Multi-decadal trends of low clouds at the Tropical Montane Cloud Forests

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Abstract

Clouds are critical to the biodiversity and function of Tropical Montane Cloud Forests (TMCF). These ecosystems provide vital services to humanity and are considered hotspots of endemism, given that the number of species is restricted to their microclimates. Cloudiness (e.g., the fraction of low-clouds) in these ecosystems is projected to decline owing to global warming, but recent temporal trends remain unclear. Here, we evaluated trends in low-cloud fractions (CF) and other Essential Climatic Variables (ECV) (e.g., surface temperature, pressure, soil moisture, and precipitation) for 521 sites worldwide with TMFCs from 1997 to 2020. Thus, we hypothesize that recent traces of global warming over the last few decades have led to decreases in low-cloud cover on TMCFs. The previous study was also evaluated globally and among biogeographic realms to identify regional trends. We computed trends by aggregating hourly observations from ERA5 reanalysis and CHIRPS into annual averages and then used linear regressions to calculate slopes (i.e., rate of change) (Δ, year⁻¹). Our results suggest that CF trends at the TMCFs range between -64.7 × 10⁻⁴ and 51.4 × 10⁻⁴ CF year⁻¹, revealing that 70% of the assessed sites have experienced reductions in CF. Declines in low-clouds in these ecosystems are 253% more severe than tropical landmasses when peak values of density distribution are compared (TMCFs: -7.8 × 10⁻⁴ CF year⁻¹; tropical landmasses -2.3 × 10⁻⁴ CF year⁻¹). Despite this, CF trends tend to differ among biogeographic realms, as those TMCFs from the Neotropics and Indomalayan realms have the most pronounced declines. Decreases in CF were also associated with increases in surface temperature and pressure and decreases in soil moisture, revealing that the TMCF’s climate is changing to warmer environments. These climatic shifts may represent a fingerprint of global change on TMCFs, highlighting a current threat to species and essential ecosystem services that these ecosystems provide.

1 1. Introduction

Tropical Montane Cloud Forests (TMCFs) are ecosystems located at mid to upper elevations of low mountain systems with high humidity regimes owing to mist or cloud immersion (Bruijnzeel et al., 2011b). The functioning of these ecosystems is driven by the frequency of clouds and the conditions created around them (i.e., solar radiation, horizontal rain, and soil moisture) (Goldsmith et al., 2013; Oliveira et al., 2014). Given their upwind location at high elevations, TMCFs are characterized as filters for capturing atmospheric water
(Bruijnzeel, Mulligan et al., 2011). This confers a vital ecosystem service that supports watersheds for human settlements and prevents erosion on mountainous terrain (Bruijnzeel, Scatena et al., 2011; Oliveira et al., 2014). In many instances, TMCFs have also been considered hotspots of biodiversity and endemism, as they host many species restricted by their microclimates and topography (Gentry, 1992; Karger et al., 2021). However, many of these species are endangered, given their restricted distribution and limited protection of these ecosystems (Betts et al., 2017; Karger et al., 2021).

Current studies suggest that the TMCF’s climate will likely change in coming decades because recent lowland deforestation and global warming can impact their cloud dynamics (Foster, 2001; Helmer et al., 2019; Lawton et al., 2001; Ponce-Reyes et al., 2012). Lowland deforestation can affect cloud dynamics by changing the boundary layer over land (Wang et al., 2009) increasing the orographic cloud base height upwind (Lawton et al., 2001) and reducing cloud formation (Chagnon, 2004; Smith et al., 2023). Likewise, temperature increases can impact cloud dynamics by increasing the base height and evapotranspiration regimes (Still et al., 1999). Changes in cloud regimes, and thus the TMCF’s climate, will likely trigger losses in biodiversity and ecosystem services. For instance, decreases in the abundance of birds, reptiles, and amphibians have been associated with increases in temperature and their effects on cloud-base lifting in these ecosystems (Pounds et al., 2006, 1999). Thus, knowing how cloud regimes have been changing and to what magnitude is critical for the future conservation of these ecosystems.

