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Consistency assessment of latent heat flux and observational
datasets over the Amazon basinVitor F V V Miranda^{1,2,*} , J C Jimenez² , E Dutra^{1,3} and I F Trigo^{1,3} ¹ Earth Observation Unit, Portuguese Institute of Sea and Atmosphere, 1749-077 Lisbon, Portugal² GCU-IPL, Universitat de València, 46100 Paterna, Valencia, Spain³ Instituto Dom Luiz (IDL), University of Lisbon, Campo Grande 1749-016, Lisbon, Portugal

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E-mail: vitor.miranda@ipma.pt, JuanCar.Jimenez@uv.es, emanuel.dutra@ipma.pt and isabel.trigo@ipma.pt**Keywords:** satellite observations, latent heat flux, land surface temperature amplitude, leaf area indexSupplementary material for this article is available [online](#)

Abstract

The Amazon basin plays a crucial role in the global hydrological cycle and the climate system. Removal of latent heat from the surface covered by the tropical forest through evapotranspiration is a key process that still requires further research due to the complex nature of the involved processes, lack of observations and different model assumptions. Here we present an assessment of the consistency between different latent heat fluxes datasets through an indirect comparison against the daily amplitude of surface temperature and vegetation status estimated from satellite observations. Our study is based on the hypothesis that the observational satellite data can be used to provide hints on how realistically fluxes are represented in different datasets. Results evidence that datasets diverge inside the basin in both space and time, but it is possible to figure out areas under water-limited conditions, especially around the borders of the basin and some regions over eastern/southeastern Amazonia. In despite of these differences, a clear link between daily amplitude of surface temperature, leaf area index and latent heat flux can be observed over particular areas and seasons, where also correlations reach values closer to -0.98 (0.94) for surface temperature (leaf area index) indicating that satellite observations are suitable for assessing the representation of the partitioning of energy fluxes in models and widely used datasets.

1. Introduction

Tropical rainforests, such as the Amazon, significantly influence the water cycle mostly through run-off and evapotranspiration (ET) (Marengo 2006, Baker *et al* 2021b). ET encompasses the exchange of water between the surface and atmosphere, comprising the evaporation and plant transpiration (Wang *et al* 2014). While ET represents the combined loss of water at the surface, surface latent heat flux (SLHF) quantifies the energy required for ET. SLHF is conditioned by soil moisture availability, solar radiation, vegetation state, and hence closely related with land surface temperature (LST). Accurate SLHF estimation is essential to predict global hydrological changes under diverse climate scenarios (Teuling *et al* 2009, Mu *et al* 2011, Moazenzadeh *et al* 2018).

SLHF can be inferred from various sources: in situ measurements (e.g. eddy covariance sensors—Rosa and Tanny 2015); satellite products (e.g. MOD16—Running *et al* 2021, ECO3ETPTJPL—Hook and Fisher 2019, SSEBop—Senay *et al* 2014); or reanalysis datasets (e.g. ERA5—Hersbach *et al* 2020, FLDAS—McNally *et al* 2017, GLDAS—Rodell *et al* 2004). Eddy covariance sensors are sparse and unevenly distributed in space, with most observation sites lying in mid-to-high latitudes and very few available in tropical regions. Local observations require challenging adjustments to ensure the closure of the energy budget and also the station fetch (Wilson *et al* 2002, Foken 2008, Snyder *et al* 2015). ET products (e.g. derived from satellites, reanalysis, or other models) are an alternative, but the uncertainties of existing products or datasets are still high, often misrepresenting ET values for regions such as the Amazon

basin (Baker *et al* 2021a, Baker *et al* 2021b, Baker and Spracklen 2022).

Given these challenges, an indirect assessment of SLHF is recommended. Daily and seasonal amplitudes of temperature are closely linked with evaporative fraction (i.e. the fraction of available surface energy partitioned into latent or sensible heat flux) and, therefore, observations of LST daily maxima or amplitude can provide insights into surface energy fluxes. Maximum daily LST and daily LST amplitudes (AMP-LST) over regions where evapotranspiration is controlled by soil and surface water availability (Seneviratne *et al* 2010, García-García *et al* 2023) are higher than those expected if water is not a limiting factor, since latent heat is more efficient in dissipating available energy at the surface (Seneviratne *et al* 2004, Donat *et al* 2017, Panwar *et al* 2019, Feldman *et al* 2019, Dirmeyer *et al* 2021, Orth 2021). Moreover, vegetation plays a relevant role in extracting soil water for transpiration, being known to influence the redistribution of heat and moisture (Forzieri *et al* 2020). Leaf area index (LAI), a parameter describing vegetation state and structure, is, thus, also closely linked with surface energy fluxes (Scherrer *et al* 2023).

The Amazon basin, abundant in water, has ET primarily controlled by solar radiation (Hasler and Avissar 2007, Karam and Bras 2008), making soil-moisture and ET coupling lack direct correspondence. In regions with sufficient soil moisture, atmospheric evaporative demand limits ET (Maloney *et al* 2019). AMP-LST and LAI are independent datasets (Fang and Liang 2008, Hulley *et al* 2019) that can assess energy flux evolution. Understanding SLHF dynamics is crucial, given the changes taking place in the basin, together with the intensification of extreme events (Espinoza *et al* 2011, Jiménez-Muñoz *et al* 2016, Marengo and Espinoza 2016, Silveira *et al* 2022).

Assessing land surface processes representation through extensive regions like the Amazon basin remains essential. This study proposes a novel indirect evaluation of several SLHF datasets by comparing their temporal and spatial variability with satellite AMP-LST and LAI estimates. The analysis provides for the first time a detailed understanding of how this satellite data offers insights into realistic SLHF variations over the Amazon.

