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## Intra-annual relationship between precipitation and forest disturbance in the African rainforest

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## LETTER

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**Abstract**

Analysis of forest disturbance patterns in relation to precipitation seasonality is important for understanding African tropical forest dynamics under changing climate conditions and different levels of human activities. Newly available radar-based forest disturbance information now enables an investigation of the intra-annual relationship between precipitation and forest disturbance in a spatially and temporally explicit manner, especially in the tropics, where frequent cloud cover hinders the use of optical-based remote sensing products. In this study, we applied cross-correlation on monthly precipitation and forest disturbance time series for 2019 and 2020 at a 0.5° grid in the African rainforest. We used the magnitude of the correlation and time lag to assess the intra-annual relationship between precipitation and forest disturbance, and introduced accessibility proxies to analyse the spatial variation of the relationship. Results revealed that a significant negative correlation between forest disturbance and precipitation dominates the study region. We found that significant negative correlations appear on average closer to settlements with overall smaller variations in travel time to settlements compared to grid cells with non-significant and significant positive correlation. The magnitude of the negative correlation increases as the travel time to settlements increases, implying that forest disturbances in less accessible areas are more affected by precipitation seasonality and that in particular human-induced disturbance activities are predominantly carried out in the drier months. Few areas showed a significant positive correlation, mainly resulting from natural causes such as flooding. These new insights in the interaction between forest disturbance, precipitation and accessibility provide a step forward in understanding the complex interactions that underlie the complexity of forest loss patterns that we can increasingly capture with Earth Observation approaches. As such, they can support forest conservation and management in coping with climate change induced changes of precipitation patterns in African rainforest countries.

**1. Introduction**

The African humid tropical forests is the second largest rainforest and among the most biodiverse ecosystems in the world (Malhi *et al* 2013, Sullivan *et al* 2017). It accounts for 28% of the aboveground biomass in the world's tropical forests (Baccini *et al* 2012), with an aboveground biomass ranging

between 200 and 400 Mg ha<sup>-1</sup> (Lewis *et al* 2009, 2013). Being an important natural carbon sink (Pan *et al* 2011), the African rainforest plays a fundamental role in the global carbon cycle (Ploton *et al* 2020). However, the African rainforest experiences increased forest disturbances rates with over 7 Mha forest loss for the period between 2002 and 2020 (Hansen *et al* 2013). Forest disturbance rates will

likely further increase in the upcoming decades due to an expected strong population growth in the region (Tyukavina *et al* 2018).

Forest disturbances in the African rainforest are largely driven by smallholder agriculture (Curtis *et al* 2018), with more recent major contributions from logging, mining and commercial agriculture (Mitchard 2018, Pacheco *et al* 2021). For example, Tyukavina *et al* (2018) related 84% of forest disturbance in the Congo Basin to smallholder agriculture. Specific anthropogenic forest disturbance activities can vary locally (Teegne *et al* 2016), with major selective logging operations in Gabon (Tyukavina *et al* 2018), cocoa agroforestry in Ghana and Côte d'Ivoire (Ruf *et al* 2015), large-scale agriculture in Cameroon (Pacheco *et al* 2021), and fuelwood and charcoal production in the northern part of the Democratic Republic of Congo (DRC) (Pacheco *et al* 2021).

As forest disturbance is dominated by smallholder agriculture with the majority of which is rain-fed (FAO 2016), analysing the relationship between precipitation and forest disturbance is important to understand the trend and pattern of anthropogenic forest disturbance in the African rainforest. Various local-to-regional scale studies in the African rainforest have investigated the interactive effects between forest cover, forest disturbances, and precipitation (Malhi and Phillips 2004, Malhi *et al* 2013, Kosmowski *et al* 2016, Desbureaux and Damania 2018, Leblois 2021). Precipitation has a direct impact on the distribution of the rainforest cover (Malhi *et al* 2013). Small changes in precipitation total or in intensity or duration of the dry season can cause large-scale changes in African rainforest cover (Malhi *et al* 2013). Precipitation changes can affect the occurrence of natural forest disturbances by altering the frequency, intensity, duration and timing of fire, droughts and flooding (Overpeck *et al* 1990, Dale *et al* 2001).

Besides the effect of precipitation on forest cover extent and natural forest disturbance, recent studies have focused on the impact of precipitation on human-induced forest disturbance. Precipitation is considered as an underlining driver for human-induced forest disturbance, the influence of which is mainly exerted through altering the pattern of land management. Forest disturbance patterns can be influenced by changes in the total, frequency and intensity of precipitation, and a shift in seasonality (Aragao *et al* 2008, Costa and Pires 2010, Lawrence and Vandecar 2015). Extensive studies in the Amazon rainforest indicate that a longer or more intense dry season can lead on average to higher amounts of forest being converted to croplands (Leite-Filho *et al* 2020, Staal *et al* 2020). Similar patterns have been observed in African rainforest regions in Madagascar (Desbureaux and Damania 2018) and West Africa (Leblois 2021).

Drier conditions facilitate human-induced forest disturbance in the tropics mainly in two ways. Firstly,

traditional slash-and-burn agriculture or clearing of undergrowth by fire, is easier when the conditions are drier (Barlow *et al* 2020, Staal *et al* 2020). Secondly, drier conditions produce negative impacts on crop productivity, which in turn can lead to more clearing of forests for agriculture (Costa and Pires 2010, Desbureaux and Damania 2018, Sonwa *et al* 2020, Leblois 2021). Kosmowski *et al* (2016) concluded that changes in the rainy season length influences decisions of farmers in Niger on when and how much to open new fields, leading to different forest disturbance patterns. Droughts and a short rainfall season have shown to lead to a large forest disturbance increase, with studies in Madagascar (Desbureaux and Damania 2018) and Western Africa (Leblois 2021) showing up to 17% and 20% increase in forest disturbance respectively, mainly as a response to decreased agricultural productivity.

Accessibility is found to be a dominant predictor for forest disturbance in the African rainforest (Ernst *et al* 2013, Sandker *et al* 2017). Roads facilitate forest disturbance by providing access for resource extraction and/or conversion (Chomitz and Gray 1996, Kleinschroth *et al* 2019), and by reducing travel time to markets which further boosts agriculture or selective logging activities (Ordway *et al* 2017, Jayathilake *et al* 2021). Moreover, a positive correlation between forest fragmentation and forest disturbance has been found in primary forest in the tropics (Hansen *et al* 2020). Fragmented forest with better accessibility are more targeted by logging or agricultural activities compared to intact forest (Bogaert *et al* 2008). Complex interaction exists between accessibility, forest disturbance and changing precipitation patterns in the African rainforest (Asefi-Najafabady and Saatchi 2013, Staal *et al* 2020, Leblois 2021).