Although Helmer et al. (2019) predicted that the frequency of clouds at TMCFs will likely decrease in coming decades, it remains unclear whether changes are currently occurring and, if so, how severe they are. Current cloud studies based on simulations or observations in TMCFs have focused on describing their geographic extent (Los et al., 2021; Wilson and Jetz, 2016) or projecting their future climate or extent according climatic scenarios (Helmer et al., 2019; Ponce-Reyes et al., 2012; Rojas-Soto et al., 2012) but not on investigating recent trends in cloudiness. Surprisingly, characterization and monitoring of clouds over TMCFs are rare, with minimal direct observations.

This study highlights the recent climate changes faced by TMCFs and their potential implications for the conservation of this unique ecosystem. Here, we compare current trends in low-cloud fractions (CF) and Essential Climatic Variables (ECV) of 521 TMCFs with tropical areas. In doing so, we hypothesized that recent traces of global warming over the last two decades have led to a decrease in low-clouds on TMCFs. We evaluated this using low-cloud fraction (CF) estimations from ERA5 reanalysis (Hersbach et al., 2020) between 1997 and 2020 and their patterns among biogeographic realms. Overall, CF is defined by ERA5 as the proportion of an area covered by clouds at the lower level of the troposphere, a level at which clouds may occur with a pressure greater than 0.8 times the surface pressure (Hersbach et al., 2018). It is likely that the presence of clouds at low levels represents the phenomenon of cloud immersion in TMCFs; thus, they could be used as a potential descriptor of the cloudiness that prevail in these ecosystems.

2 2. Materials and Methods

2.1 2.1 Tropical Montane Cloud Forests

The spatial distribution of TMCFs has been explored by several authors (Aldrich et al., 1997a; Helmer et al., 2019; Los et al., 2021; Wilson and Jetz, 2016). However, there is no consensus on zoning or delimiting its global distribution. The United Nations Environment Programme - World Conservation Monitoring Center (UNEP-WCMC) efforts have helped identify 529 TMCFs distributed worldwide (Aldrich et al., 1997a). These TMCFs were identified by a global directory of experts that described main sub-national cloud forest regions and sites along with their latitude and longitude (details in Aldrich et al., 1997b). Here, we used these TMCFs to select and extract climatic trends associated with these ecosystems (Section 2.3). Similarly, to evaluate how climatic trends are affected by the spatial distribution of these ecosystems, we classified these TMCFs according to their distribution into biogeographic realms using Dinerstein et al. (2017) layers. This helped
us differentiate TMCFs within five macro-ecological locations: Neotropical \((n = 254)\), Palearctic \((n = 90)\), Indomalayan \((n = 119)\), Australasia \((n = 57)\), and Oceania \((n = 1)\). Eight sites defined by UNEP-WCMC were excluded, given their inconsistency in their location (Table S1). In addition, we used a mask of tropical landmasses to compare how trends in low CF at TMCFs differed from those in other tropical regions. We considered tropical landmasses as areas between the Tropic of Capricorn and Cancer that fall within country polygons obtained from Natural Earth (www.naturalearthdata.com). We used also country boundaries from Natural Earth to visualize CF trends among nations.

2.2 2.1 Climatic datasets

We used nine global climatic datasets associated with low-cloud fraction (CF), surface temperature (average, minimum, and maximum) \((K)\), surface pressure \((Pa)\), volumetric solid water content between 7-28 cm below the surface \((VSWC)\) \((m^3 \ m^{-3})\), precipitation \((\text{mm day}^{-1})\), dew point \((K)\), and potential evapotranspiration \((\text{PET})\) \((\text{mm month}^{-1})\). Except for precipitation, all environmental datasets mentioned were derived directly or indirectly (i.e., PET) from ERA5. ERA5 is a fifth-generation atmospheric reanalysis of global climate produced by the Copernicus Climate Change Service at the European Center for Medium-Range Weather Forecasts (Hersbach et al., 2020). ERA5 is the direct successor to ERA-Interim reanalysis and provides global, hourly weather data at a regular grid of 0.25 ° (≈30 km) (Hersbach et al., 2020). The PET dataset was indirectly derived from ERA5 using the Penman-Monteith equation following the FAO-56 Method (Zotarelli et al., 2010). For this, additional parameters such as wind speed, ground pressure, incoming solar radiation, and clear-sky solar radiation were also obtained from ERA5, as detailed in Table S3. On the other hand, the precipitation dataset was obtained from CHIRPS (Climate Hazards Infrared Precipitation with Stations) (Funk et al., 2015). The former is a quasi-global rainfall product spanning 50°S – 50°N with 38 years of daily estimations. This precipitation dataset incorporates satellite imagery with \textit{in situ} station data with a spatial resolution of 0.05° (≈5.5 km).

