \left(\frac{\sum_i (Q_{\mathrm{o}i} - Q_{\mathrm{m}i})}{\sum_i (Q_{\mathrm{o}i} - \overline{Q_{\mathrm{o}}})} \right)^2 \qquad (2)$$

Where $Q_{\mathrm{o}i}$ and $Q_{\mathrm{m}i}$ are the observed and modeled runoff values at time step i, respectively, and $\overline{Q_{\mathrm{o}}}$ is the average observed value.

$$\tau = \frac{n_{\mathrm{c}} - n_{\mathrm{d}}}{n(n-1)/2} \qquad (3)$$

Where n_{c} and n_{d} are the number of concordant and discordant pairs and the denominator is the total number of possible pairings.

2.3.6 Performance of vegetation and LAI modeling

A crucial part of how MAPSS determines runoff is the relationship between actual transpiration and LAI, since it not only determines water available for runoff, but the potential vegetation type that can be supported on site. For this purpose two observed LAI datasets were chosen to assess model output performance (Table 1): EOS-Terra-MODIS (Yang et al., 2006a) and the GLOBCARBON-ESA European Remote Sensing (ERS-2)-ENVISAT-SPOT sensors (Plummer et al., 2006) (MODIS-LAI and GLOBCARBON-LAI, respectively).

Both LAI datasets were used to test whether the model was simulating runoff under realistic conditions of vegetation leaf area, as this can be a relevant factor affecting spatial and temporal variability of runoff at large scales (Peel et al., 2004). Both LAI products rely on actual, not potential, land cover maps: MODIS-LAI is based on an 8-biome map derived from MODIS data (Friedl et al., 2002) and GLOBCARBON-LAI on the Global Land Cover 2000 (GLC2000) map from SPOT-VEGETATION satellite (EC-JRC, 2003) (with approximate resolutions of 8 and 1 km, respectively). Comparisons were made only in pixels where each land cover map matched the ecosystem type on the Central America Ecosystem map (WB and CCAD, 2001). We used this map as a reference because it is based on extensive field work and high resolution imagery (28.5 m pixel) from Landsat TM. In contrast, within the studied region there is only one validation point for the GLC2000 land cover underlying the GLOBCARBON-LAI product (Mayaux et al., 2006), and none for the land cover map underlying the MODIS-LAI (MODIS Land Team, 2009). Additionally, both land cover maps have a much lower resolution (1 km^2) than Landsat TM. A comparison of the land cover sources used in the two LAI products shows best agreement on the Atlantic side of Mesoamerica and larger differences on the Pacific side, Southern Mexico, and Southern Panama (Giri et al., 2005).

2.3.7 Uncertainty analysis

Analysis of uncertainty from model parameters was performed based on Zaehle et al. (2005) and using SimLab 2.2.1 software[4]. The uncertainty analysis is based on the probability distribution functions (PDFs) of model parameters and their effect on model output. The PDFs for 61 parameters of model components controlling rainfall interception, evapotranspiration, and soil site conditions were built based on a literature review of field studies. To be conservative in the uncertainty assessment, a uniform distribution was assumed for all parameters within the range of values found in the literature. A 30% variance was assumed for conceptual parameters that are used to simplify complex processes and are not measurable in experiments (Zaehle et al., 2005; see Table 1 in Supplemental material: http://www.hydrol-earth-syst-sci-discuss.net/7/801/2010/hessd-7-801-2010-supplement.pdf).

The space of parameter PDFs was explored using a Monte Carlo-type approach,

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[4] Available at http://simlab.jrc.ec.europa.eu/

the Latin-Hypercube sampling (LHS) method, to build a stratified sample of random sets of parameter values. The LHS method has the advantage of building a stratified representation of all parameters with a reduced variance due to additive effects of parameters on model output. The parameter sample consisted of 610 parameter combinations to be tested in model runs. Some runs had parameter combinations outside model boundaries leading to crash-runs, leaving a total of 456 runs, well within the recommended amount between 3/2 (92 runs) to 10 times (610 runs) the number of parameters (EC-JRC, 2009).

3 Results and discussion

3.1 Performance of calibrated model assessed by statistical tests

Calibration and validation of total annual runoff for LTSA catchments showed good overall agreement across the whole range of runoff values (1–4774 mm) and an underestimation of modeled runoff of around 12% (Fig. 3). In turn, calibration and validation results for the TSA dataset, were also satisfactory but modeled annual runoff was underestimated by approximately 20% (data not shown, N=251, Slope=0.81, Intercept=36 and R^2=0.78). A similar trend was obtained when MAPSS simulated runoff for the United States because the model simulates potential vegetation which has higher evapotranspiration when compared to actual vegetation cover (Neilson, 1995). Vörösmarty et al. (1989) has a similar trend when coupling water balance and water transport models for a large scale application in South America. Results with un-calibrated MAPSS gave a similar slope and correlation but the intercept increased to 145 mm.

After splitting the dataset by rainfall category we found that model performance was lower in dry areas than in wetter areas (data not shown). Similar lower performance in dry catchments was found by Gordon et al. (2004) when evaluating six terrestrial ecosystem models in the United States, although the runoff range they analyzed is much lower than for Central America. Lower model performance is probably due to the effect of higher uncertainties in precipitation; including rainfall frequency and local heterogeneity (rainstorms) of runoff in drier regions due to non-linearity of the runoff generation process (Fekete et al., 2004). It is thus possible that in dry areas, the observed runoff is dominated by few daily events of intense precipitation that cannot be captured at our working monthly time steps.

The monthly model performance, according to classes for NS and τ statistical criteria in Table 3, is fair or better for 46% and 78% of catchments, respectively (Table 4). Annual runoff is modeled fairly or better for 48% of the catchments (Table 4). In general, our model performance is similar to that of other studies (Artinyan et al., 2007; Linde et al., 2008) but slightly less than that found over France with the SIM model (Quintana Segui et al., 2009; 61% fair or better). Given the very large number of small catchments, complex orography, and climate uncertainties found in Mesoamerica, we considered our model performance satisfactory.