Understanding the intra-annual relationship between precipitation and forest disturbance and how the relationship varies in areas with different accessibility will help to unravel the complexity of forest disturbance patterns in response to the changing precipitation patterns. This is particularly important in the African rainforest where the length and frequency of dry seasons is predicted to increase due to changing climate patterns (Paeth and Friederichs 2004, Jiang *et al* 2019, Bennett *et al* 2021). It seems reasonable to hypothesise that precipitation change has a strong impact on anthropogenic forest disturbance in African rainforest, where 95% of the small-scale agriculture is rain-fed (FAO 2016). However, the relationship is understudied in both scale and temporal frequency as no study has yet looked at the intra-annual relationship between precipitation and forest disturbance in the African rainforest. In addition, spatially explicit analysis of the influence of accessibility on the relationship between precipitation and forest disturbance over the whole African rainforest region is still missing.

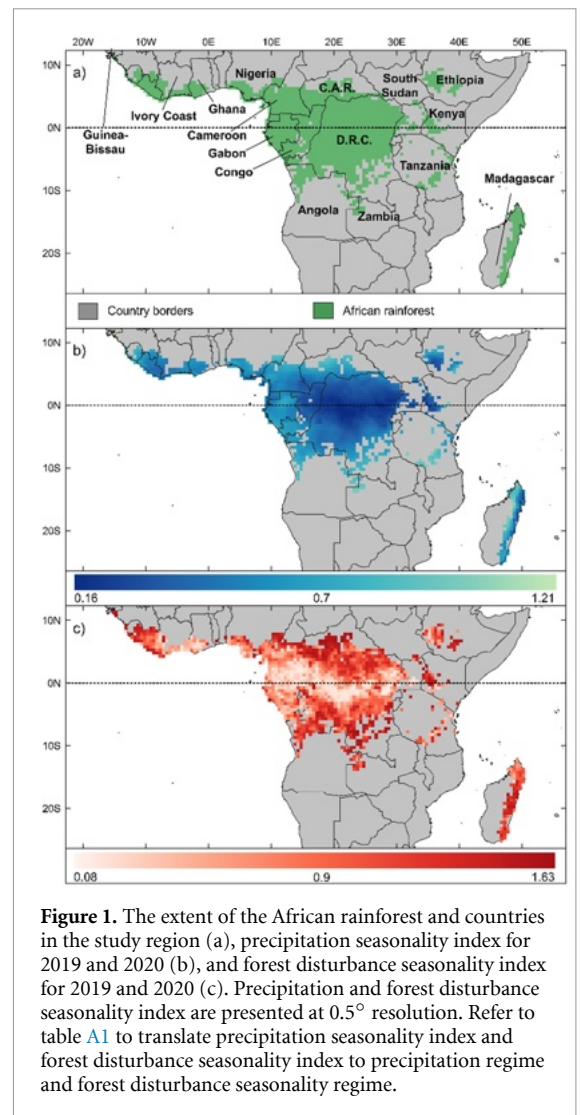
Although precipitation data provides more temporal details (e.g. in monthly, daily or even hourly), forest disturbance data was not available with such high temporal resolution. Most studies assessing the relationship between precipitation and forest disturbance depended on annual forest disturbance data derived from optical remote sensing imagery (Asefi-Najafabady and Saatchi 2013, Desbureaux and Damania 2018, Staal *et al* 2020, Leblois 2021). Other studies aggregated data across a large geography (e.g. entire Amazon basin) and neglect important spatial variation in precipitation and forest disturbance by, for example, averaging opposing seasonality of locations north and south of the equator (Aragao *et al* 2008). Relying on annual information does not allow for a detailed assessment on forest disturbance seasonality and on how this seasonality is affected by precipitation seasonality. Additionally, persistent cloud coverage in the African tropics often decreases the availability of optical satellite imagery, resulting in omission errors or strongly delayed detection of forest disturbances (Hirschmugl *et al* 2020, Reiche *et al* 2021). The missing temporal detail and potential delays in detecting forest disturbances are a research gap that can be tackled by generated radar-based forest disturbance maps. With temporally dense imagery from the cloud-penetrating Copernicus Sentinel-1 radar satellites forest disturbance can now be mapped at a high temporal and spatial detail (Reiche *et al* 2021).

Here, we combined monthly precipitation and monthly forest disturbance time series to assess how forest disturbances respond to precipitation seasonality in the African rainforest and to what extent accessibility affects this relationship. More specifically, we:

- Assessed the spatially explicit intra-annual relationship between precipitation and forest disturbance in the African rainforest.
- Investigated the influence of accessibility on the intra-annual relationship between precipitation and forest disturbance.

## 2. Study area

The study area covers the African rainforest ranging across 26 countries with the majority located in the Congo basin (figure 1(a)). Other major rainforests are located in the Guinean Forests of West Africa, the Coastal Forests of Eastern Africa and the forests of Madagascar (Turubanova *et al* 2018). We define the African rainforest extent for the year 2018 as primary humid tropical forest (Turubanova *et al* 2018) with 2001–2018 annual forest loss (Hansen *et al* 2013) and mangrove (Bunting *et al* 2018) removed. The annual precipitation for the study area varies between a minimum of 600 mm at the edge of the rainforest and up to 3000 mm along the equator (Funk *et al* 2014). The precipitation seasonality is also highly variable



**Figure 1.** The extent of the African rainforest and countries in the study region (a), precipitation seasonality index for 2019 and 2020 (b), and forest disturbance seasonality index for 2019 and 2020 (c). Precipitation and forest disturbance seasonality index are presented at  $0.5^\circ$  resolution. Refer to table A1 to translate precipitation seasonality index and forest disturbance seasonality index to precipitation regime and forest disturbance seasonality regime.

and covers annual (one wet season per year), bi-annual (two wet seasons per year) and humid (may not exhibit a dry season in all years) precipitation seasonality regimes (Dunning *et al* 2016). Over the last decade major deforestation fronts in the African rainforest were located in Cameroon, Gabon, and DRC (Pacheco *et al* 2021). New forest disturbance fronts have also appeared in West and East Africa (e.g. Liberia, Ivory Coast, Ghana and Madagascar) (Pacheco *et al* 2021) (figure 1(c)).