2. Materials and methods

2.1. Regions and study area

Our study is focused on the Amazon basin (5° N to 20° S latitude, 80° W to 50° W longitude; figure 1). A first assessment is performed considering most of the South America (SA), where Amazon is located, while later we also look into the three sub-regions identified in the Intergovernmental Panel on Climate Change (IPCC) for subcontinental analysis

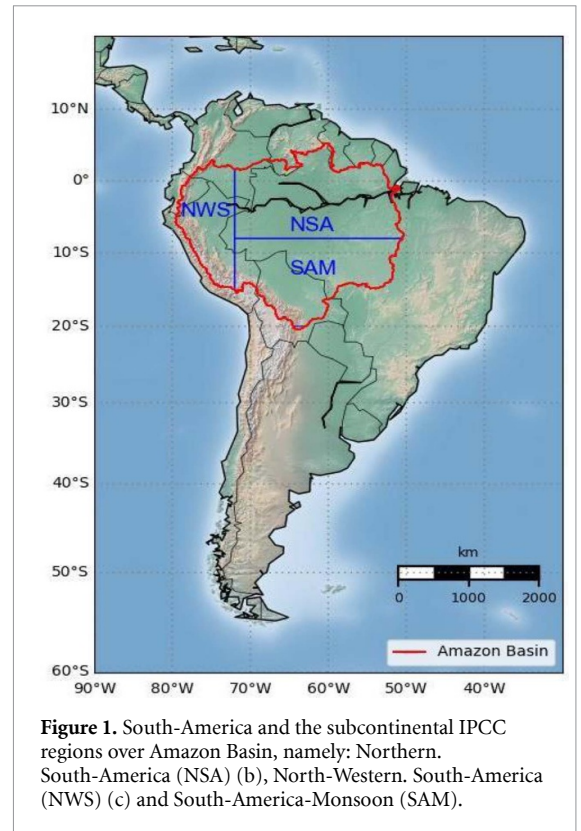


Figure 1. South-America and the subcontinental IPCC regions over Amazon Basin, namely: Northern South-America (NSA) (b), North-Western South-America (NWS) (c) and South-America-Monsoon (SAM).

(Iturbide *et al* 2020), namely: Northern South-America (NSA), South-America-Monsoon (SAM) and North-Western South-America (NWS), but considering only the portions inside of the Amazon basin (figure 1). Despite that other studies have considered the whole Amazon Basin as a single and homogeneous area, we have chosen to focus on the IPCC regions to account for the different ecological and climatological characteristics within the Basin. We have chosen to focus on the IPCC regions because numerous studies regard the Amazon as a homogeneous region, but our results indicate otherwise.

2.2. Datasets

2.2.1. Turbulent fluxes

We have considered surface fluxes from seven commonly used datasets, namely: GLDAS-2.1 (Rodell *et al* 2004); GLDAS-2.2 (Li *et al* 2019); FLDAS (McNally *et al* 2017); ERA5land (Muñoz-Sabater *et al* 2021); ERA5 (Hersbach *et al* 2020); GLEAM-3.6-a,b (Miralles *et al* 2011, Martens *et al* 2017), based on their spatial resolution ($\sim 0.25^\circ$ or higher) (table 1). Because of the different starting period within the datasets, we have considered a common period between 2003–2021. Flux values were converted to monthly and seasonal averages with the same units (see supplementary material). We have also computed the Evaporative Fraction (EF) for selected datasets (see supplementary material).

Table 1. Specifications for the chosen SLHF datasets. Details of the acronyms and datasets used to force the models are described in the supplementary material. All datasets were obtained as monthly averages, except GLDAS-2.2, which were only available as daily values.

	GLDAS-2.1	GLDAS-2.2	FLDAS	ERA5-Land	ERA5	GLEAM-3.6a	GLEAM-3.6b
	(Rodell <i>et al</i> 2004)	(Li <i>et al</i> 2019)	(McNally <i>et al</i> 2017)	(Muñoz-Sabater <i>et al</i> 2021)	(Hersbach <i>et al</i> 2020)	(Miralles <i>et al</i> 2011, Martens <i>et al</i> 2017)	(Miralles <i>et al</i> 2011, Martens <i>et al</i> 2017)
Spatial resolution	0.25°	0.25°	0.1°	0.1°	0.25°	0.25°	0.25°
Temporal availability (Start-end)	(2000–present)	(2003–present)	(2000–present)	(1940–present)	(1940–present)	(2003–2021)	(2003–2021)
Land surface model	NOAH-LSM	CLSM	NOAH-LSM	CH-TESESEL	H-TESESEL	GLEAM	GLEAM
Forcing and data assimilation*	GDAS, GPCP, AGRMET	ECMWF, GRACE*, AVHRR	CHIRPS, MERRA-2	ERA5	Different remote sensing and <i>in-situ</i> observations	MSWX, MSWEP, GSNOW, NSIDC, VODCA, ESA-CCI*, MEaSUREs	CERES, AIRS, MSWEP, GSNOW, NSIDC, ESA-CCI*, VODCA, MOD44B

The datasets from Land Data Assimilation System (i.e. GLDAS-2.1, GLDAS-2.2 and FLDAS) are provided by different land surface models, forced with different analysis, forecasts or interpolated fields, as described in table 1. GLDAS-2.2 and FLDAS, also combine data from satellites, such as the Gravity Recovery and Climate Experiment (GRACE) (Li *et al* 2019) and the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (Funk *et al* 2015). ERA5 combines model data with observations (from remote sensing and *in-situ* measurements), through data assimilation, from across the world. Together with ERA5, there is a downscaled land product, ERA5land, forced with ERA5 atmospheric data, but with a finer/more detailed description of land surfaces. GLEAM datasets have two versions used here: 3.6a and 3.6b, where the ‘a’ version is based on satellite and reanalysis data, while the ‘b’ version is largely driven by satellite data.

2.2.2. Satellite

LST retrievals from clear sky satellite observations were used to assess the performance of the different SLHF datasets. Direct measurements of thermal infrared radiances at the top of atmosphere are transformed to surface temperature through atmospheric and surface emissivity corrections. Therefore, LST satellite products can be considered as a quasi-observational dataset, since it does not rely on the application of a land surface model as occurs with the reanalysis or other fluxes datasets. It is also important to remark that LST refers to the temperature of the surface being observed, so it is different from the commonly used air temperature.