3.2 Performance of the model assessed by comparison with a "poor man" model

We compared the results of MAPSS with those of a "poor man" model where the runoff is modeled to be proportional to annual rainfall only, that is runoff=alpha×rainfall. We tested all potential values of alpha, and the performances were always poorer than those of MAPSS, irrespective of the statistical criteria used. This test shows that useful information is contained in the MAPSS parameterization that improves the simulation of runoff in Central America, even though the model is based upon potential vegetation and runs on a monthly time step.

3.3 Modeled versus observed LAI distribution

Figure 4a shows the modeled LAI by MAPSS, and the difference between modeled LAI and observed from MODIS and GLOBCARBON (Fig. 4b and c, respectively). Agricultural areas and other disturbed land cover types were excluded from the LAI comparison. Over naturally vegetated areas, the comparison was made over pixels where both the land cover map used to generate MODIS and GLOBCARBON LAI products, and the MAPSS vegetation, match the vegetation type on the Central American ecosystems map (used as the reference). Both criteria define the excluded areas category in Fig. 4b and c.

The general feature is an under prediction of LAI in the northern part of the Mesoamerica region and an over prediction in the South. Discrepancies appear when comparing MODIS and GLOBCARBON LAI (Fig. 4b and c). This could be due to misclassifications of land cover, particularly between classes with different architecture and foliage optics (Myneni et al., 2002; Yang et al., 2006a). Atmospheric and cloud conditions are also problematic over tropical areas, where MODIS-LAI values are calculated by the simpler NDVI (Normalized Difference Vegetation Index) based backup algorithm (Myneni et al., 2002). Yang et al. (2006b), for example, found that broadleaf forests (covering most of our study area) can be underestimated by as much as 3.4 LAI units. Accordingly, we found that areas with under prediction are dominated by the main algorithm and those with over prediction by the backup algorithm, except for small areas in Southern Panama.

3.4 Residuals distribution and uncertainty analysis

There was no systematic trend in the residuals as a function of annual precipitation, elevation or percentage of potential vegetation cover (Fig. 5a, b and c, respectively). However, larger residuals were found for small catchments (<1000 ha or 10 pixels), probably due to larger uncertainty in the delineation of each catchment.

The model systematically underestimates runoff by around 12% (Fig. 3). We could not detect a positive trend in the residuals with decreasing potential vegetation cover (Fig. 5c). Consequently, it appears that the 12% under prediction in annual runoff (Fig. 3) cannot be attributed here to the potential vegetation cover assumed by MAPSS (Neilson, 1995). We explored the possibility of missing rainfall due to cloud forest horizontal interception (Bruijnzell, 2005; Holder, 2004; Zadroga 1981) and results showed an improvement when this type of forests are accounted for (see section on sensibility to precipitation datasets).

Figure 6 shows annual runoff results for each catchment from the uncertainty analysis, along the annual precipitation range. For each catchment, we show the range of values modeled by 456 parameter combinations from the set of parameters samples built with the LHS method. The average range of modeled annual runoff values within one standard deviation is within 36% of the total modeled range and equals 42% of the observed annual runoff. No apparent trend in uncertainty is found along the precipitation range, suggesting a constant effect of parameters uncertainty along the dry to wet gradient.

3.5 Seasonal bias

Figure 7 shows the seasonality of precipitation and runoff for two selected catchments with different storage terms (Δs in Eq. 1). Storage term refers to accumulation of water in unsaturated and saturated zones (aquifers). In Fig. 7a, monthly modeled runoff mimics the observed time course which corresponds to a situation with small Δs. In Fig. 7b, the modeled time course crosses two times the observed curve, indicating a period of water accumulation in the basin between July and November and a period of discharge later on. Zadroga (1981) found a similar situation in Costa Rica by analyzing runoff and weather station data across 7 watersheds. Similar results were also found by Heyman and Kjerfve (1999) in Belize, probably due to the release of water from limestone aquifers. In Nicaragua, Calderon Palma and Bentley (2007) identified shallow local recharge-discharge systems and a deep system that recharges in higher mountains and discharges in the central and lower plains. Moreover, using isotopes in Costa Rica, Guswa et al. (2007) showed that orographic precipitation (wind driven precipitation and fog interception) contributed to the dry season base flow and the delayed contribution of the rainy season precipitation to dry season streamflow.

MAPSS has good performance on an annual time scale. Given that MAPSS does not simulate the ground water storage processes controlling the Δs seasonal variation, it remains valid on a monthly time scale only for the selected catchments were the storage term is not significant. MAPSS monthly performance analysis falls to 26% (fair) when considering all catchments, but increases to 54% after excluding those with a significant storage term (see model performance and efficiency section).

3.6 Sensitivity to different precipitation input datasets

The modeled standard deviations are lower than observations (A) and correlation coefficients similar for all precipitation forcing datasets (Fig. 8). The TRMM (G) and Wind PPT (H) have good correlations (0.84 and 0.85, respectively) but the lower regression slope among the datasets (0.66 and 0.64), probably due to extreme precipitation variations (Fekete et al., 2004), with differences of more than 1000 mm over large areas compared to other datasets (data not shown). Wind PPT (H) has a lower regression intercept (140 mm) compared to TRMM (G) (209 mm) indicating and improvement when accounting for winds in precipitation estimates. Accounting for cloud forests in precipitation estimates slightly improved regression results, from FCLIM (B) to TMCF (F), by increasing slope (from 0.88 to 0.93) and keeping similar correlations and intercepts. MAPSS original parameterization (D) has good performance (Slope=0.85 and correlation=0.92) but the intercept is positive (133 mm). FCLIM (B) has an improved correlation, smallest RMS, slope closest to 1 and standard deviation closest to that of observed values showing the calibration improvement when compared to MAPSS original parameterization (D).

Based on the uncertainty analysis runs, we also assessed the model sensitivity to its parameters. We estimated the Ranked Partial Correlation Coefficient (RPCC) for model parameters based on average annual runoff of the study area in each run of the uncertainty analysis (Zaehle et al., 2005). MAPSS is most sensitive to the parameter that sets the ceiling for maximum stomatal conductance for all vegetation types (RPCC=0.47).