## 3. Data and methods

We investigated the intra-annual relationship between precipitation and forest disturbance for the African rainforest for 2019 and 2020 on a monthly and grid cell basis. We masked each dataset at a 30 m resolution using the forest baseline product defined in section 2, before resampling it to the grid cell scale. We defined a grid size of  $0.5^\circ$  ( $\sim 3080 \text{ km}^2$ ) and removed grid cells without precipitation data, or with forest disturbance totals  $< 10 \text{ ha}$ . In total, 1498 out of the total 2002 forested grid cells are considered for the analysis.

**Table 1.** Precipitation, forest disturbance and accessibility indexes used in this study.

	Index	Definition	Reference
Precipitation	Precipitation total	Accumulated sum of monthly precipitation	Data: CHIRPS (Funk <i>et al</i> 2014)
	Precipitation seasonality index	Degree of variability in monthly precipitation throughout the year. A relative measure that assesses seasonal contrasts between precipitation amounts rather than defines wet or dry season in an absolute sense. Increasing index values show a more defined dry season (figure 1(b) and table A1).	Data: CHIRPS (Funk <i>et al</i> 2014) Method: Walsh and Lawler (1981)
	Number of precipitation peaks	Number of months with precipitation larger than their two neighbouring months.	Data: CHIRPS (Funk <i>et al</i> 2014) Method: Kendall (1976)
	Length of dry season	Number of consecutive months with monthly precipitation < 100 mm.	Data: CHIRPS (Funk <i>et al</i> 2014) Method: Otto <i>et al</i> (2013)
Forest disturbance	Forest disturbance total	Accumulated sum of monthly forest disturbance.	Data: RADD (Reiche <i>et al</i> 2021)
	Forest disturbance seasonality index	Degree of variability in forest disturbance throughout the year. A relative measure that assesses seasonal contrasts between forest disturbance amounts rather than defines low or high forest disturbance intensities in an absolute sense. Increasing index values show a more defined forest disturbance season (figure 1(c) and table A1).	Data: RADD (Reiche <i>et al</i> 2021) Method: Walsh and Lawler (1981)
	Number of disturbance peaks	Number of months with forest disturbances larger than their two neighbouring months.	Data: RADD (Reiche <i>et al</i> 2021) Method: Bogaert <i>et al</i> (2000)
Accessibility	Forest edge-interior ratio	Ratio between edge and interior pixels of all forest patches in 2018. It is a measure of the forest fragmentation.	Data: RADD (Reiche <i>et al</i> 2021) Method: Kendall (1976)
	Travel time to settlements	Travel time to the nearest settlements with populations over 5000.	Data and method: Nelson <i>et al</i> (2019)

### 3.1. Precipitation total and seasonality

Monthly precipitation data from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) version 2.0 were used to generate monthly precipitation time series (Funk *et al* 2014). We resampled data from the original resolution of  $0.05^\circ$  to  $0.5^\circ$  using the average and calculated the accumulated sum for both years. We further derived the precipitation seasonality index, number of precipitation peaks and the length of dry season from the time series to describe the temporal distribution of precipitation on a monthly basis (table 1). The precipitation seasonality index was calculated for 2019 and 2020. Number of precipitation peaks was calculated as the number of local maxima of the kernel smoothed time series. We only included local maxima greater than median/2 of the respective time series.

### 3.2. Forest disturbance total and seasonality

Monthly time series of forest disturbance were derived from the Radar for Detecting Deforestation (RADD) alerts (Reiche *et al* 2021). The RADD alerts

provide forest disturbance information every 6 or 12 d at a pixel spacing of 10 m. To account for delay in forest disturbance detection due to the 6- or 12 d repeat cycle of the Sentinel-1 satellites, 3 and 6 d were subtracted from the detection date, respectively. We summed up all detected disturbances with the adjusted detection date within a  $0.5^\circ$  grid cell to generate monthly forest disturbance data.

Forest disturbance total and its temporal distribution measured by forest disturbance seasonality index and number of disturbance peaks were derived from the monthly forest disturbance time series (table 1). Forest disturbance seasonality index was calculated for 2019 and 2020. Number of forest disturbance peaks was calculated as the number of local maxima of the kernel smoothed time series. We only included local maxima greater than median/2 of the respective time series.

### 3.3. Accessibility

We introduced forest edge-interior ratio and travel time to settlements to study the influence of

accessibility on the magnitude of the intra-annual correlation between precipitation and forest disturbance (Asefi-Najafabady and Saatchi 2013, Aguiar *et al* 2022). Because the interior of a forest is likely to be less accessible to human-induced disturbances, a lower edge-interior ratio normally corresponds to a less fragmented forest or landscape with more circular-shaped forest patches, which leads to less accessibility to forest resources. We located all forest patches within the boundaries of the 2018 African rainforest extent (section 2). A one-pixel edge buffer (30 m) was applied to define the edge pixels, whilst the remaining pixels were defined as interior pixels. The edge-interior ratio was calculated by dividing the number of edge pixels by the number of interior within each 0.5° grid cell.

Travel time to settlements was derived from a suite of global accessibility indicators for 2015 (Nelson *et al* 2019), and was averaged from its original resolution of 1 km to 0.5° grid cell. We define settlements as locations with populations over 5000.

### 3.4. Analysis of the intra-annual correlation between precipitation and forest disturbance

Due to varying forest disturbance processes, management practices and shifts in rainfall seasonality, there might be delays in forest disturbance in response to precipitation. We used cross-correlation functions (CCFs) to analyse the time-lagged relationships between forest disturbance and precipitation. The CCFs are based on auto-correlation functions which detect seasonality of a univariate time series by calculating the correlation of a shifted version of itself (Venables and Ripley 2013). The CCFs use the same principle for multi-variate time series in order to calculate the similarity between two signals as a function of their displacement relative to one another (Holmes *et al* 2021).