Among the different existing LST satellite datasets, we selected the Moderate Resolution Imaging Spectroradiometer (MODIS) standard product

onboard the AQUA platform (MYD21C3, Hulley and Hook 2021), which provides the users with monthly LSTs at a global grid of $0.05^\circ \times 0.05^\circ$. The results presented in this work use MYD21C3 product, which uses the Temperature-Emissivity (TES) algorithm, based on thermal infrared MODIS bands, as described in Hulley and Hook (2021); we have also repeated the analysis using MYD11C3 product, i.e. MODIS LST derived using a generalized split-windows algorithm (Wan *et al* 2021) also driven by observations in the thermal infra-red. Since the results obtained with MYD11C3 and MYD21C3 are similar, we only show the latter. MODIS LST products have been validated over different environments, including similar tropical environments such as the Amazon Basin, with accuracies within or below 1 K (Hulley and Hook 2017, Li *et al* 2021). MODIS imagery from the Aqua satellite is acquired around 1:30 pm and 1:30 am, thus providing daily observations very close to the maximum and minimum daily LST, respectively the AMP-LST was computed here as the difference between day and night acquisition. Here we consider either monthly or seasonal fields, which are computed from the monthly/seasonal day-time and night-time LST values, respectively.

Monthly LAI, corresponding to MODIS MCD15A2H product, was also used in our analysis, which is based on a radiative transfer model fed with spectral reflectances in the visible and near infra-red regions (Myneni *et al* 2021). Although both (LST and LAI) satellite products are derived from MODIS acquisitions, they use observations from different spectral regions, thus being independent from each other. Although both (LST and LAI) satellite products are derived from MODIS acquisitions, they use observations from different spectral regions, thus being independent from each other. Furthermore, none of

the SLHF datasets considered here uses satellite LST, nor LAI as input, although monthly climatologies of LAI may be used to characterize surface model parameters (Boussetta *et al* 2013).

2.3. Satellite and flux datasets relationship

To assess the agreement/disagreement among different datasets, we have first plotted latitudinal profiles, then applied Pearson linear correlations among AMP-LST, LAI and SLHF fields. The Amazon basin was then divided into IPCC subcontinental regions (as described in section 2.1) selecting only pixels that are inside the basin and discarding those totally or partially covered by ocean. Finally, we have compared EF, AMP-LST and LAI seasonal averages for these IPCC regions.

3. Results

3.1. Latitudinal profiles

Figure 2 shows the latitudinal profiles (i.e. average values per latitude) of SLHF (a, b, c and d) for the seven datasets, together with the AMP-LST and LAI (e, f, g and h) for almost the entire South America (10° N– 40° S). Maximum values can be observed in the tropics, between about 5° N and 5° S, coinciding with the core of the Amazon Forest. GLDAS-2.2 is however an exception and shows local minima in those latitudes in MAM and JJA, where also the local maxima in the GLDAS-2.2 do not match those of other datasets either. Indeed, the maxima in SLHF referred above (i.e. most datasets, except GLDAS 2.2) roughly overlap the maximum values of the LAI meridional profile (green line, figures 2(e)–(h)), which as expected, lies in the latitude ranges where the Amazon Basin is widest in longitude. The decrease in SLHF for latitudes south of 5° S follows the decrease in LAI with higher portions of land area outside the Amazon Basin, as seen in supplementary material.

The SLHF profiles reveal different seasonal variability among the datasets. Over the 5° N– 5° S latitudinal range, dominated by the Amazon forest, the SLHF maximum variation (i.e. the seasonal amplitude) is of the order of 150 Wm^{-2} . The GLEAM datasets, versions 3.6-a and 3.6-b (red and dark red lines), exhibit the highest values of SLHF. If we ignore the anomalous GLDAS-2.2 behavior, both ERA5 and ERA5land datasets (blue and dark blue lines) show the lowest seasonal variability and also the lowest absolute values (close to 100 Wm^{-2}). FLDAS and GLDAS-2.1 (green and dark green lines) show values between ERA datasets and both GLEAM datasets (ranging between 50 and 100 Wm^{-2}). In JJA and SON, most SLHF datasets show a clear inflection point close to 5° S, marking the start of the steady decrease in fluxes towards higher latitudes. The location of latitudinal maxima or inflection points

is less marked or more variable among datasets for the remaining seasons. Nevertheless, the latitudinal profiles of fluxes follow those of LST daily amplitude and vegetation density (here represented by LAI). Both, AMP-LST (black line, figures 2(e)–(h)) and LAI (green line, figures 2(e)–(h)) profiles are marked by the transition from the central region of the Amazon Basin to its margins and higher latitudes, where vegetation becomes less dense and LST daily amplitudes increase—see in particular the latitudinal range between $\sim 5^{\circ}$ S and $\sim 15^{\circ}$ S. The AMP-LST profiles show very little variation in the equatorial area (reaching values between 5 to $\sim 10 \text{ K}$), which also coincides with very small intra-annual variability; indeed, AMP-LST is nearly constant between around 10° N to 5° S and also nearly constant throughout the year. Around 5° S, the AMP-LST profile shows an inflection point, marking the increasing trend in AMP-LST with latitude, at least up to 20° S. This inflection is also detected in LAI, which shows an opposite decreasing pattern going from $\sim 20 \text{ m}^2 \text{ m}^{-2}$ (in its peak in the equatorial area) from $\sim 5 \text{ m}^2 \text{ m}^{-2}$ in higher latitudes. Except for GLDAS-2.2 in JJA, all the datasets for SLHF also display this inflection point in the dry seasons (JJA and SON).

To analyze how coherent is the behavior of latent heat fluxes profiles compared to LST and LAI profiles over Amazonia (latitudinal band between 10° N and 20° S), we computed the Pearson's linear correlation coefficient (table 2). Overall, SLHF tends to be anticorrelated (correlated) with AMP-LST (LAI)—not surprisingly, since AMP-LST and LAI are themselves anticorrelated. Stronger (weaker) correlation values are found in JJA and SON (DJF). Nevertheless, some of the datasets present very different behavior: the GLEAM 3.6a and 3.6b datasets do not show the decrease in correlation values that is observed for the remaining datasets in DJF; GLDAS-2.2 shows significantly weaker correlations with AMP-LST and with LAI than other datasets, particularly in MAM and JJA.