3.7 Regional mapping

After the model calibration and validation steps, we simulated runoff across the entire region and analyzed model outputs. Modeled runoff and evapotranspiration maps shows a mean annual runoff and evapotranspiration of 552 and 1200 mm, respectively, with highest values distributed mostly in the southern part of the region and in mountain areas in the North Pacific side (Fig. 9a and b, respectively).

We explored the water balance partitioning along the annual precipitation gradient. Figure 10 shows the relationship between the evapotranspiration:runoff ratio (E/R) and precipitation classes, each E/R value being an average for 100 mm annual precipitation classes. Below the 1500 mm annual precipitation threshold, evapotranspiration becomes a key component of the water balance, justifying the need of a SVAT model such as MAPSS for reliable modeling of the annual water balance.

Potential vegetation types are also simulated by the model and correspond to forest types that appear along available humidity across the year from evergreen forests to dry tropical savanna (Fig. 11). This gradient is also characterized by a gradient of LAI values from trees, shrubs and grasses. A detailed description of each forest type is provided by Neilson (1995).

4 Conclusions

We calibrated and validated the SVAT hydrological model MAPSS (Neilson, 1995) for the Mesoamerican region at 1 km resolution, after building a new database of observed runoff of 466 catchments. We presented a regionally calibrated version of MAPSS and output maps of runoff, evapotranspiration, leaf area index (LAI) and potential vegetation.

Runoff prediction performed similarly to other large scale studies. A general underestimation of 12% has been attributed by Neilson (1995) in temperate conditions to the fact that MAPSS simulates potential vegetation. However, our residual analyses did not confirm that hypothesis. We suspect that large horizontal interception of precipitation could play an important role in tropical mountain areas.

MAPSS simulation of monthly runoff was consistent only in catchments were the storage term (Δs) is not significant, as this component is not simulated by the model. Availability of spatial information to estimate Δs is a crucial limitation to improve monthly performance of the model.

Accounting for wind and cloud forests in precipitation estimates improved results indicating the importance of precipitation horizontal interception for runoff generation in our study area.

Modeled LAI was consistent with remotely sensed observations (MODIS and GLOBCARBON) except in humid areas Mesoamerica where high levels of LAI have been measured directly in the field and cloud cover is frequent. In these areas remotely sensed LAI is known to have lower quality estimates.

It is important to use a SVAT model to explicitly model actual evapotranspiration, especially in drier areas, below 1500 mm of annual precipitation, where ETR represents a very large fraction of the water balance.

Future steps with our calibrated MAPSS version will focus on simulating the impacts of climate change on water balance and vegetation of the Mesoamerican region.

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Table 1. Data sources for model input, calibration and validation.

Name	Variable	Resolution/Time period	Source
		SOILS AND TOPOGRAPHY	
NS Soils	Percentage of clay, sand and depth to bedrock	1:200 000 (Costa Rica) 1:250 000 (Guatemala, Mexico) 1:500 000 (Honduras) Not reported for Panama	Pérez et al. (1979) Simmons et al. (1959) Simmons (1969) IDIAP (2006) INEGI (1984)
World Soils	Percentage of clay, sand and depth to bedrock	1:5 000 000	FAO (2003)
SRTM	Elevation	30 arc s	Jarvis et al. (2008)
		CLIMATE	
CRU CL2.0	Temperature precipitation, wind speed	10 min/1961–1990	New et al. (2002)
WorldClim	Temperature, precipitation[b]	30 arc s/1950–2000	Hijmans et al. (2005)
FCLIM	Precipitation[a,b]	5 km/1960–2000	University of Santa Monica[c]
Wind_PPT	Precipitation[a,b]	1 km/1997–2006	Mulligan (2006)
TRMM 2b31-Based Rainfall Climatology Version 1.0	Precipitation[a,b]	1 km/1997–2006	Mulligan (2006)
		LEAF AREA INDEX	
GLOBCARBON-LAI	Leaf area index	1 km/1998–2007 average	http://geofront.vgt.vito.be
MODIS-LAI	Leaf area index	1 km/Mar 2000–May 2009 average	Boston University[d]
		VEGETATION COVER	
Global biomes	Vegetation type	8 km/2006	Boston University[d]
Global land cover 2000	Vegetation type	1 km/2000	EC-JRC (2003)
Cloud forests	% of cloud forest	1 km	Mulligan and Burke (2005)

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Table 1. Continued.

			RUNOFF		
Country	No. of catchments	Time steps (smaller)	Series length	Average	Data provider
Panamá	84	Monthly	Yes	All years	Empresa de Transmisión Eléctrica S.A. (ETESA)
Costa Rica	128	Daily	Yes	Year	Instituto Costarricense de Electricidad (ICE)
Nicaragua	33	Monthly	Yes	Year	Ministerio del Ambiente y los Recursos Naturales (MARENA)
Honduras	48	Monthly	Yes	Year	Secretaría de Recursos Naturales y Ambiente
El Salvador	22	Monthly	Yes	All years	Ministerio del Ambiente y Recursos Naturales
Guatemala	6/31/73	Monthly/ Monthly/ Year	Yes/ No/ No	Year/ All Years/ All years	Instituto Nacional de Sismología, Vulcanología, Meteorología e Hidrología
Mexico (12 southern most states)	603	Daily	Yes	Year	Instituto Mexicano de Tecnología del Agua

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[a] Worldclim temperature was used here

[b] CRU wind speed was used here

[c] http://www.geog.ucsb.edu/~diego/projects/rainfall/climatologia.html

[d] http://cybele.bu.edu/modismisr/index.html

Table 2. Modified parameter values from the original MAPSS configuration for calibration.

Parameter	Original	Calibrated
Intermediate layer thickness (soil)	1000	3000
Deep layer thickness (soil)	1500	4600
Maximum conductance (tropical grass)	5.5	6.5
Wilting point (tropical grass and tree)	−1.5	−2.2
Transpiration constant (tropical grass, needleleaf)	4.25	6.25
Transpiration constant (tropical grass, broadleaf)	3.35	5.35

Table 3. Categories of model performance with the NS (monthly match), τ (monthly match of ranked values) and WB (bias in annual runoff) statistical measures.