We shifted the forest disturbance time series forward and backwards in time (resulting positive and negative time lag respectively) with precipitation time series being stationary. For each monthly shift the correlation coefficient between two time series was calculated (equation (1), based on Vio and Wamsteker (2001)). We limited the shift to 3 months to avoid including seasonality from previous and/or following years, especially in biannual climate areas. The direction of the shift was determined by the direction of the relationship at the initial time step of both time series. The forward shift meant that forest disturbance peak was more correlated to the peak of the precipitation; whilst a backward shift represented a stronger correlation between the forest disturbance peak and the driest months of the year. We used a 95% confidence interval to distinguish between significant and non-significant correlations. The significance level of the relationship was based on the length of the time series and the time lag, calculated by equation (2) (Vio and Wamsteker 2001, Hanson and Yang 2008,

Holmes *et al* 2021). With the length of 24 months for our investigation, a time lag of 0, 1, 2 and 3 months resulted in  $\pm 0.408$ ,  $\pm 0.417$ ,  $\pm 0.426$ , and  $\pm 0.436$  as the threshold for the significance level for a negative and a positive correlation respectively.

Five indicators were generated from the CCFs: (a) the highest correlation coefficient of all calculated time shifts, (b) the direction of the highest correlation coefficient, (c) the number of shifts needed to reach this correlation coefficient, (d) the direction of the shift, and (e) the significance level of the correlation. They were used to identify the nature of the intra-annual relationship between precipitation and forest disturbance and how they are correlated in time.

We examined the locations where the significant and non-significant, positive and negative correlation coefficient occur and investigated the spatial distribution of the magnitude of the correlation coefficient and their corresponding accessibility.

$$CC_{\text{Cor}_{\text{tlag}k}} = \frac{\sum_{t=1}^{n-k} (y_t - \bar{y})(x_{t+k} - \bar{x})}{\sqrt{\sum_t^n (y_t - \bar{y})^2 \sum_i^n (x_i - \bar{x})^2}} \quad (1)$$

with  $CC_{\text{Cor}_{\text{tlag}k}}$  being the correlation coefficient for the time lag  $k$ ,  $y_t$  being the precipitation at time  $t$ ,  $\bar{y}$  being the mean of precipitation,  $x_t$  being the forest disturbance at time  $t$ ,  $\bar{x}$  being the mean of forest disturbance and  $k \in -3, -2, -1, 0, +1, +2, +3$  being the applied shift to  $x$ .

$$\pm \frac{2}{\sqrt{n-k}} \quad (2)$$

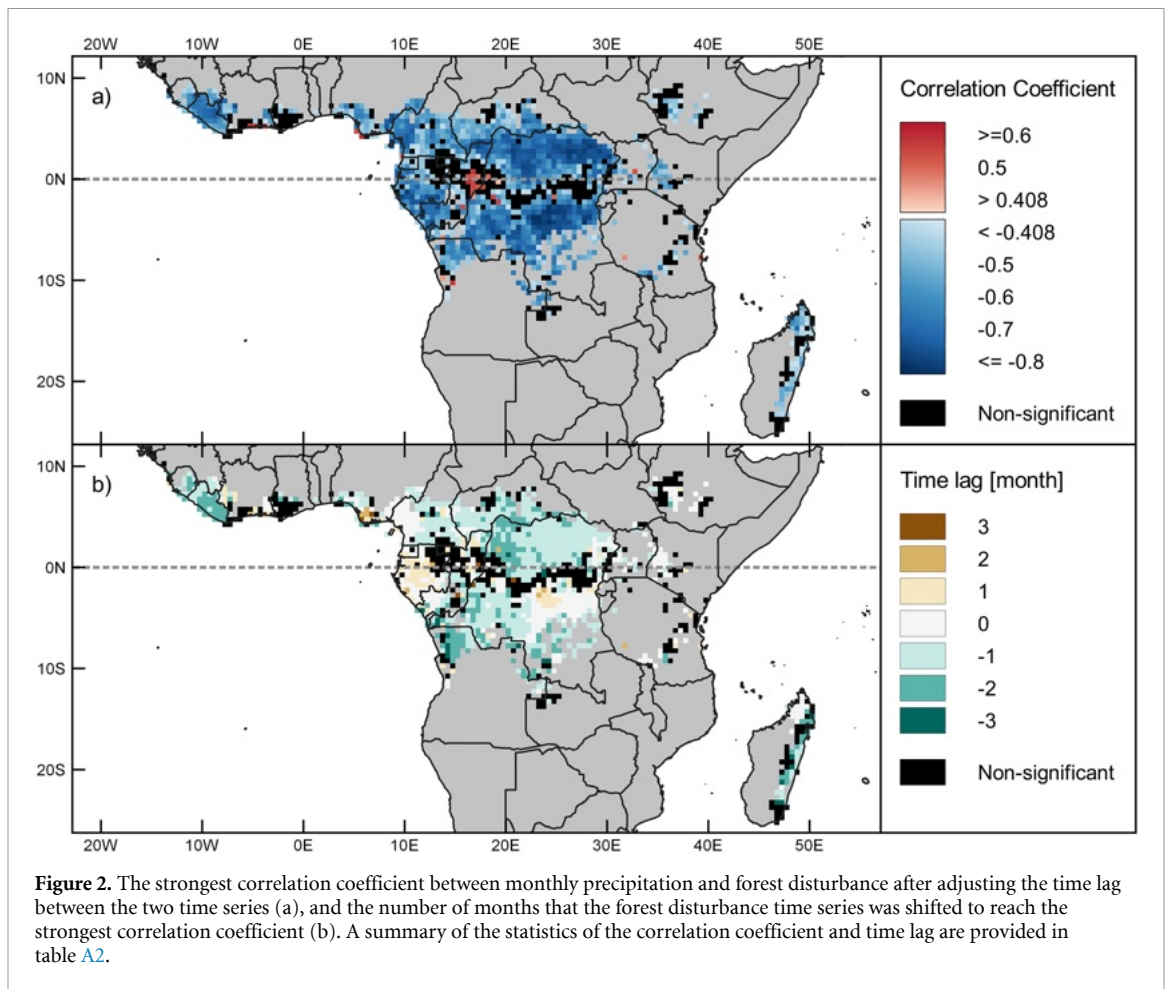
with  $n$  being the length of the time series and  $k$  the absolute value of the time lag.