3.2. Seasonal and regional analysis

Figures 3(a)–(d) shows monthly averages for each dataset (SLHFs and AMP-LST) over the IPCC areas (NSA, NWS and SAM) and also the whole Amazon Basin (AMZ). NSA presents the lower AMP-LST values (overall $< 10^{\circ}\text{C}$), with a smooth seasonal cycle peaking in Sep–Oct and with a secondary maximum in Feb–Mar. AMP-LST in NWS is similar, although LST daily amplitudes are higher (vary between $\sim 11^{\circ}\text{C}$ and $\sim 13^{\circ}\text{C}$). Fluxes in these regions also present smooth seasonal cycles, with the exception of GLDAS-2.2 in NSA. Furthermore, the monthly SLHF values are nearly in phase with AMP-LST. Nevertheless, it is worth noting that (i) in NSA, both FLDAS and GLDAS-2.1 peak around July, while AMP-LST and other datasets have annual maxima

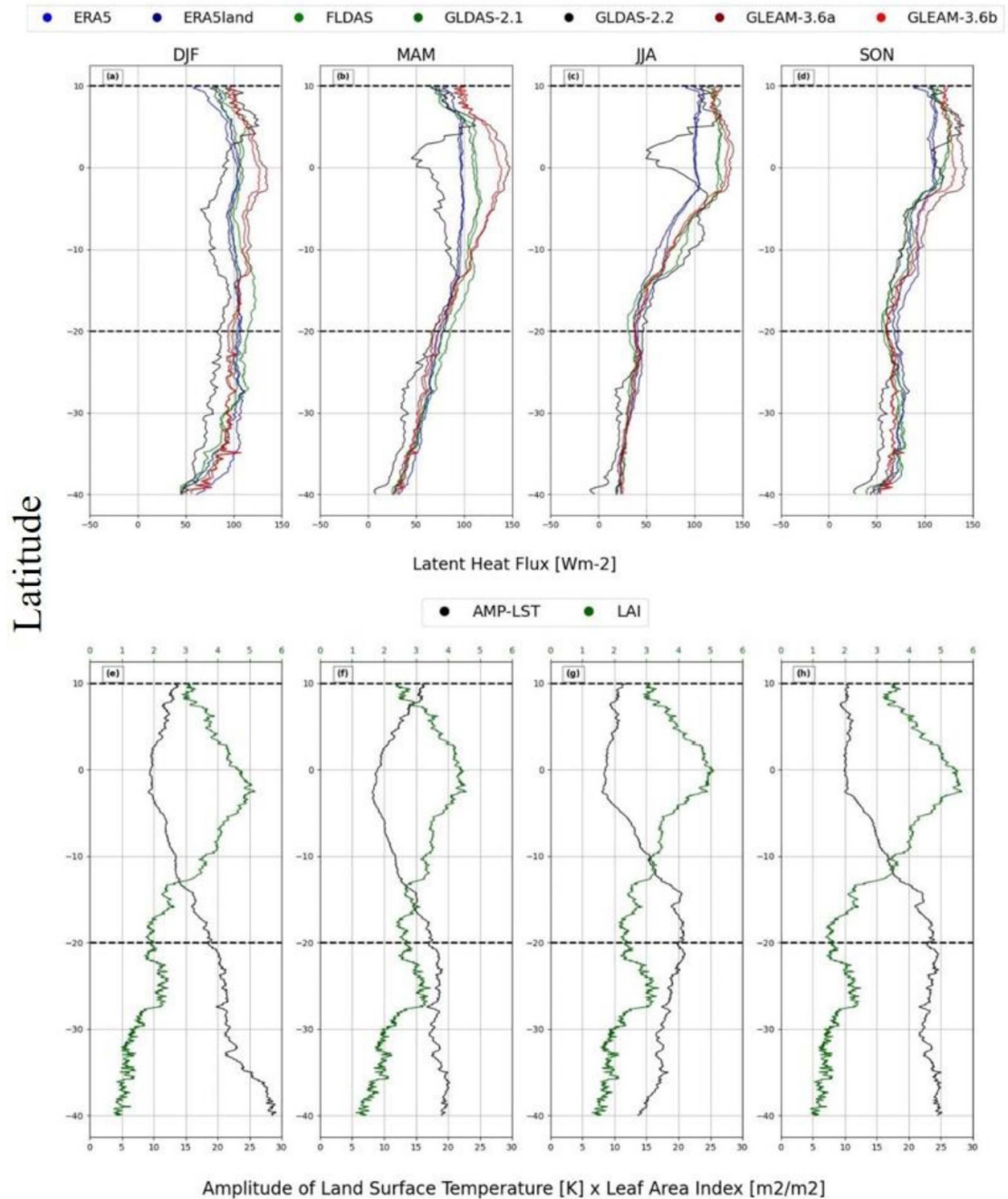


Figure 2. Latitudinal profiles over the South American region between 10° N–40° S. Panels (a)–(d) show profiles of surface latent heat flux (SLHF) extracted from the different datasets (see table 1), whereas panels (e)–(h) show profiles of land surface temperature amplitude (AMP-LST, bottom horizontal axis) and leaf area index (LAI, top horizontal axis). The Amazon basin is confined to the latitudes marked by the dashed lines.

later in the year; (ii) GLEAM datasets show significant higher flux values, particularly for the NSA area. The SAM region shows a very different picture, with the seasonal cycles of AMP-LST and fluxes nearly out of phase. In this region, the monthly variability of AMP-LST is much higher than that observed in the remaining regions—in SAM, AMP-LST varies between ~11 °C and about 17 °C (Aug–Sep). ERA5 and GLEAM-3.6a (FLDAS and GLDAS-2.1) peaks earlier (later) than AMP-LST maxima for SAM. This,

together with a higher seasonal variability of SLFH for most datasets, attaining their minima when (or close to) AMP-LST reaches its annual maximum, suggest SAM is at least partially water-stressed during the dry season.