Overall, biases around ERA5 and CHIRPS climatic datasets have been evaluated in several studies (Bonsboms et al., 2022; Dommo et al., 2022; McNicholl et al., 2022; Tetzner et al., 2019). Despite this, we acknowledge that the reliability of these global products remains uncertain at varying temporal and spatial scales at certain regions. We used these datasets as state-of-the-art climatic products (Muñoz-Sabater et al., 2021) that may help us to provide a comprehensive overview of the trends that are likely to prevail in these ecosystems and not as factual observations of what these ecosystems are experiencing.

2.3 2.2. Temporal analysis

We calculated temporal trends for all the above datasets for each TMCF using observations from 1997 to 2020. For this purpose, hourly observations were aggregated to an annual average. Linear regressions were then performed to calculate trends (i.e., slope or rate of change) \((\Delta, \text{year}^{-1})\). Regional studies tend to evaluate climatic trends from ERA5 using monthly average (i.e., Lei et al., 2020; Yilmaz, 2023), here we use annual average instead to provide a global perspective of temporal changes in low-clouds and other ECVs. The latter was performed using the IBM PAIRS Geoscope platform using a pixel-based approach. This cloud-based platform enables the deployment of user-defined functions on ERA-5 and CHIRP datasets without downloading raw data but obtains the regression coefficients directly (Lu et al., 2016). Trends were extracted from 1997 and not previous decades (e.g., 1940) given the availability of data in IBM PAIRS Geoscope and the reliability of products from recent decades that leverage on new available remote sensing and meteorological observations (Yilmaz, 2023). After extracting the trends, we performed Bayes one-sample \textit{t-tests} (Kruschke, 2013) to compute mean estimates of trends and evaluate the probability of these differing from zero. In addition, we performed an analysis at the realm level to determine how trends in low-clouds and ECV depend on the biogeography of these ecosystems. Bayes one-sample \textit{t-test} analyses were performed on R (R Core Team, 2023) using 30000 Markov chain Monte Carlo iterations in the BayesianFirstAid package.
ΔThe PLSR models were performed in R using the pls package (Liland et al., 2021), whereas the VIP was of each ECV in describing the variable of importance of prediction (VIP). Knowing the optimal number of components, we then developed a final iterative PLSR model. This last model was the average of 5000 iterations, each using 50% of the data randomly selected to build the model and test it using all the samples. We evaluated the model performance for each iteration by examining the coefficient of determination (R²) and the Root Mean Square Error of Prediction (RMSEP). We used Partial Least-Squares Regression (PLSR) models to evaluate the importance of ECV’s trends in describing the ΔCF variability. We first estimated the optimal number of components required for the model using 10-fold cross-validation models repeated 100 times following (Kuhn and Johnson, 2016). The optimal number of components was selected as the lowest Root Mean Squared Error of Prediction (RMSEP). All statistical analyses (including those in the following section) were weighed by the pixel projected area according to the TMCFs location to account for the latitudinal variation of the pixel area.

2.4 2.3. Climatic associations

We used Partial Least-Squares Regression (PLSR) models to evaluate the importance of ECV’s trends in describing the ΔCF variability. We first estimated the optimal number of components required for the model using 10-fold cross-validation models repeated 100 times following (Kuhn and Johnson, 2016). The optimal number of components was selected as the lowest Root Mean Squared Error of Prediction (RMSEP). Knowing the optimal number of components, we then developed a final iterative PLSR model. This last model was the average of 5000 iterations, each using 50% of the data randomly selected to build the model and test it using all the samples. We evaluated the model performance for each iteration by examining the coefficient of determination (R²) and the Root Mean Square Error of Prediction (RMSE). We also assessed the importance of each ECV in describing the ΔCF variability by estimating the Variable of Importance of Prediction (VIP). The PLSR models were performed in R using the pls package (Liland et al., 2021), whereas the VIP was estimated using the plsVarSel package (Mehmood et al., 2012). We did not split our data into training and testing datasets because our goal was to disentangle the association between ECVs and ΔCF more than creating a prediction model.