## 4. Results

### 4.1. Seasonality of forest disturbance, precipitation, and their intra-annual relationship

We found 77% (1151) and 2% (29) out of the grid cells (1498) to have a significant negative and positive correlation between forest disturbance and precipitation, respectively (figure 2(a)). For 21% (318) of the grid cells a non-significant correlation was found.

For the majority of the significantly negatively correlated grid cells (79%, 907 out of 1151) the highest correlation was found with no time lag or a time lag of one month, meaning that forest disturbance peaks one month before (with positive time lag) or after (with negative time lag) the driest month(s) of the year (figure 2(b)). A clear seasonal pattern of both precipitation and forest disturbance time series are necessary to result in a significant negative correlation (figure 3(a)). Most of the significantly negatively correlated grid cells have a precipitation seasonality index between 0.3 and 0.7, which falls within the precipitation regime of 'Rather seasonal with a short drier season' or 'Seasonal', and with a length of dry



season ranging between 2 and 4 months (figure A1). The forest disturbance seasonality of these grid cells exhibit a marked pattern with one peak per year (figure A1).

We found 79% (23 out of 29) of the significantly positively correlated grid cells to have the peak of forest disturbance one month before or after the peak of precipitation (figure 2(b)). Grid cells with a significant positive correlation cluster near the equator, at the border between the Republic of Congo and the DRC (figure 2(a)) in regions with mainly ‘*Precipitation spread throughout the year*’ (precipitation seasonality index between 0 and 0.4) (figure 1(b)). Various patterns of forest disturbance seasonality are found in those grid cells, but generally with a lower magnitude of forest disturbances compared to grid cells with a significant negative correlation (figure A1).

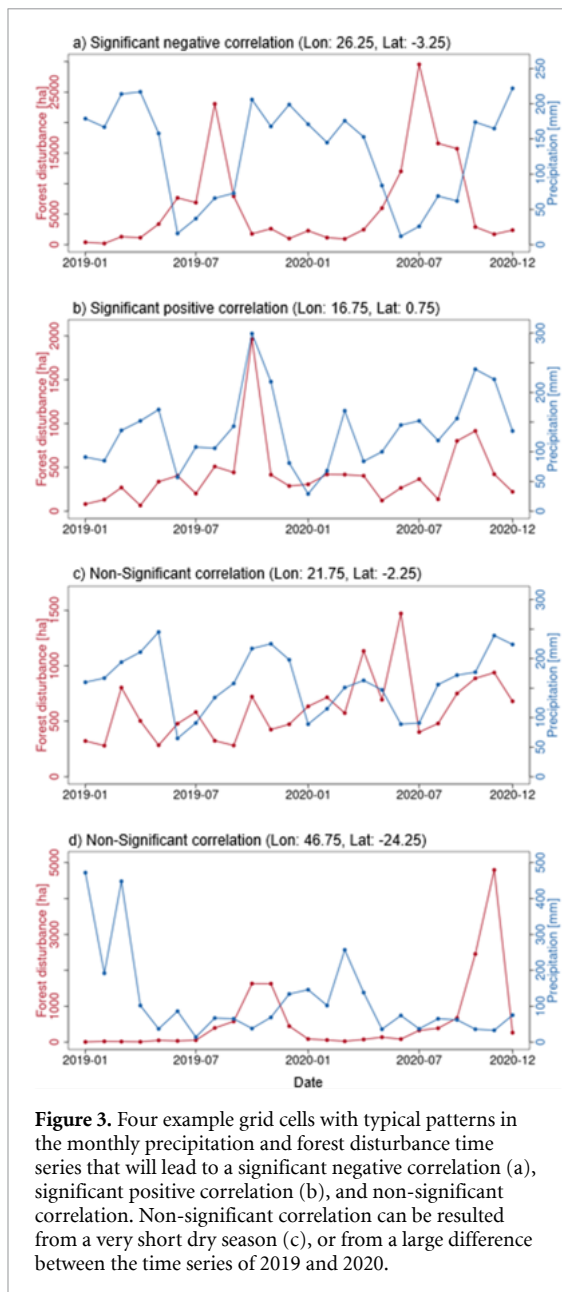
Grid cells with a non-significant correlation are located either in the dense rainforest near the equator, or at the edge of the rainforest (figure 2(a)). Various precipitation and forest disturbance seasonality patterns can be found in those grid cells, for example, areas with less precipitation seasonality (humid all year or very short dry season, figure 3(c)), and areas with major differences in forest disturbance or precipitation amounts between 2019 and 2020

(figure 3(d)). In general, they have less forest disturbance seasonality compared to the other two groups (figure A1).

The time lag to reach the highest correlation coefficient between the precipitation and forest disturbance shows a distinct spatial distribution (figure 2(b)). Gabon is dominated by a one-month positive time shift. Other positive time lag grid cells clustered in small regions in the Southeast of the DRC and Nigeria. Grid cells with no time shift locate along the coast of Cameroon, in the southeast of the DRC, and between Gabon and the Republic of the Congo. Grid cells with a one-month negative time shift occupy large areas in the DRC, Central African Republic and Cameroon. Liberia and clusters in Angola and at the borders between the Republic of the Congo and DRC show a 2–3 month negative shift.

#### 4.2. Influence of accessibility on the precipitation-forest disturbance relationship

We found that significant negative correlation appears on average closer to settlements with overall smaller variations of travel time to settlements ( $238 \pm 200$  min) compared to grid cells with a non-significant ( $341 \pm 326$  min) and significant



**Figure 3.** Four example grid cells with typical patterns in the monthly precipitation and forest disturbance time series that will lead to a significant negative correlation (a), significant positive correlation (b), and non-significant correlation. Non-significant correlation can be resulted from a very short dry season (c), or from a large difference between the time series of 2019 and 2020.

positive ( $443 \pm 430$  min) correlation (figure 4(a)). Moreover, among all grid cells with a significant negative correlation, stronger negative correlation showed longer time travel to settlements than grid cells with weaker negative correlation. Grid cells with a significant positive correlation showed an increasing trend in travel time to settlements with a big variation as the correlation increased.