Figure 4 depicts temporal correlations, at each grid point, between SLHF for four selected datasets (ERA5land, FLDAS, GLDAS-2.1 and GLEAM-3.6b) and AMP-LST; the hatched lines indicate statistically significant correlations (p -value < 0.5). We chose

Table 2. Pearson's linear correlations between (a) surface latent heat fluxes (SLHF) and land surface temperature amplitude (AMP-LST), and (b) SLHF and leaf area index (LAI) for the latitudinal region between 10° N and 20° S. Linear correlation coefficients between LAI and AMP-LST are also included (c). Significant values (p -value < 0.05) are in bold and with *. Colors: from −0.75 to −1 are dark blue; −0.5 to −0.75 light blue; from −0.25 to 0.25 are gray; from 0.25 to 0.5 are light orange; from 0.5 to 0.75 are dark orange and from 0.75 to 1 are red.

(a) AMP-LST				
	DJF	MAM	JJA	SON
ERA5	0,20*	−0,85*	−0,97*	−0,94*
ERA5land	0,24*	−0,91*	−0,97*	−0,96*
FLDAS	0,51*	−0,80*	−0,98*	−0,95*
GLDAS-2.1	0,03	−0,94*	−0,98*	−0,93*
GLDAS-2.2	−0,02	0,35*	−0,56*	−0,90*
GLEAM-3.6a	−0,80*	−0,93*	−0,98*	−0,97*
GLEAM-3.6b	−0,77*	−0,94*	−0,98*	−0,97*

(b) LAI				
	DJF	MAM	JJA	SON
ERA5	−0,05	0,77*	0,81*	0,86*
ERA5land	−0,16	0,86*	0,79*	0,77*
FLDAS	−0,45*	0,74*	0,85*	0,78*
GLDAS-2.1	0,06	0,87*	0,83*	0,75*
GLDAS-2.2	−0,19*	−0,41*	0,29*	0,70*
GLEAM-3.6a	0,84*	0,95*	0,88*	0,88*
GLEAM-3.6b	0,79*	0,94*	0,87*	0,84*

(c) AMP-LST x LAI				
	DJF	MAM	JJA	SON
	−0,96	−0,91	−0,87	−0,88

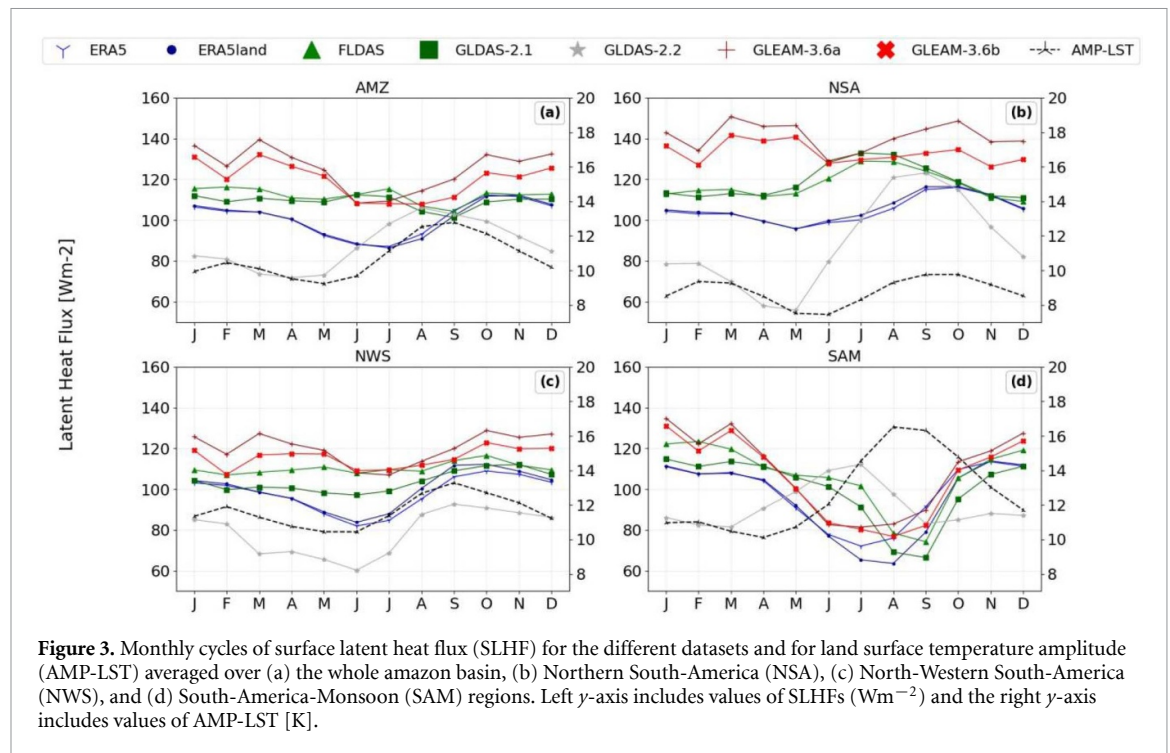
these datasets because: (i) ERA5 (GLEAM-3.6a) and ERA5land (GLEAM-3.6b) present very similar results, and (ii) GLDAS-2.2 dataset showed an anomalous behavior when compared with the remaining datasets or AMP_LST (see figure 2) and it also revealed unrealistic evaporative fraction values (see figure S1, supplementary material). We find that, with a few exceptions, statistically significant values occur in regions/seasons where the correlation is negative. The datasets show mostly positive correlations in DJF and MAM with no statistical significance, except in small areas near the northern and southern edges of the basin. The highest spatial extensions of negative and statistically significant correlations are observed in JJA and SON seasons. The largest differences among datasets are also observed in these seasons. ERA5land shows a marked contrast between the northern and southern part of the basin, while the other datasets show an area with negative correlations to the south of the basin in JJA, although with smaller extent. The negative (significant) correlations are confined to the eastern and southern part of the domain in SON.

EF characterizes the partition of surface available energy into heat fluxes. EF estimated using seasonally averaged fluxes is expected to be related to seasonal means of AMP-LST, since this will translate not only the dependence of daily LST values on net radiation, but also how efficiently this is used for evapotranspiration. Figure 5 shows scatterplots of seasonal EF versus the AMP-LST grouped into LAI values for

all the data points included inside the basin. As expected, the scatterplots show an overall increase in AMP-LST with decreasing EF and less dense LAI for all the areas and seasons. The NSA region shows the smallest range of EF (between around 0.5 and 1) and AMP-LST (below 20 K) for all datasets and seasons. Apart from differences in the strength of the linear relationship between EF and AMP-LST, these four models are fairly consistent over NSA. Over NWS and SAM, EF reaches lower values (with more points below 0.5), while AMP-LST may increase up to 40 K. In DJF, i.e. in the rainy season, the NWS points show an almost linear relationship with AMP-LST, while in JJA EF seems to reach its minimum value for AMP-LST above ~20 K (around 0.5 for ERA5-land and lower for other datasets). The SAM scatterplots suggest a flattening for higher AMP-LST, as can be observed in the DJF season or even more pronounced in the JJA season.