3 3. Results

3.1 3.1 Trends of low-cloud fraction

Our results reveal that the ΔCF on global landmasses ranges between -104.2 ×10⁻⁴ and 68.7 ×10⁻⁴ CF year⁻¹ (Fig. 1), with a mean that decays (i.e., becomes negative) over time at the rate of -7.4 ×10⁻⁴ CF year⁻¹. On tropical landmasses between the Tropic of Cancer and Capricorn, ΔCF ranges between -104.2 ×10⁻⁴ and 61.2 ×10⁻⁴ CF year⁻¹, with a mean rate of -13.9 ×10⁻⁴ CF year⁻¹(Fig. 2). The ΔCF distribution of these tropical landmasses appeared to have negative skewness (skewness: -1.75). Thus, the peak value of their density distribution (-2.3 ×10⁻⁴ CF year⁻¹) is likely to be a better descriptor of the overall trends that prevail in the region. At the TMCFs, specifically, ΔCF ranges between -64.7 ×10⁻⁴ and 51.4 ×10⁻⁴ CF year⁻¹ with a peak density distribution value 235% lower (-7.8 ×10⁻⁴ CF year⁻¹) than that of the tropical landmasses. The mean estimate of ΔCF in these ecosystems indicated a rate of change of -6.49 ×10⁻⁴CF year⁻¹ (CI: -7.69 ×10⁻⁴ – -5.31 ×10⁻⁴ CF year⁻¹) with a high probability (0.99) of being lower than zero (Table S2). Our trends also revealed that 70% of the evaluated sites showed negative ΔCF; however, this percentage appears to differ among biogeographic realms. For instance, 79.1% of the Neotropic TMCF present negative ΔCF, while at the Indomalayan, Palearctic, and Australasia realms, the percentages are lower (70.6%, 60.0%, and 47.4%, respectively). A comparison of the peak values of the distributions (Fig. 2), Neotropic and Indomalayan TMCFs show ΔCF that are 346% (-10.4 ×10⁻⁴CF year⁻¹) and 266% (-8.55 ×10⁻⁴ CF year⁻¹) lower than that of tropical landmasses. Mean estimates of ΔCF at these realms indicate rates of -11.33 ×10⁻⁴ CF year⁻¹ (CI: -13.23 ×10⁻⁴ – -9.45 ×10⁻⁴ CF year⁻¹) and -4.90 ×10⁻⁴ CF year⁻¹ (CI: -7.11 ×10⁻⁴ – -2.75 ×10⁻⁴ CF year⁻¹), respectively with a high probability (0.99) of being lower than zero (Table S3). Less contrasting, Australasia and Palearctic TMCFs present peak values of distribution that are 128% (-5.25 ×10⁻⁴ CF year⁻¹) and 78% (-4.16 ×10⁻⁴ CF year⁻¹) lower than that of tropical landmasses. Despite this, mean estimates of ΔCF at Australasia’s TMCFs are more likely to be higher than zero (0.87) with rates of changes of 2.60 ×10⁻⁴ CF year⁻¹ (CI: -2.07 ×10⁻⁴ – 7.19 ×10⁻⁴ CF year⁻¹). Although many Palearctic’s TMCFs show positive and negative trends of ΔCF, there is a high probability (0.95) that the mean estimate at this macro-ecological region is lower than zero (μ: -1.51 ×10⁻⁴ CF year⁻¹; CI: -3.30 ×10⁻⁴ – 0.36 ×10⁻⁴ CF year⁻¹). The only TMCF present in Oceania has a trend of 5.9 ×10⁻⁴ CF year⁻¹.
Fig. 1. Distribution of TMCF and low-cloud fraction trends (ΔCF) between 1997 and 2020 (a). Panels b, c, d, and e provide a zoom into the TMCF located in Neotropic (b), Palearctic (c), Indomalayan (d), and Australasia (e). For visualization purposes, the color gradient was truncated between $-70 \times 10^{-4}$ and $70 \times 10^{-4}$ CF year$^{-1}$. Map lines delineate the study areas and do not necessarily depict accepted national boundaries. A clone of this figure without the TMCF distribution is provided in Fig. S1 to detail low-cloud fraction trends.
3.2 Trends of ECVs