The Forest edge-interior ratio showed differences between grid cells with weak (correlation coefficient between  $-0.408$  and  $-0.7$ ) and strong negative correlation (correlation coefficient  $\leq -0.7$ ). The negative correlation becomes stronger as forest become less fragmented (figure 4(b)). Overall, grid cells with strong negative correlation show the lowest edge-interior ratio in the mean and the standard deviation ( $0.22 \pm 0.20$ ), whilst grid cells with weak

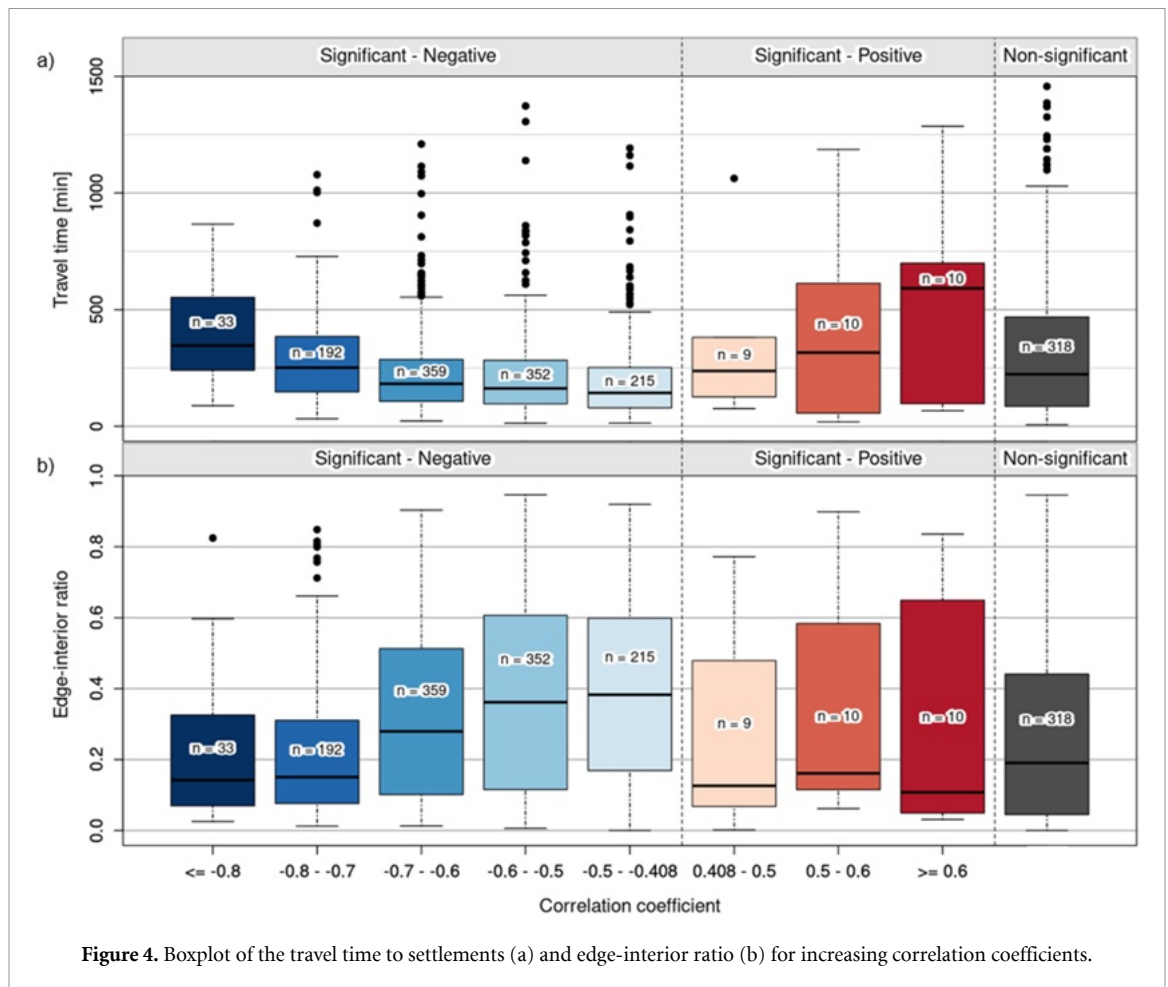
negative correlation show the highest edge-interior ratio ( $0.36 \pm 0.26$ ). In contrast, grid cells with a significant positive correlation show on average less fragmentation albeit with a high spread of values ( $0.29 \pm 0.30$ ). Grid cells with a non-significant correlation depicted a similar trend with the weaker negatively correlated grid cells with a mean and a standard deviation of  $0.27 \pm 0.25$ .

## 5. Discussion

The majority of the African rainforest (figure 2) showed a significant negative correlation between precipitation and forest disturbance seasonality with more forest disturbances during the drier months, which is in accordance with findings from the Amazon rainforest (Aragao *et al* 2008). Our findings suggest that the strength of a significant negative correlation is driven by accessibility (figure 4). By correlating monthly precipitation data and weather-independent monthly forest disturbance data, we showed that the negative correlation between precipitation and forest disturbance not only existed as an annual relationship (Asefi-Najafabady and Saatchi 2013, Desbureaux and Damania 2018, Staal *et al* 2020, Leblois 2021), but also as a significant intra-annual relationship.

Stronger negative correlation generally occurred further away from the edges and inside remote and less fragmented intact forests (figure 4), and further away from the equator (figure 2). A stronger negative correlation found in less accessible areas showed that the forest disturbance peak was exclusively and strongly correlated to the driest months of the year. Forest disturbances in the African rainforest are strongly associated to road accessibility (Ernst *et al* 2013, Sandker *et al* 2017) and land availability for the extension of cropland (Leblois 2021). Areas with less accessibilities can potentially prohibit continued access to the forest interior in the wet season (Kleinschroth *et al* 2019), and are less likely to be limited by land availability (Leblois 2021). This leads to the strong correlation between forest disturbance and precipitation in less accessible areas. The findings suggest that less accessible areas will likely be more influenced by precipitation change and forest disturbance activities are more likely to be exclusively carried out in the drier months (figure 4). This result is in line with findings, based on annual forest disturbance data, in West and Central Africa where a short rainfall season led to a higher increase in forest disturbance in unconnected areas with a small proportion of crop area, compared to more connected areas, or areas with significant forest cover (Leblois 2021). Asefi-Najafabady and Saatchi (2013) observed a strong response to drought with widespread canopy disturbance in fragmented landscapes of the northern Congo Basin and West Africa, whilst intact





**Figure 4.** Boxplot of the travel time to settlements (a) and edge-interior ratio (b) for increasing correlation coefficients.

humid forest in Central Africa showed no significant response to the same drought events. Recent theory-driven results in Argentina (Aguar *et al* 2022) and existing land use theories and neo-classical economic theories of land rent also support our findings (Meyfroidt *et al* 2018). Longer or more intensive dry seasons may increase forest fragmentation by facilitating the escape of fires into larger neighbouring areas in already fragmented landscapes, potentially making more accessible areas even more attractive for subsequent forest disturbance activities (Staal *et al* 2020). However, whether a production loss from precipitation change will push smallholder farmers to increase the size of the cultivated area is also dependent on the presence of alternative income sources and the availability of land for the extension of cultivated area (Leblois 2021). Both factors are also strongly influenced by accessibility, with more accessible areas likely to have other income sources and less available land, and thus under less impact from precipitation change (Leblois 2021).