4. Discussion

The Amazon Basin is crucial for comprehending environmental processes, however, estimating energy and water surface fluxes poses challenges. Studies reveal varying results for heat and water fluxes (Huffman *et al* 1997, Gomis-Cebolla *et al* 2019, Papastefanou *et al* 2022, de Ávila *et al* 2023, Yin *et al* 2023). Here, we have compared and assessed different datasets of SLHF (table 1), notably revealing different spatial and temporal variations over the



region. Our study is based on the hypothesis that AMP-LST and/or LAI are independent observational data that can be used to provide hints on how realistically SLHF is represented in different datasets. This is corroborated by the comparison of latitudinal profiles over South America, with a focus on the 10° N to 20° S latitudinal band encompassing the Amazon Basin. The spatial coherence between most datasets and mean LST daily amplitudes is striking: in MAM, JJA and SON the SLHF and AMP-LST profiles are anti-correlated. These high anti-correlated values are, at least, partially linked to the transition from the core of the Amazon Basin ($\sim 0^{\circ}$ – 5° S; see also figure 1) to its southern outskirts, where vegetation density decreases. Indeed, the same datasets that are strongly anti-correlated with AMP-LST also present high correlations with LAI; the absolute values are lower, as the latitude of flux maxima is less aligned with LAI maximum than AMP-LST minima. Nevertheless, this first assessment indicates GLDAS-2.2 falls behind the other datasets, presenting somewhat unrealistic profiles when compared with those of AMP-LST and LAI. DJF shows a very different behavior: this roughly coincides with the wet season in the 20° S– 0° band, with very little latitudinal variation in the ERA5/ERA5-Land, FLDAS, and GLDAS-2.1 datasets; only the GLEAM fluxes maintain significant anti-correlation with AMP-LST, which may be attributed to the role of water availability in this dataset.

We have further analyzed the seasonal cycle of SLHF over the Amazon Basin and over a set of sub-areas, following the most recent IPCC regions. The

NSA is characterized by dense broadleaved forest that spreads around a large river network at the core of the Amazon region, where water is abundant and SLHF is expected to be essentially driven by available energy (Hasler and Avissar 2007, Karam and Bras 2008, Liu *et al* 2023). The monthly averages of AMP-LST are also fairly low over that region, attaining the lowest seasonal variability among the studied sub-areas (figure 3). In this area, AMP-LST is expected to follow net radiation (primarily influenced by solar energy), with annual maximum values damped by SLHF, given its high efficiency in dissipating available energy (Bateni and Entekhabi 2012, Feldman *et al* 2019). Following this reasoning, we would expect the seasonal cycle of SLHF to follow that of AMP-LST in NSA—roughly agreeing with the months of ET annual maximum and minimum identified by Fleischmann *et al* (2023), for wetland complexes in the equatorial Amazon region. Although none of the SLHF datasets under study matches the annual maxima and minima of the observed AMP-LST, these seem reasonably aligned with ERA5/ERA5land and GLEAM datasets, and to some extent with GLDAS-2.2 dataset, although with very different values. The SAM region, where changes in vegetation/land cover and also a transition from carbon sink to source due to the deforestation have occurred during the last decades (Davidson *et al* 2012, Ruiz-Vásquez *et al* 2020, Gatti *et al* 2021), presents the most contrasting behavior with respect to NSA: the significantly higher AMP-LST in the drier season are compatible with low SLHF, as somehow followed by all datasets (except GLDAS-2.2). The NWS,