Our mean estimates of ECVs (Table S4) suggest that there is a high probability (0.99) that TMCFs face increases in surface temperature (average, minimum, and maximum), dewpoint, pressure, volumetric soil water content (VSWC), and potential evapotranspiration (PET) (Fig. 3). Among these, VSWC was the only one with a moderate increase at a rate of \(0.6 \times 10^{-4} \text{ m}^3\text{m}^{-3} \text{year}^{-1}\) (CI: \(0.2 \times 10^{-4} - 1.0 \times 10^{-4}\text{m}^3 \text{m}^3 \text{year}^{-1}\)). Interestingly, increases in average surface temperature (\(\mu: 3.1 \times 10^{-2} \text{ K year}^{-1}\); CI: 3.0 - 3.2 \(\times 10^{-2}\text{ K year}^{-1}\)) in conjunction with pressure (\(\mu: 1.5 \text{ Pa year}^{-1}\); CI: 1.5 – 1.6 \text{ Pa year}^{-1}\)) are likely to lead the observed increases in dewpoint (\(\mu: 3.1 \times 10^{-2} \text{ K year}^{-1}\); CI: 2.9 \(\times 10^{-2} - 3.2 \times 10^{-2}\text{ K year}^{-1}\)). Moreover, mean estimates of precipitation have a modest probability (0.92) to decrease at a rate of \(-1.9 \times 10^{-3} \text{ mm}^3 \text{day}^{-1} \text{year}^{-1}\) (CI: \(-0.2 \times 10^{-3} - 0.9 \times 10^{-3} \text{ mm}^3 \text{day}^{-1} \text{year}^{-1}\)), while PET tends to increase at 0.3 mm^3 month^-1 year^-1 (CI: \(-0.1 \times 10^{-3} - 0.6 \times 10^{-3}\text{mm}^3 \text{month}^{-1} \text{year}^{-1}\)) with an observed probability (0.95) of being higher than zero. Among biogeographic realms, increases in surface temperature (i.e., average, minimum, and maximum), dew
point, pressure, and PET appeared to follow trends similar to those described above (Table 1). However, temperature, pressure, and PET increases seemed more severe in the Neotropical and Paleartic TMCFs than in other regions (excluding Oceania). Our results also indicate a high probability that Neotropical TMCFs face significant decreases in precipitation and VSWC at $-1.1 \times 10^{-3}$ mm$^3$ day$^{-1}$ year$^{-1}$ (CI: $-1.4 \times 10^{-3} - 0.6 \times 10^{-3}$ mm$^3$ day$^{-1}$ year$^{-1}$) and $-1.4 \times 10^{-4}$ m$^{-3}$m$^3$ year$^{-1}$ (CI: $-2.0 \times 10^{-4} - 0.7 \times 10^{-4}$ m$^{-3}$m$^3$ year$^{-1}$), respectively. Conversely, the Indomalayan and Australasia TMCFs showed a high probability of increases in precipitation and VSWC, with the latter having the most significant gains. Paleartic TMCFs had a low probability of increasing or decreasing precipitation, and VSWC.

![Graphs showing temperature, pressure, and PET trends in TMCFs between 1997 and 2020.](image)

**Fig. 3.** Trends ($\Delta$) in Essential Climatic Variables in Tropical Mountain Cloud Forests between 1997 and 2020. Histograms describe the distribution of average, minimum, and maximum surface temperatures (a, b, and c), precipitation (d), dew point (e), atmospheric pressure (f), volumetric soil water content (VSWC) (g), and potential evapotranspiration (PET) (h). The vertical long-dashed lines represent the mean estimate based on the Bayes t-test, whereas the dotted lines represent the credible intervals.

**Table 1.** Temporal trends ($\Delta$) of Essential Climatic Variables in the TMCFs between 1997 and 2020. Upper values represent the mean estimates based on the Bayes t-test, while values between parentheses represent credible intervals. Oceania values belong to a single TMCF category. Acronyms represent volumetric soil water content (VSWC) and potential evapotranspiration (PET).