About 2% of the study area showed a positive relationship, mainly areas located along the equator and within the Cuvette Centrale, the single largest peatland complex known in the tropics (Dargie *et al* 2017). The Republic of the Congo part of the Cuvette

Centrale is very sparsely populated and human forest activities are rare (Dargie *et al* 2019, OCHA 2019a). The positive correlation can be linked to flooding-related forest disturbances peaks during the wet season month. In October 2019 heavy rains caused a major flood and forest disturbances along the Congo and Ubangi River (figure 3(b)) (Sunnen and Yama 2019).

In general, non-significant correlation was either found in regions with consistently high precipitation rates in combination with consistently low forest disturbance rates resulting in weak seasonality for both parameters (figure 3(c)), or in regions with a large difference in forest disturbance seasonality in 2019 and 2020 (figure 3(d)). A non-significant correlation can also reflect a mix of forest disturbance processes which lead to a weak seasonality pattern in forest disturbance. For example, the DRC part of the Cuvette Centrale was also hit by the described 2019 flooding event (OCHA 2019b). Contrary to its adjacent part in the Republic of the Congo, a non-significant correlation instead of a positive correlation was detected (figure 2(a)). This might be explained by the fact that the region also experiences major commercial logging activities (Dargie *et al* 2019) during the dry season and this signal is mixed up with the signal from

flooding-related forest disturbances during the wet season.

In summary, a significant negative correlation is observed in areas dominated by human-induced forest disturbances including commercial logging or smallholder agriculture (e.g. DRC), while significant positive correlation was observed mainly in areas dominated by natural flood-related forest disturbances. Non-significant correlation occurred in areas dominated by various forest disturbance drivers. This indicates that correlation coefficients alone are not sufficient to separate different forest disturbance processes. Follow-up studies with longer time series in areas dominated by different forest disturbance processes may reveal more information on how the strength of the intra-annual relationship between precipitation and forest disturbance is linked to different deforestation processes. One example can be the DRC part of the Cuvette Centrale where recently large areas of commercial logging concessions were granted (Farand 2021).

Our results suggest a clear spatial distribution of the time lag between the monthly precipitation and forest disturbance time series. Forest disturbance in most regions peaks  $\pm 1$  month around the driest month(s) of the year. The distinct spatial pattern in time lags (figure 2) might link to certain forest disturbance processes in the African rainforest. For example, positive time lags were visible especially in Gabon, showing that forest disturbance peaks one month before the driest month(s) of the year. Large-scale commercial agriculture and selective logging are the main driving factors for forest disturbance in Gabon (Legault and Cochrane 2021, Pacheco *et al* 2021). Heavy machinery commonly used for selective logging might allow for the beginning of logging activities very early in the dry season or end of the wet season resulting in a positive time lag (Tyukavina *et al* 2018). Further investigation is needed to assess whether observed time shifts can be causally linked to varying forest disturbance processes.

Although the availability of dense radar-based forest disturbance information (Reiche *et al* 2021) limited our study period to two years, the correlation found between monthly precipitation and monthly forest disturbance is statistically significant and exhibited a clear spatial distribution. The cross-correlation showed great ability in exploring the lagged intra-annual relationship between precipitation and forest disturbance (Vio and Wamsteker 2001). Compared to an exponentiation model without considering the time shifts between two time series, we found nearly 55% more grid cells to show a significant relationship (without shift 51%, and with shift 79%). Furthermore, using a

cross-correlation can overcome potential late detection of forest disturbances due to various environmental influences (e.g. soil moisture) on the radar signal (Reiche *et al* 2021).

With continuing and increasingly longer time series of spatially and temporally detailed dense radar-based forest disturbance information, analysing the long-term intra-annual interaction between climate and land use dynamics will become feasible. This is particularly important for the African rainforest, where various climate models have projected increased drought periods and frequencies and change in dry seasons (Paeth and Friederichs 2004, Jiang *et al* 2019, Bennett *et al* 2021). Considering the strong negative correlation found for most areas in the African rainforest, these changes in precipitation might lead to even further increased forest disturbances in the African rainforest. Although annual forest disturbance already provides important indications on how anthropogenic forest disturbance responds to climate change, understanding the seasonal interactions and factors that affect this relationship will help to better understand the impact of climate change in bi-annual and humid climate regimes. Moreover, this intra-annual relationship could help to reveal different forest disturbance processes. This information may provide further insights for forest management in African rainforest to predict when and where the hotspot or high-risk areas will be under the changing climate.

## 6. Conclusion

For the first time temporally dense and spatially detailed forest disturbance information derived from cloud-penetrating radar satellites provides the level of temporal detail that enables the investigation of the intra-annual relationship between precipitation and forest disturbances in the African rainforests. We analysed the response of forest disturbance to precipitation using the direction and magnitude of the correlation coefficient and time lag needed to reach this correlation.

A significant negative correlation between forest disturbance and precipitation dominates the study region, with the magnitude of the negative correlation strongly correlating with accessibility. Stronger negative correlation occurred in less accessible areas, suggesting a stronger influence of precipitation change in those areas. Most forest disturbance activities happen during the driest month(s) of the year with a time lag of  $\pm 1$  month. The few areas with a significant positive relationship were most likely caused by natural disturbances such as flooding. Non-significant correlation is found in regions with weak precipitation or forest disturbance seasonality.

