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Relative Humidity Verification Over Vietnam in ECMWF Medium-Range Forecasts for a Dengue Early Warning System

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ABSTRACT

Dengue fever outbreaks impose a severe healthcare burden in Vietnam; therefore, the development of a Dengue early warning system is key to improve public health planning and mitigate this burden. This study assesses the ECMWF medium-range (up to 10 days) forecast skill for relative humidity in Vietnam—a key factor for vector-borne disease transmission—in re-forecasts between 2001 and 2020. Analysis focused on the rainy season (May–October) with ERA5 reanalysis as a reference dataset. Re-forecast data were pre-processed using a lead-time dependent quantile mapping technique to reduce the bias between forecasted and observational data, and skill was assessed using climatology and persistence as a reference. Rank histograms showed that the humidity forecast is reliable up to 10 days, and continuous ranked probability skill score (CRPSS) values show that the forecast is more skilful than the climatology up to 10 days. Nonetheless, when using persistence as a reference, CRPSS values are lower in South Vietnam, which was associated with the inaccurate representation of 2 m dew point temperature in the tropical regions, and the fact that persistence is a hard reference to beat in the tropics, hindering model forecast skill. Results from this study demonstrate that ECMWF ensemble forecasts of relative humidity are suitable to use as inputs for a Dengue early warning system up to 10 days in advance.

1 | Introduction

1.1 | Motivation

Dengue fever is transmitted by the mosquito *Aedes aegypti* and it is considered the fastest spreading tropical disease in all the continents (Bhatt et al. 2013; Do et al. 2014). This disease produces mild illness and it can occasionally turn into a life-threatening disease (Brunette 2017; Trinh et al. 2018). In endemic areas, seasonal outbreaks of this disease are able to overwhelm health services, imposing a huge health, economic, and political burden on the affected countries. Additionally, during the last decade the range and extension of this disease rose globally and it is expected to keep increasing in the future (Anne 2013; Choi et al. 2016; Lee et al. 2017; Ramachandran et al. 2016). This trend is partially linked to the rise of temperatures, rainfall, and humidity associated with climate change (IPCC 2022; VARCC 2009).

Prior research stated that certain environmental and meteorological factors affect vector population mechanics and pathogen transmission, thus influencing Dengue incidence and spread (Cheong et al. 2013; Chien and Yu 2014; Xiang et al. 2017; Yu et al. 2023). From these variables, temperature, precipitation, and humidity showed the strongest link to Dengue incidence (Choi et al. 2016; Lee et al. 2017; Ramachandran et al. 2016; Schmidt-Thome et al. 2015). Nonetheless, this link is non-linear, showing the highest correlations when the temperature, rainfall, and humidity data is lagged between 0 and 3 months (Bett et al. 2019; Colón-González et al. 2021; Vu et al. 2014). Additionally, extreme weather events such as heat waves or floods also influence the size and duration of Dengue outbreaks, as they directly affect *Aedes aegypti* development/growth. For example, high precipitation creates bodies of water in which *Aedes aegypti* can lay their eggs, but extreme rain can flush their eggs away and reduce Dengue incidence. By contrast, high temperatures usually favour *Aedes aegypti* development, but if they are high enough, it increases *Aedes* mortality (Nosrat et al. 2021; Yang et al. 2009).

Thus, due to the non-linear link between meteorological variables and Dengue incidence, having reliable and accurate weather forecast data is key to the development of an early warning system that can provide useful information for healthcare planning and decision-making for mitigating the burden of this disease.

Prior studies developed Dengue incidence prediction models combining weather variables and epidemiological data (Colón-González et al. 2021; Nguyen et al. 2022; Weyn et al. 2021). In Vietnam, there is an operational Dengue prediction model called D-MOSS (Colón-González et al. 2021), which provides a seasonal Dengue incidence forecast in a regional scale by combining observational data and seasonal predictions from the model Global Seasonal Forecast System v5. However, there is a need for a district scale forecast of Dengue as interventions to mitigate Dengue outbreaks in Vietnam are mostly done on a local-district scale (Ho Chi Minh City Party Committee 2025).

Dengue Advanced Readiness Tools (DART) is a project funded by the Wellcome Trust whose goal is to develop an early Dengue outbreak warning system in Vietnam on a district scale, aiming to produce Dengue incidence forecasts at a district scale combining weather forecast data between 10 and 14 days in advance with high resolution disease data. One of the first steps of DART is to perform an evaluation of the European Centre for Medium-Range Weather Forecast (ECMWF) weather forecast data for Vietnam.