<table>
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<th>Realm</th>
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<th>Climatic dataset (°C year$^{-1}$)</th>
<th>Climatic dataset (°C year$^{-1}$)</th>
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<td>$1.7 (1.5 - 1.8)$</td>
<td>$1.6 (1.4 - 1.7)$</td>
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<tr>
<td>Australasia (n=57)</td>
<td>$2.6 (2.3 - 2.9)$</td>
<td>$1.5 (1.4 - 1.6)$</td>
<td>$1.3 (1.2 - 1.4)$</td>
</tr>
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</table>
### 3.3 Low-Cloud Fraction and ECVs

Although the above section describes climatic shifts in some ECVs, it is unclear how these variabilities are associated with $\Delta$CF. Our PLSR models evaluated previous results, indicating that $\Delta$CF is strongly related to changes in ECVs (Fig. 4). Overall, eight components were required as optimum to explain the $\Delta$CF variability (Fig. 4a), which was equal to the number of predicting variables. Using this number of components, the PLSR models could predict $55 \pm 0.67\%$ of the $\Delta$CF variance (Fig. 4b). Such models provided a mean RMSE of $10.16 \pm 0.07 \times 10^{-4}$ CF year$^{-1}$ (Fig. 4c) with a relative RMSE close to $8.76 \pm 0.06\%$. The VIP of these models also revealed that $\Delta$VSWC, all surface temperature trends (i.e., average, min, max), and $\Delta$Pressure are highly important for predicting $\Delta$CF among ECVs (Fig. 3d).

![Fig. 4.](image)

**Fig. 4.** Partial Least Square Regression models to evaluate the potential association between trends from Essential Climatic Variables (ECVs) and trends of low-cloud fraction ($\Delta$CF). **a.** Describe the number of latent components required to optimally explain the $\Delta$CF variability, **b.** illustrates observed and predicted relationships, **c.** displays the Root Mean Squared Error (RMSE) of 5000 iterative observed-predicted models, and **d.** presents the Variable of Importance of Prediction (VIP) of each ECVs. Error bars represent the standard deviation in all panels.
4 4. Discussion

The cloudiness of TMCF is vital to the functioning of these ecosystems. It has been predicted that the cloudiness of these ecosystems will likely decline (Helmer et al., 2019), but until now, recent trends have not been formally quantified. Using state-of-the-art climatic databases, our study assessed trends of low CF in these ecosystems, revealing that most of the evaluated TMCF already present low-cloud reductions. We further unpack the association of the observed trends with other ECVs globally and regionally at the biographical realm level. The following sections highlight the key aspects of our findings and offer broad insights into future TMCF.

4.1 4.2 4.1 Trends of low-cloud fraction

Our results based on ERA5 reanalysis indicate that TMCFs face reductions in low-clouds at higher rates than tropical landmasses. Our estimates and their uncertainties at the biogeographic realm level also reveal that the decline in low-clouds might be associated with regional drivers; thus, it cannot be concluded that all TMCFs are experiencing cloudiness decreases. In this sense, Neotropical TMCFs are among the sites with the highest reductions in low-clouds. Neotropical TMCFs are also likely to be the most affected, given their substantial increases in surface temperature, dew point, pressure, and PET, and their significant reductions in precipitation and VSWC. Predictions by Helmer et al. (2019) suggest that 57% to 86% of the existing Neotropical TMCF zone area will experience decreases in cloud immersion. Similarly, our results indicate that 79.1% of the evaluated Neotropical TMCFs already showed reductions in low-clouds. Furthermore, our perception that regional factors may be responsible for cloudiness declines in some TMCF is supported by Los et al. (2021), who observed an increase in cloud base height in America’s TMCFs over the past four decades, but a decrease in Asia’s TMCFs. Helmer et al. (2019) predictions, Los et al. (2021) findings, and our results support the idea that Neotropical TMCFs are under threat, and thus species and essential ecosystem services that these ecosystems provide (Mayer et al., 2022; Mulligan, 2021).

4.3 4.2 Trends of ECVs and their association with low-clouds.

Beyond low-cloud trends, our results also indicate that most TMCFs exhibit shifts in their climate to warmer environments. Such changes are described mainly by increases in the surface temperature (i.e., average, minimum, and maximum), dew point, and pressure. On a decadal basis, the observed increases in average temperature (0.31 K per decade) might suggest that these ecosystems are warming at higher rates when compared with tropical forest regions (0.26 K per decade) (Malhi and Wright, 2004) or global estimations (0.2 K per decade) (Allen et al., 2018). Warming rates could be even stronger than global when TMCFs are detailed at the macro-ecological level as occurs in Neotropic and Indomalayan TMCFs (0.35 and 0.31 K per decade, respectively). However, we acknowledge that the comparison among other studies should be performed with caution, given the differences in methods.