New insights on the interaction between forest disturbance precipitation and accessibility—as presented here—provide a step forward in understanding the complex interactions that underlie forest loss. These new insights can support forest conservation and management in dealing with climate change induced changes of precipitation patterns in African rainforest countries. In the future, the increasingly longer time series data offer the potential to assess long-term forest disturbance processes and its drivers in a more detailed way.

### Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI:

[www.wur.nl/en/Research-Results/Chair-groups/Environmental-Sciences/Laboratory-of-Geo-information-Science-and-Remote-Sensing/Research/Sensing-measuring/RADD-Forest-Disturbance-Alert.htm](http://www.wur.nl/en/Research-Results/Chair-groups/Environmental-Sciences/Laboratory-of-Geo-information-Science-and-Remote-Sensing/Research/Sensing-measuring/RADD-Forest-Disturbance-Alert.htm); <https://www.chc.ucsb.edu/data/chirps>.

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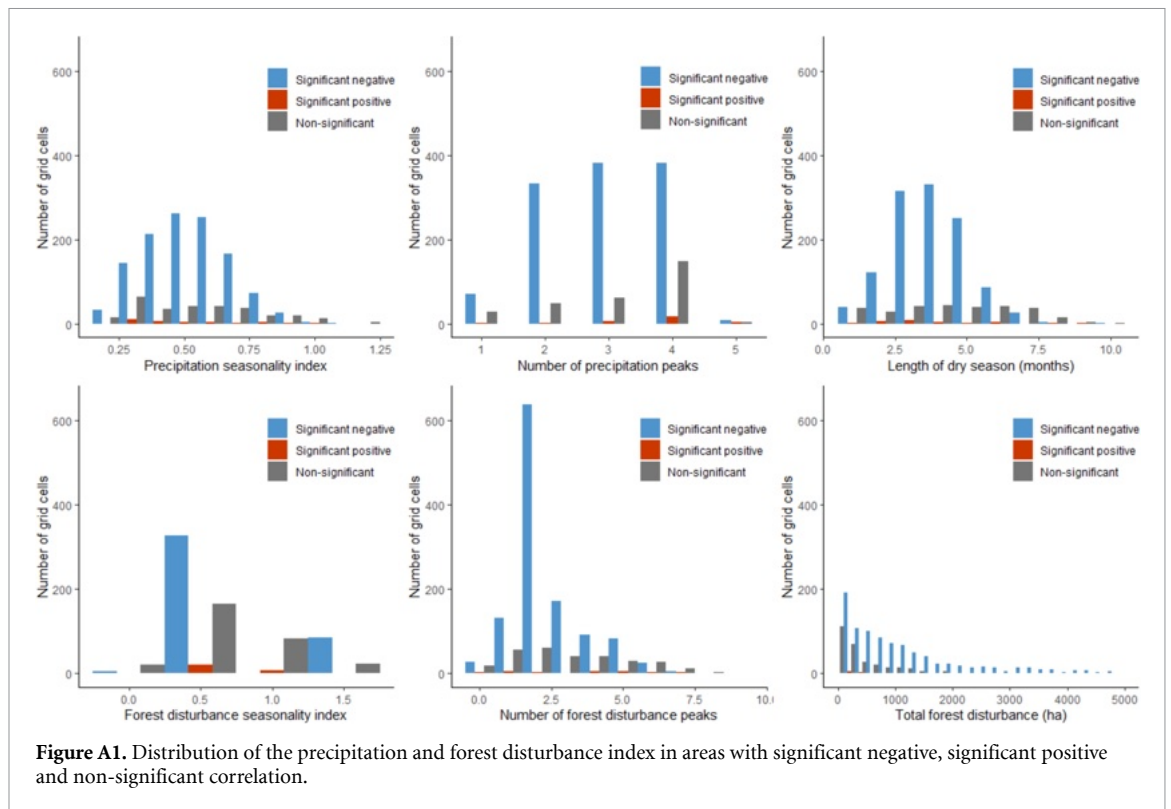
## Appendix

**Table A1.** Precipitation seasonality index with related precipitation regime and forest disturbance seasonality index with related seasonality regime adopted from Walsh and Lawler (1981).

Index value	Precipitation regime	Forest disturbance seasonality regime
0.00–0.19	Precipitation through the year	Forest disturbance through the year
0.20–0.39	Precipitation through the year, but with a definite wetter season	Forest disturbance through the year, but with a definite break
0.40–0.59	Rather seasonal with a short drier season	Rather seasonal with a short break
0.60–0.79	Seasonal	Seasonal
0.80–0.99	Marked seasonal with a long dry season	Marked seasonal with a long break
1.00–1.19	Most precipitation in 3 months	Most forest disturbance in 3 months
$\geq 1.20$	Extreme seasonality, with almost all precipitation in 1–2 months	Extreme seasonality, with almost all forest disturbance in 1–2 months

**Table A2.** Statistics of the correlation coefficient and time lag found for each class.

	Significance level	Correlation coefficient (mean $\pm$ standard error)	Class (cc is the abbreviation for correlation coefficient)	Number of grid cells	Correlation coefficient (mean $\pm$ standard error)
Correlation coefficient (cc)	Significant positive correlation	$0.56 \pm 0.08$	$cc \geq 0.6$	10	$0.65 \pm 0.04$
	Non-significant correlation	—	$0.6 > cc \geq 0.5$	10	$0.55 \pm 0.02$
			$0.5 > cc \geq 0.408$	9	$0.47 \pm 0.02$
			—	318	—
	Significant negative correlation	$-0.61 \pm 0.10$	$-0.5 < cc \leq -0.408$	215	$-0.46 \pm 0.02$
Time lag	—	—	$-0.6 < cc \leq -0.5$	352	$-0.56 \pm 0.03$
			$-0.7 < cc \leq -0.6$	359	$-0.65 \pm 0.03$
			$-0.8 < cc \leq -0.7$	192	$-0.74 \pm 0.03$
			$cc \leq -0.8$	33	$-0.82 \pm 0.02$
			3	27	$-0.14 \pm 0.33$
			2	23	$-0.09 \pm 0.44$
			1	143	$-0.36 \pm 0.37$
			0	413	$-0.51 \pm 0.28$
-1	574	$-0.56 \pm 0.20$			
-2	264	$-0.53 \pm 0.15$			
-3	54	$-0.36 \pm 0.19$			



**Figure A1.** Distribution of the precipitation and forest disturbance index in areas with significant negative, significant positive and non-significant correlation.

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