Performance	NS or τ	WB
Very Good	>0.9	<5%
Good	0.8–0.9	5–10%
Fair	0.8–0.5	10–25%
Poor	<0.5	>25%

Table 4. Modeled runoff qualified by percentage of catchments in each performance category for the LTSA dataset and, in parenthesis, the TSA dataset.

Performance	NS	τ	WB
Very Good	2(2)	13(11)	13(10)
Good	19(14)	22(18)	6(5)
Fair	25(22)	43(51)	29(22)
Poor	54(62)	22(20)	52(63)

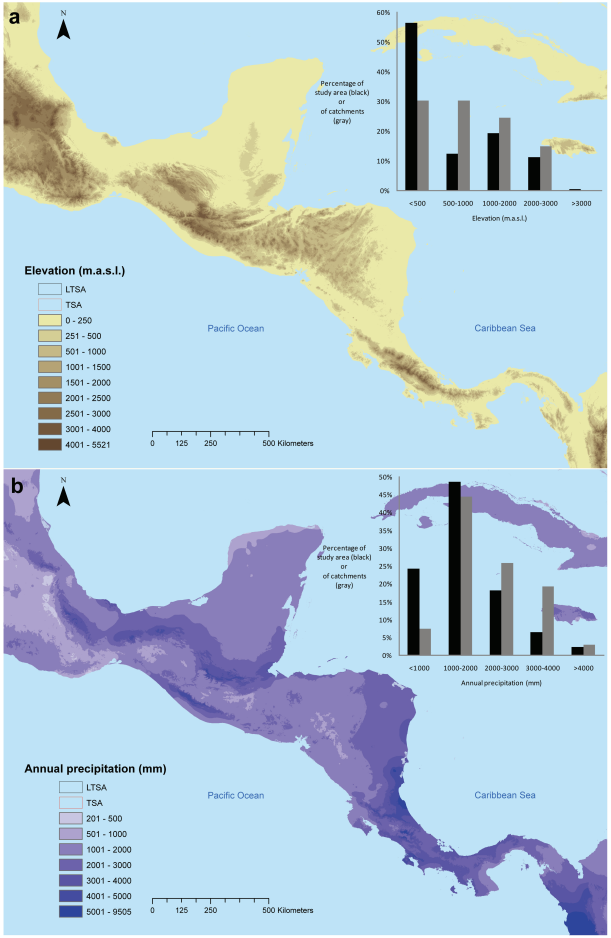

Fig. 1. Map of the digital elevation model **(a)** and annual precipitation **(b)** in the Mesoamerican region and in Long Time Series Average (LTSA) and Time Series Average (TSA) catchments.

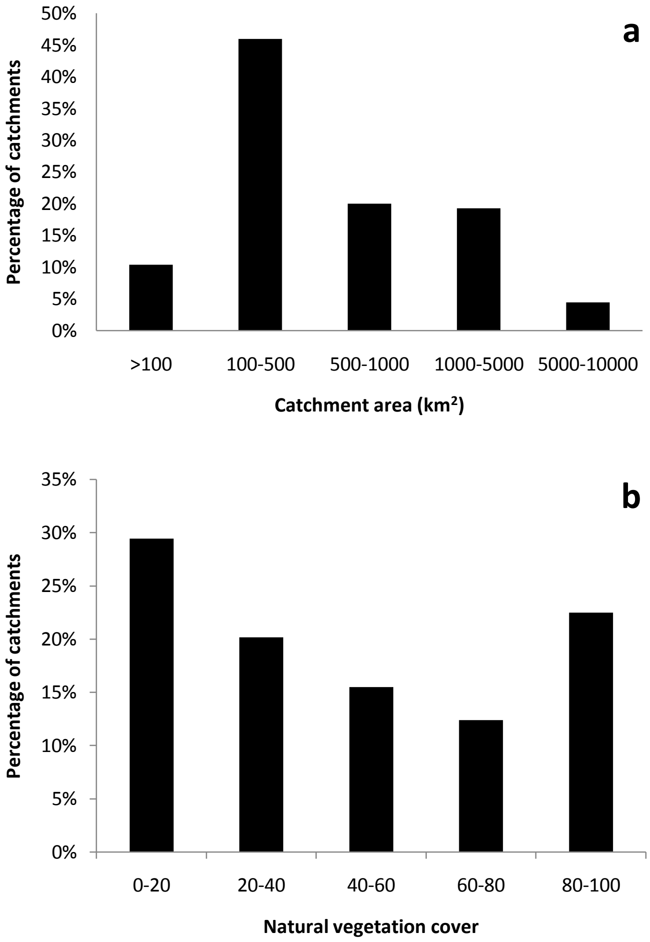

Fig. 2. Percentage distributions of long term series average (LTSA) catchments according to size of catchment **(a)** and percent of catchment under natural vegetation cover **(b)**.

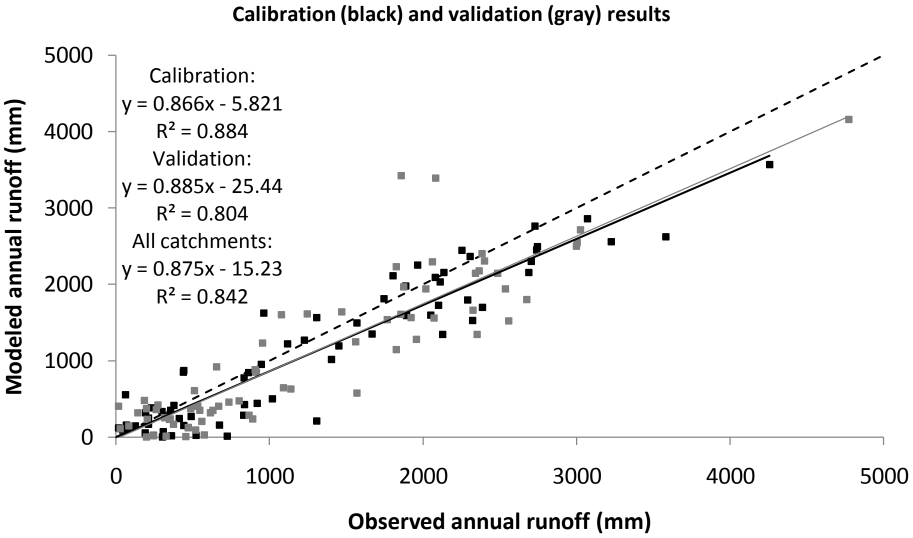

Fig. 3. Observed versus modeled annual runoff (mm) of catchments used for calibration (N=69, black dots), validation (N=69, gray dots), and all (N=138). Each dot represents observed average annual runoff for one catchment.