Although it is expected that the warming of TMCFs also leads to increases in evapotranspiration and presumably PET (Still et al., 1999), its association with ΔCF was not as important as VSWC. It may be considered that increases in PET driven by lowland warming correlate with cloud formation upwind (Still et al., 1999). However, we evaluated the ΔPET - ΔCF association as an in-situ factor without considering the potential movement of moist masses. On the other hand, it could be expected that the variability in VSWC would be more consistent with changes in CF, as changes in clouds have the potential to drive mist interception and water availability. Previous studies have shown similar patterns where high soil moisture in lowland and mountainous areas is related to cloud base heights and their regimes (Lawton et al., 2001; Nair et al., 2008; Ray et al., 2006). At some Neotropical TMCFs (e.g., Monteverde, Costa Rica), negative trends in VSWC and precipitation could be tied together with increases in the number of dry days (Pounds et al.,
2006, 1999). An increasing number of dry days in a year is likely to reduce annual averages of VSWC; thus, increases in their frequency over time may also lead to VSWC declines. The coherent variation of VSWC with dry days, low-clouds, or precipitation may suggest the former is an indirect indicator of cloud dynamics which could be used to for the local monitoring the of TMCFs forest health. The reliability of VSWC as an indicator of forest health at the TMCF’s should be evaluated in detail by future studies.

Overall, our results appear congruent with the climatic mechanisms associated with changes in clouds at the TMCFs. Our observed increases in surface temperature and its implication in negatives $\Delta CF$ could exemplify the warming effects on cloud formation as well as the rising of cloudbanks. Likewise, our observed increases in temperature are likely to lead increases evapotranspiration which may implies decreases in cloud formation. Despite this, there is an important variance that our PLSR model does not explain according to the coefficient of determination. Differences among TMCFs associated with orographic effects, proximity to water bodies, El Niño Southern Oscillation (ENSO) effects, lowlands land use changes can also to contribute to the observed $\Delta CF$ (Lawton et al., 2001; Nair et al., 2011; Still et al., 1999). For instance, ENSO effects — that have shown to drive the TMCFs dry seasonal moisture (Anchukaitis and Evans, 2010) — are likely to have a higher impact on the TMCF’s cloudiness that strictly dependent on water masses from the ocean than those that strictly depend on lowland forest conditions. As such, future studies should disentangle which drivers are closely related to local cloud trends.

4.4 Broad implications and future directions

4.3 Broad implications and future directions

The interconnected web of life in TMCFs is intricately tied to cloud formation, making it imperative to address global changes to preserve these vital ecosystems and safeguard their biodiversity and invaluable services. Our results reveal that the fingerprints of global change are already having a profound impact on the cloudiness of TMCFs. Altered cloud patterns are likely to disrupt the delicate balance of these ecosystems, which may lead to significant consequences for biodiversity and ecosystem services. With a changing climate affecting the frequency of clouds and the ecosystem balance, species that rely on constant mist and humidity may need to adapt to warmer conditions or migrate to higher elevations (Feeley et al., 2020, 2011). The previous could be particularly important for species in those sites where declines in low-clouds occur at higher rates. Therefore, it is crucial for countries and conservation agencies to consider the rate of change in cloudiness as a key climatic factor in their preservation efforts and to develop appropriate management strategies. For instance, South American countries such as Colombia, Venezuela, and Bolivia, as well as Central American countries like Honduras and Costa Rica, should recognize the reduction in low-clouds as a significant threat to their TMCFs, given the pronounced declines observed in these regions and the number of sites affected (Fig. 5). However, we need to highlight that our findings are restricted to the evaluated sites described as TMCFs (Aldrich et al., 1997a), which may not represent the much broader TMCF distribution.
Fig. 5. Trends of low-cloud fraction ($\Delta$ CF) for Tropical Mountain Cloud Forests (TMCFs) between 1997 and 2020 among countries. Grey points represent the average for each nation, while color points each TMCFs according to their distribution among biogeographical realms. Country acronyms represent the ISO 3166 country codes.
The altered balance of ecosystems resulting from reduced cloud cover can also affect water supply, which not only impacts resident species but also disrupts downstream water resources, thereby affecting human settlements and industries. For example, the hydropower industry might be affected as many dams rely on water recharge from TMCFs. As such, the integration of ecosystem services that recognize TMCFs as economical assets, beyond carbon sequestration, is crucial for future conservation. Initiatives such as the Cloud Forest Blue Energy Mechanism (Narvaez et al., 2017) or Cloud Forest Bonds (Litovsky et al., 2022) which consider the economic perspective of TMCFs may serve as financial instruments to support the conservation and restoration of these ecosystems while generating financial returns.