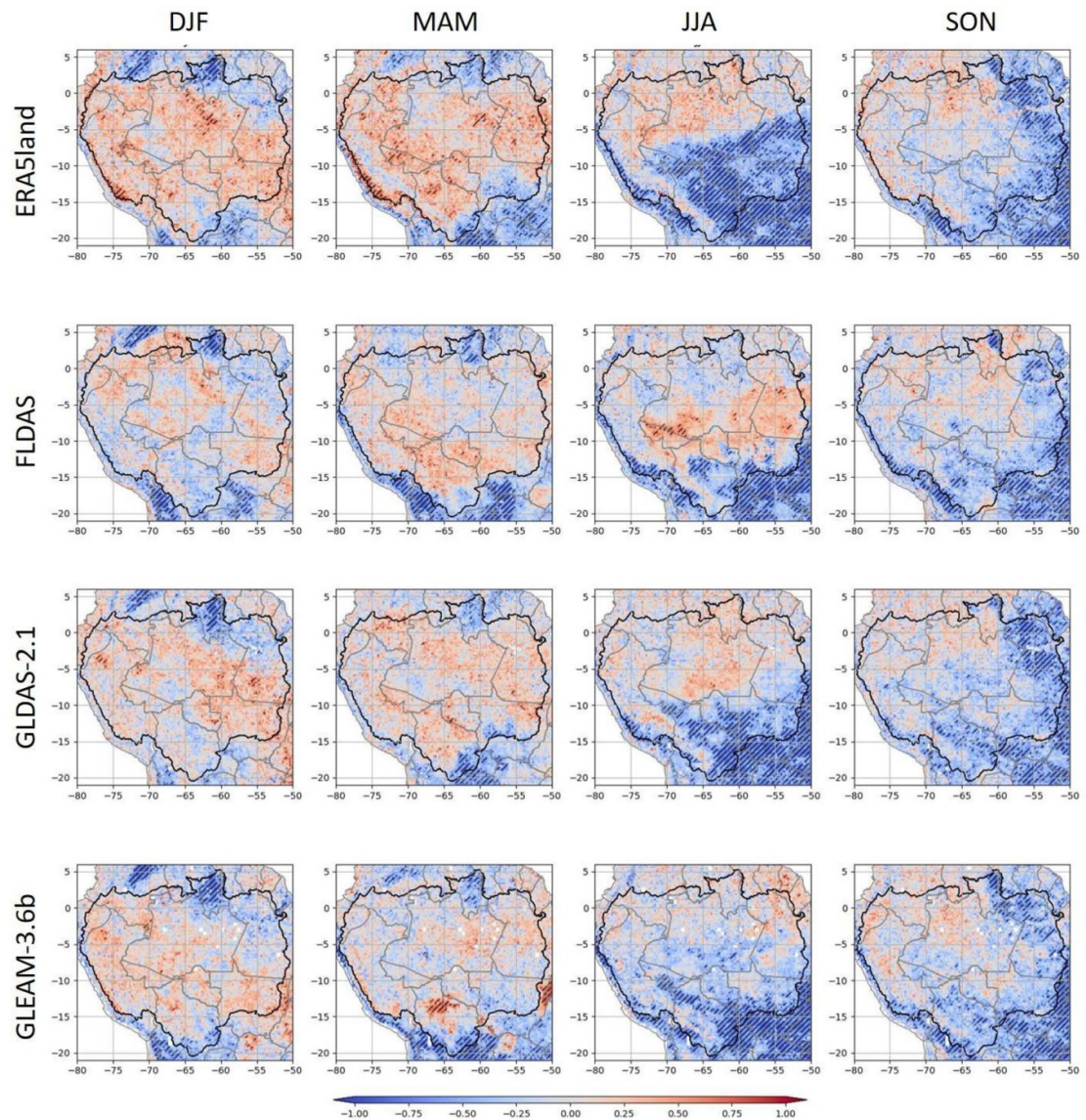


Figure 4. Spatial pattern of Pearson's linear correlation between surface latent heat flux (SLHF) for the different datasets and for land surface temperature amplitude (AMP-LST) over the Amazon basin region for DJF, MAM, JJA and SON seasons. Hatched regions represent the significant regions (p -value < 0.05) for the correlations.

encompassing part of the Andes and the extreme west border of the Amazon forest, presents intermediate behavior. Baker *et al* (2021b) and Liu *et al* (2023) have used GRACE-based observations and a water-balance approach to assess evapotranspiration over the Amazon area. The approach is sensitive to errors in precipitation and runoff and, actually, the annual cycle maxima of GRACE-based ET for the whole Amazon Basin in those studies ranges between July–August (Liu *et al* 2023) and September–October (Baker *et al* 2021b); assuming SLHF over the whole area follows an energy-driven regime, SLHF would likely be aligned with AMP-LST, and therefore peak around August–September (figure 3). Finally, we also note that, particularly in the NSA region, the seasonal variability in each of the datasets is lower than the variability among the datasets, showing that there

are large uncertainties in estimating ET. These uncertainties arise from the different driving data used as well as different model assumptions, which are beyond the scope of this study to be further investigated. A possible relevant factor could be the treatment of the interception evaporation, which is known to be relevant but highly uncertain over the tropical regions (Miralles *et al* 2010, Ghilain *et al* 2020, Chen *et al* 2022).

The spatial distribution of correlations between SLHF and AMP-LST, performed for each season (figure 4) highlights the diversity among datasets and sub-areas. The datasets generally present positive correlations (although usually not statistically significant) in DJF over most of the Basin. In the drier seasons, however, we find negative correlations emerging in the south part of the Basin (ERA datasets,

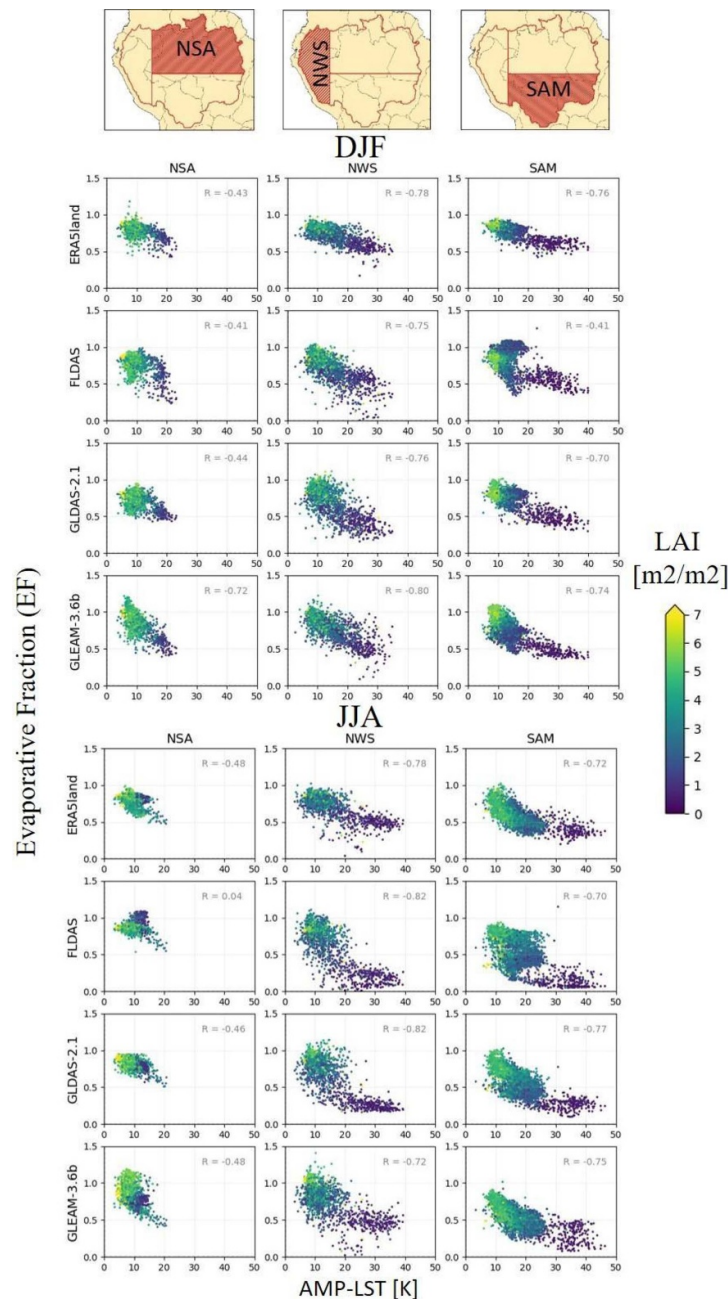


Figure 5. Scatterplots of Evaporative Fraction (EF) estimated from different datasets (ERA5land, FLDAS, GLDAS-2.1, GLEAM-3.6b) versus land surface temperature amplitude (AMP-LST) over the IPCC regions (N.South-America—NSA, N.W.South-America—NWS and South-America-Monsoon—SAM). Scatter plots are provided for DJF (Top set of panels) and JJA (Bottom set of panels) seasons. The color palette applied to data points refers to leaf area index (LAI) values.