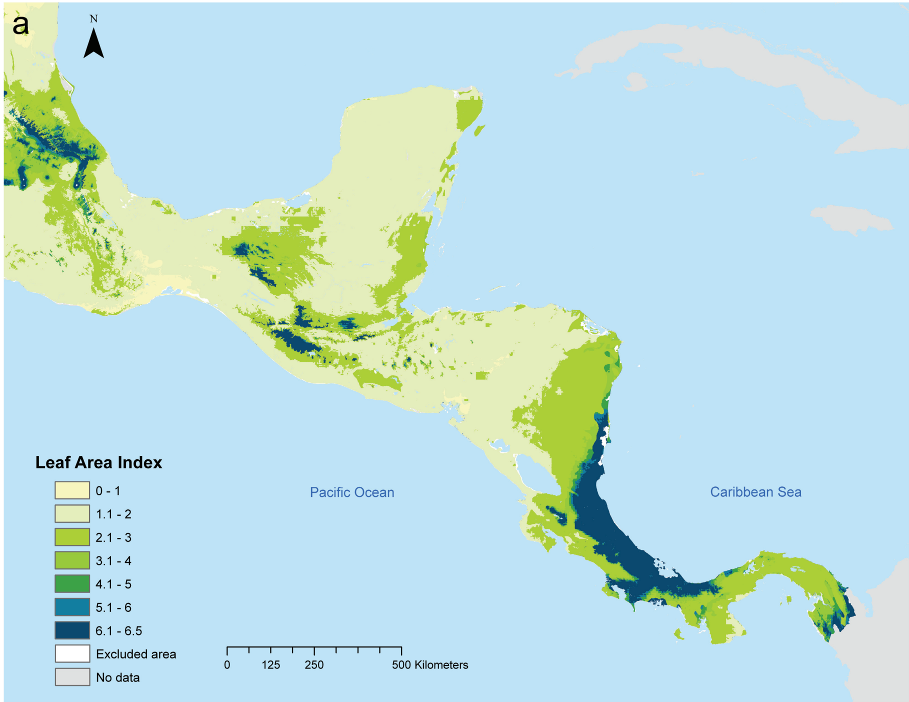

Fig. 4. Validation of MAPSS LAI output. **(a)** LAI modeled by MAPSS, **(b)** and **(c)** difference between LAI simulated by MAPSS and the MODIS and GLOBCARBON global satellite products, respectively. White areas were excluded due to land cover characteristics criteria. MAPSS LAI represents an average LAI based on 30 to 50 year climate averages, while MODIS is the LAI average between 2000 and 2009 and GLOBCARBON between 1998 and 2007.

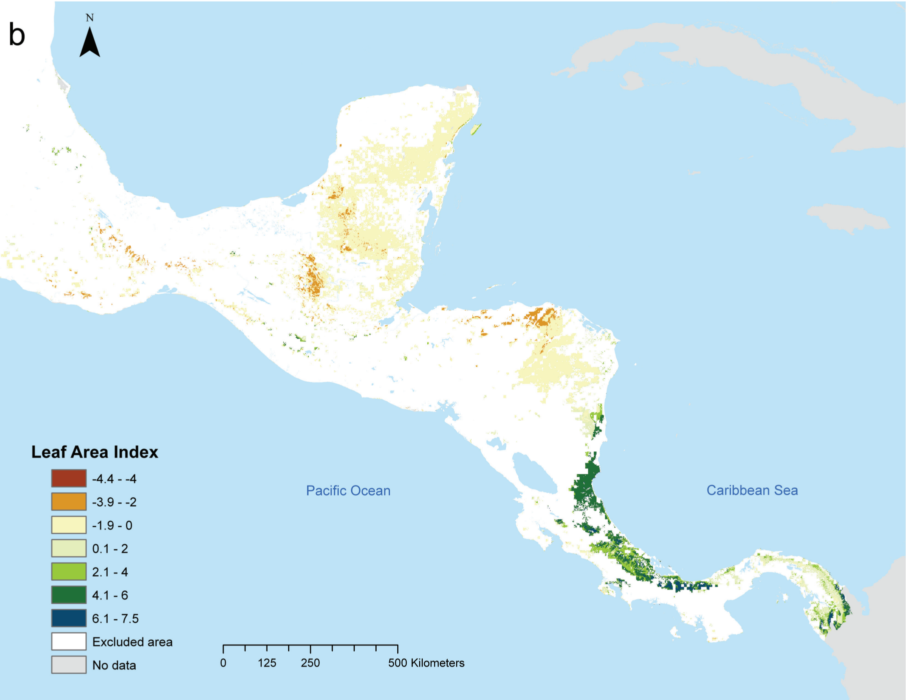

Fig. 4. Continued.