Protecting future TMCFs may depend on our ability to accurately observe and project changes in cloudiness. Despite our findings document declines in low-clouds on most of TMCFs, our results rely on the accuracy of ER5’s low-cloud to observed clouds. A study by Dommo et al. (2022) suggests that ERA5’s low-cloud product can capture the spatial distribution of low-clouds across Western Central Africa compared with other satellite products (e.g., MODIS). However, to our knowledge, no studies have assessed temporal uncertainties of ERA5’s low-cloud. Evaluations of diurnal cycles and long-term trends of ERA5’s total-cloud product (i.e., the total atmospheric column) appears to have a coherent variation with satellite imagery (Himawari-8) (Lei et al., 2020). Likewise, temporal trends of surface temperature from ERA5 have shown to be congruent as well with trends from meteorological stations (Yilmaz, 2023). If ERA5 low-clouds do not exhibit strong temporal biases, we could imply that our estimated trends are valid. This could be particularly true for observations from recent decades as ERA5 and its improved estimates leverage in available remote sensing and meteorological observations (Yilmaz, 2023). However, a temporal assessment of ERA5’s low-cloud uncertainties require further investigation. Therefore, future studies should utilize tangible cloud immersion observations to assess temporal patterns such as time-lapse photos or visibility data. These cloud immersion observations should also evaluate the spatial and temporal uncertainties of cloud observation products — such as ERA5 low-clouds — and explore their reliability at a large scale. Unfortunately, due to limited availability of local cloud observations in these remote ecosystems, it is unlikely that such assessments will occur in the near future. Consequently, our study emphasizes the need for the development of global networks for cloudiness observation in TMCFs. These networks should be conducted in partnership with countries, conservation agencies, and industries as the observation and projection of clouds can have implications in several sectors.

5 Conclusion

We established that most TMCFs sites that were evaluated face reductions in low-clouds at rates that are higher than those in other tropical regions. These reductions have a biogeographic component, suggesting that regional rather than global drivers may play an essential role in the decline of low-clouds. Our documented climatic trends beyond clouds also revealed that TMCFs are shifting to warmer environments at higher rates. Neotropical TMCFs are most likely to suffer the consequences of this climatic shift because these sites present pronounced reductions in low-clouds, precipitation, and VSWC, and significant increases in temperature, dew point, pressure, and PET. Considering these observations, the importance of regional and local drivers (e.g., deforestation, change of land use) associated with cloud regimes need further investigation to examine the causes and consequences of the observed trends. Many unknowns remain when predicting the effects of current cloud declines in the TMCFs. However, as future projections indicate increases in global warming (Diffenbaugh and Barnes, 2023), these trends will likely continue threatening the life that remains on them and the ecosystem services that they provide.
6 Data availability

The hourly ERA5 data used for this study are available at https://doi.org/10.24381/cds.adbb2d47 but were accessed through the IBM PAIRS Geoscope (https://ibmpairs.mybluemix.net). The TMCF distribution was obtained from the United Nations Environment Programme - World Conservation Monitoring Center and is available from Aldrich et al. (1997). The distribution of biogeographic realms is available in Dinerstein et al. (2017). A dataset with trends, mean estimates, and a global raster of ΔCF is available at the Tropi-Dry Dataverse (https://doi.org/10.7910/DVN/A25Q8V).

7 Code availability

All the codes for estimating the trends, statistical analysis, and visualization are available at https://github.com/Antguz/TMCF-trends with the current version 0.3 archived at Zenodo: https://doi.org/10.5281/zenodo.6476817.

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