GLEAM and to a lesser extent GLDAS-2.1) particularly in JJA, which spread to the whole eastern border in DJF. In these cases, SLHF decreases with increasing AMP-LST suggesting that SLHF may be conditioned by water availability. Although Satellite soil moisture products dominate the spatial variability in most scenarios, they are prone to significant errors in densely forested areas (Kim *et al* 2020, 2023) and therefore we have excluded these data from our analysis. Instead, we have considered satellite LAI (figure S2) to further understand the spatial distribution of SLHF model/products co-variability with AMP-LST (figure S3). The scatterplots (figure 5) of seasonal

evaporative fraction (EF, a measure of how efficiently available energy is dissipated by SLHF) against AMP-LST put into evidence not only differences between NSA and the other sub-areas, but also the role vegetation plays in all areas and datasets, as also highlighted in previous studies (e.g. Baker *et al* 2021b, de Ávila *et al* 2023, Butt *et al* 2023). All scatterplots indicate a decrease of EF with AMP-LST, in line with several previous studies (Panwar *et al* 2019, Feldman *et al* 2019, Ritchie *et al* 2022). Most of these relate EF (and also ET or SLHF) with near surface air temperature. We argue that LST is closer to the radiation budget and to the surface energy balance than air temperature, and,

therefore, we expect the links with EF (or SLHF) to be more pronounced. Nevertheless, the sensitivity of EF to AMP-LST varies significantly among regions, datasets and seasons. NSA shows the lower variability of EF and AMP-LST, but still aligning lower LAI values with higher/lower EF/AMP-LST. The variability is much larger in NWS and SAM, being clear that lower LAI are associated with larger AMP-LST and EF. In contrast with NSA, both low LAI values in NWS and SAM are associated with water stress conditions, where EF reaches minimum values. These are well aligned with the very high (well above 20 K) AMP-LST. It is also to be expected that this same behavior for low SLHF/EF values will be extended to areas where the forest is cut down or replaced, coinciding with enhanced warming of those regions (Gatti *et al* 2021, Butt *et al* 2023).

This study highlights significant differences among SLHF datasets over the Amazon Basin. These SLHF values rely on the use of (land surface) models and input data, and both, model assumptions and data uncertainties, will impact the quality of flux estimates. The absence of dynamical (i.e. interannual variability) vegetation in GLDAS, ERA5, ERA5land, and FLDAS reanalysis presents a notable limitation when studying the Amazon basin. This is particularly critical when considering that land-cover has also changed in parts of the region over the last years (Butt *et al* 2023), while vegetation variability driven by seasonal changes in precipitation, fire patterns, and vegetation growth are not adequately captured by those models. Consequently, the interpretation of land cover dynamics in the Amazon basin based on those reanalyses may overlook crucial ecological processes and limit the accuracy of environmental assessments (de Ávila *et al* 2023). GLEAM datasets incorporate a dynamical vegetation mode (based on microwave vegetation optical depth, Moesinger *et al* 2020). Nevertheless, the GLEAM datasets also rely on various data inputs (reanalyses data and/or satellite) and model parameterization choices to estimate actual evaporation (Miralles *et al* 2011, Martens *et al* 2017), all contributing to uncertainties in the final estimates. Another example concerns the GLDAS-2.2 assimilation of GRACE total terrestrial water anomaly data (Li *et al* 2019), which offers valuable insights into hydrological processes, but the assimilation of these data can introduce uncertainties, particularly in reproducing total water storage in complex surface ecosystems like the Amazon basin (Li *et al* 2019).

5. Conclusions

In this study, we assessed SLHF across the Amazon basin using seven distinct datasets, comparing SLHF spatial and seasonal variability with satellite products (AMP-LST and LAI). Significant variations were found among the datasets across different seasons and regions within the Amazon basin. Lower

vegetation cover (represented by LAI values below $2 \text{ m}^2 \text{ m}^{-2}$) corresponded well with higher AMP-LST (typically above 20 K) and generally, lower SLHF (Evaporative Fraction, EF) values (generally below 0.5, but variable among dataset), suggesting a relationship between observational datasets and SLHF estimates. Nevertheless, this relationship presents larger variability for NWS and SAM than for NSA region. Grid-points closer to the border of the Basin (outside NSA) with low LAI values (ranging from $0\text{--}2 \text{ m}^2 \text{ m}^{-2}$) also present high AMP-LST values (above 20 K), especially during dry season. In those cases, EF reaches minimum values (below 0.5) for most datasets, indicating signs of water stress conditions.

The evaluation of various SLHF datasets over the Amazon region requires careful consideration due to the scarcity of data, different model assumptions and assimilation schemes. SLHF datasets exhibit significant variability and uncertainties, particularly over dense broadleaved forest, as also identified by Schellekens *et al* (2017). In summary those uncertainties can be list as: (i) the representation of vegetation in different models, (ii) their response to available energy and, at least in some cases, to water limitation; (iii) the completeness in the representation of land surface processes (e.g. the treatment of intercepted water may be problematic); and (iv) problems in the numerous input data.

Our methodology identifies inconsistencies between datasets, suggesting a need for further investigations that are beyond the scope of this study. While not providing direct validation, the indirect consistency between datasets aids identifying problems and guiding model/data assimilation improvements.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: <https://cds.climate.copernicus.eu/>, <https://www.gleam.eu/>, <https://disc.gsfc.nasa.gov/>.

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