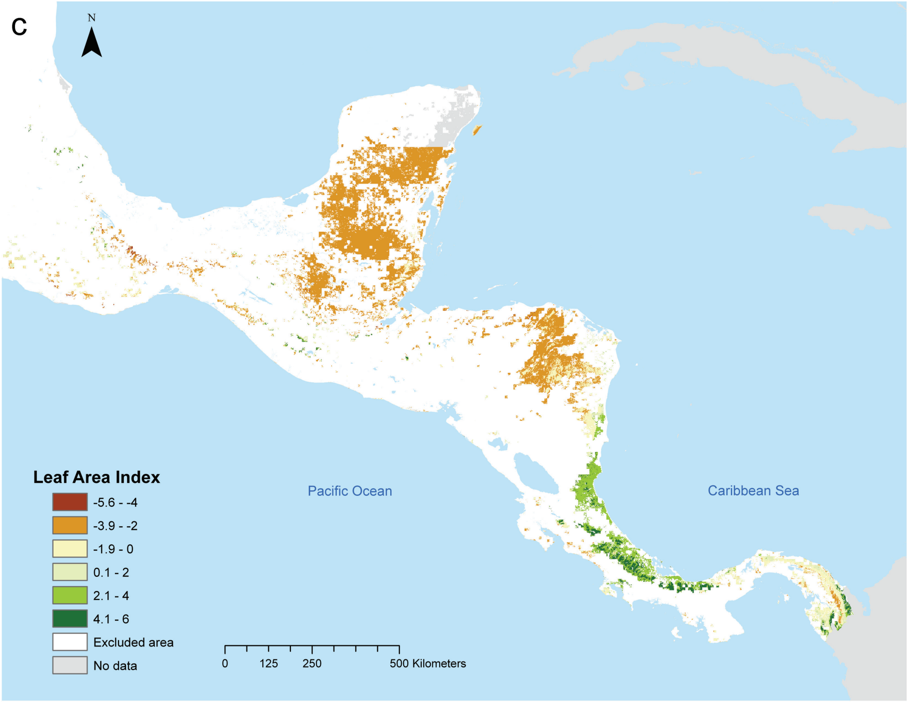

Fig. 4. Continued.

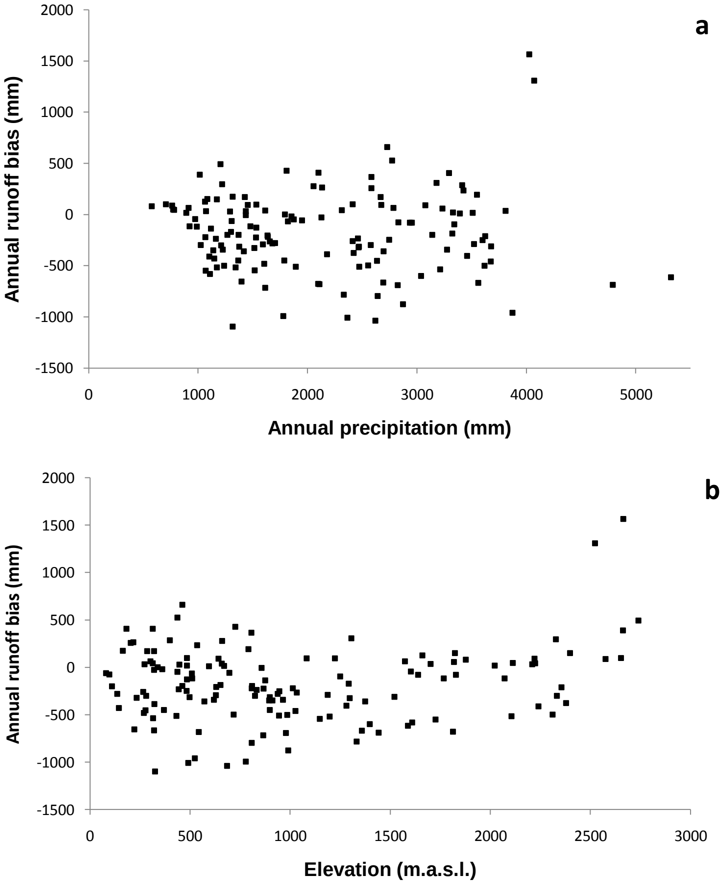

Fig. 5. Residuals distributions of annual runoff (mm) according to catchment annual precipitation **(a)**, average elevation **(b)**, percentage of potential vegetation cover **(c)** and size **(d)**. Each dot corresponds to the difference between MAPSS-modeled and observed annual runoff for each catchment.

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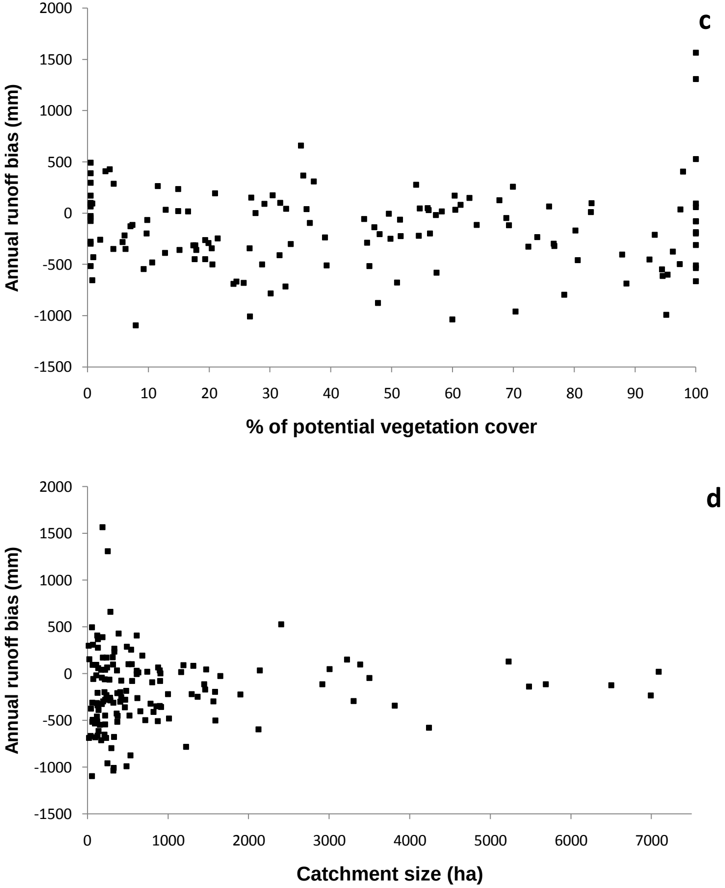

Fig. 5. Continued.

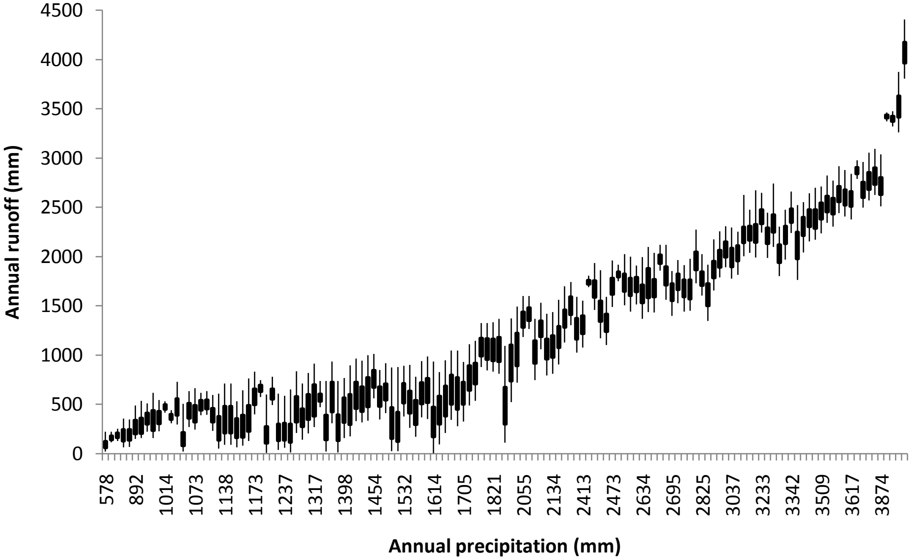

Fig. 6. MAPSS model runoff uncertainty obtained by a Monte-Carlo-type approach (Latin Hypercube Sampling). For each catchment, the black line shows the whole range of predicted values and the box ranges within one standard deviation from the mean. Catchments were ordered according to annual precipitation.

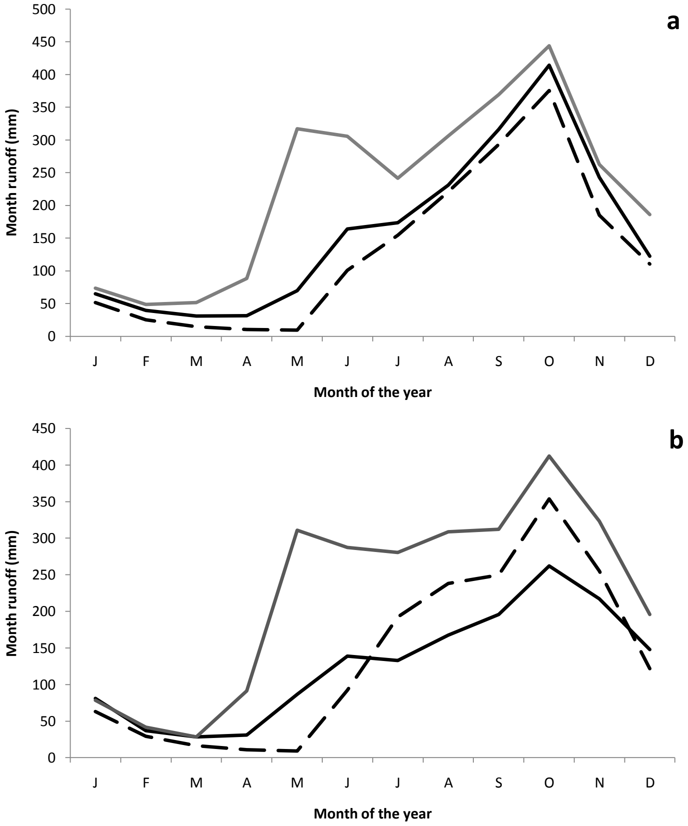

Fig. 7. Two examples of contrasting seasonal catchment behavior, according to the water storage term from Eq. (1): **(a)** a catchment without significant storage term (San Juan, Panama) and **(b)** a catchment (Los Cañones, Panama) with recharge during the rainy season (July to November) and discharge later on. Rainfall (gray straight line), observed (black straight line) and modeled (black dashed line) monthly runoff.

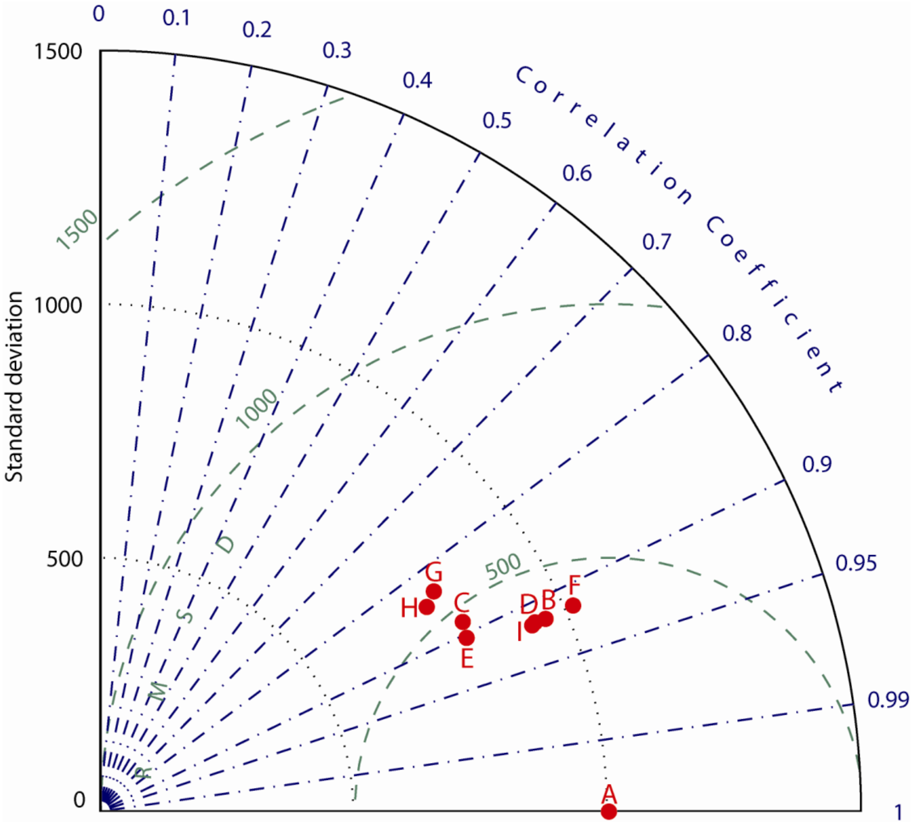

Fig. 8. Taylor plot with observed runoff (A) and modeled values using FCLIM (B), CRUCL 2.0 (C), original MAPSS parameterization (D), WorldClim (E), TMCF (F), TRMM (G), WindPPT (H) and NS (I) datasets.

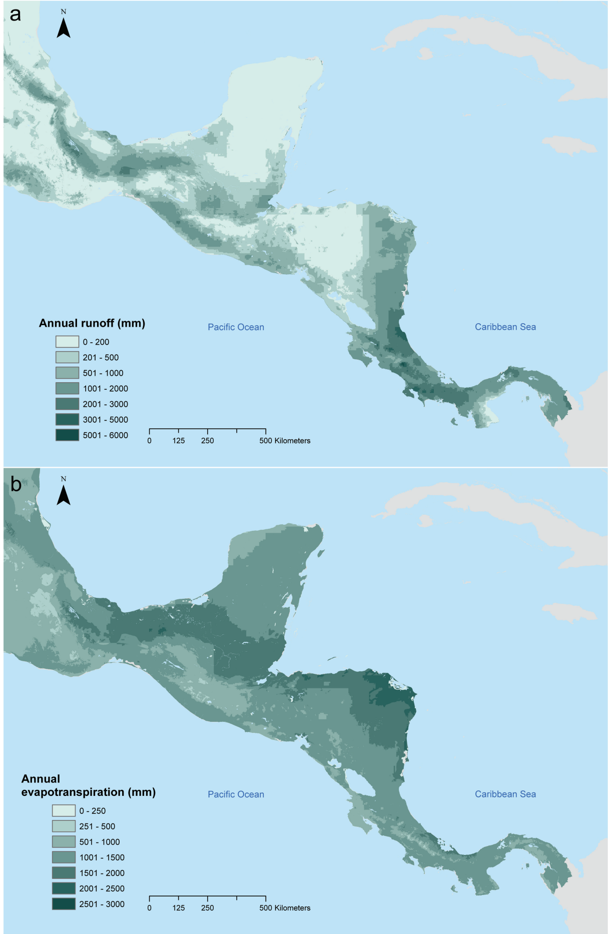

Fig. 9. Annual runoff **(a)** and evapotranspiration **(b)** (mm) of Mesoamerica modeled by MAPSS.

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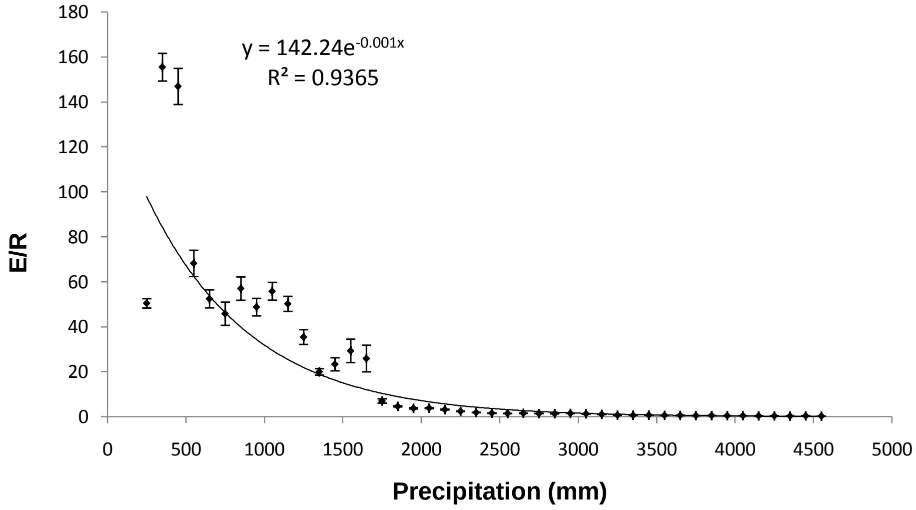

Fig. 10. Modeled evapotranspiration-runoff ratio (E/R) along the annual precipitation (mm) gradient across the Mesoamerican region. Each point represents a 100 mm annual precipitation class. Bars show standard error of each class.

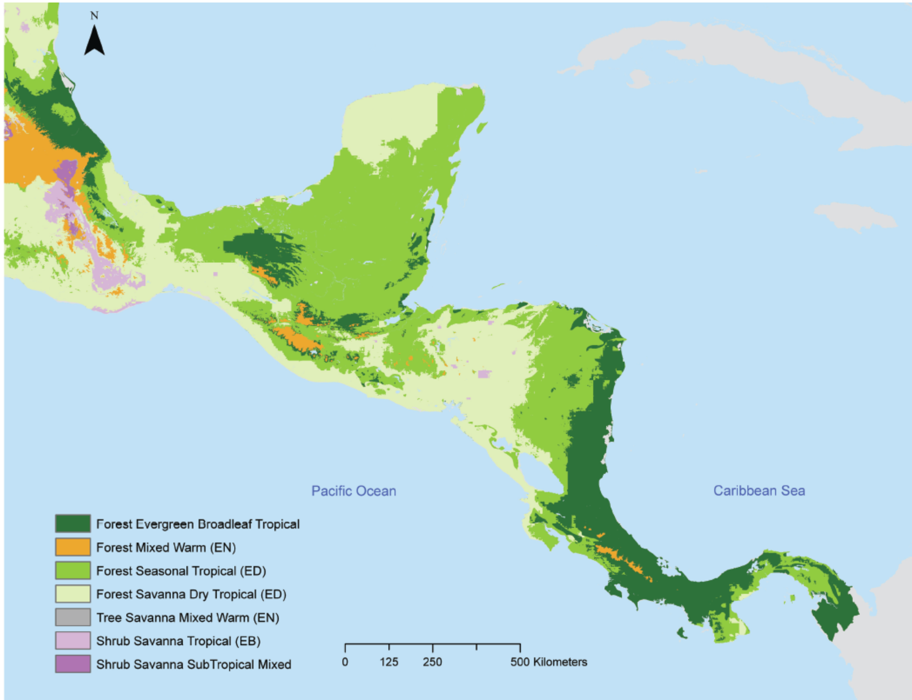

Fig. 11. Potential vegetation types of Mesoamerica modeled by MAPSS.