Prior studies in DART (Main et al. 2024) showed that the ECMWF weather forecast model is skilful at predicting surface temperature and precipitation up to 10 days in advance in Vietnam when using either persistence or climatology as a reference. Nonetheless, the prior study did not include humidity, which is a key variable in vector-borne disease transmission (Bouzid et al. 2014; Brown et al. 2023; Githeko et al. 2008) as it affects the degree of mosquito moisture stress, which can either increase or dampen the effects of very high or low temperatures in pathogen transmission (Brown et al. 2023; Bouzid et al. 2014; Githeko et al. 2008; Pérez-Díaz et al. 2012).

Thus, the goal of this study is to complement the results from Main et al. (2024) and assess the skill of the ECMWF weather forecast model for relative humidity.

1.2 | Link Between Vietnam Climate and Dengue Fever

The Asian continent's climate and weather is deeply influenced by the Asian monsoon circulation, which is a multi-scale phenomenon caused by the uneven seasonal heating between the Eurasian continent and its adjacent oceans. Between May and October, the monsoon brings heavy rain over south and east Asia and dry and hot air in the north and west of the Asian continent. Conversely, between November–April the monsoon produces heavy rains over Indonesia, northern Australia and South Pacific convergence zones (Bombardi et al. 2020; Buckley et al. 2014; Clift and Plumb 2008; Neelin 2007; Wang 2006).

Vietnam is located at the south–south-east part of the Asian continent, with an area of 331.000 km^2 and a latitudinal extension of 1650 km. Apart from the influence of the Asian monsoon, the weather and climate in Vietnam are also affected by the local topography and the great latitudinal length of the country. As a result, the weather and climate of Vietnam differ between the North and the South; for example, Hanoi (the capital of Vietnam) is in the northern region and has a four-season subtropical climate, with wet summers and relatively cold and dry winters. On the other hand, Ho-Chi-Minh city (HCMC), located in the southern region, has a two-season tropical climate with marked dry and rainy seasons and stable temperatures throughout the whole year. In the case of precipitation, nearly 70% of Vietnam's precipitation falls in the rainy season (May–October), although with slight differences between regions. These weather and climate conditions favour the development of Dengue outbreaks, making Vietnam one of the most vulnerable countries to this disease (Yu et al. 2023).

As a result of the non-linear interaction between Dengue and weather variables, Dengue activity in Vietnam varies regionally and seasonally. In North Vietnam, Dengue incidence is mainly seasonal, being the highest during the rainy season (May–October) and the lowest during winter. By contrast, Dengue is hyper endemic in South Vietnam, reaching its peak activity between September and November, and its lowest during the dry season (November–April) (Do et al. 2014; World Health Organization 2009). In addition, the severity of the outbreaks shows high inter-annual variability in both regions (Cuong et al. 2011, 2013; Do et al. 2014; Rabaa et al. 2013; Thai et al. 2010).

1.3 | Inclusion of Weather Forecast Data Into Dengue Early Warning System

Numerical weather prediction (NWP) models solve geophysical fluid dynamics equations for the atmosphere and ocean, predicting their future state. Weather forecasts up to 10 days can be skilful because the forecast is constrained by initial conditions (Palmer 2000). Due to the chaotic nature of the atmosphere, beyond 10 days the initial conditions are not relevant for forecast skill. It is also worth mentioning that the source of skill differs between the tropics, subtropics and extra-tropics. For example, NWP performance might decrease initially in the tropics compared to subtropics as the convective processes are not well represented due to the lack of observational data (Main et al. 2024; Vogel et al. 2020), although it is also known that forecast skill is usually better in the tropics compared to subtropics at subseasonal scale (10–30 days) due to the persistence of the weather conditions.

The early warning Dengue prediction system developed in DART consists of a machine learning model trained for predicting Dengue incidence at a district level using both meteorological (2 m temperature, relative humidity and total precipitation) and non-meteorological variables, such as socio-economic and health data, as input. The relationship between the input variables and Dengue incidence is both non-linear and complex. By integrating high quality data, including skilful meteorological forecasts, into the model, advanced warning of potential outbreaks can be given, maximising lead times for mitigation strategies to be enacted. The operational version of the model will use weather forecast data to predict future Dengue incidence, which will be presented to key stakeholders through clear and intuitive bespoke visualisations. The structure and integration of the DART model pipeline is described in detail in Dasgupta et al. (2025), in the latter study, they state that the pipeline: "supports data integration, enabling incorporation into climate-disease modelling applications and more broadly real-time modelling tasks."

The article is structured as follows: Section 2 provides a description of the area of study and the datasets applied. Section 3 describes the bias correction technique applied to the forecast data and describes the metrics applied to assess forecast skill. Section 4 describes the humidity patterns of Vietnam and verification results and Section 5 summarises the study and presents the conclusions and suggestions for further studies.

2 | Data and Area of Study

2.1 | Area and Period of Study

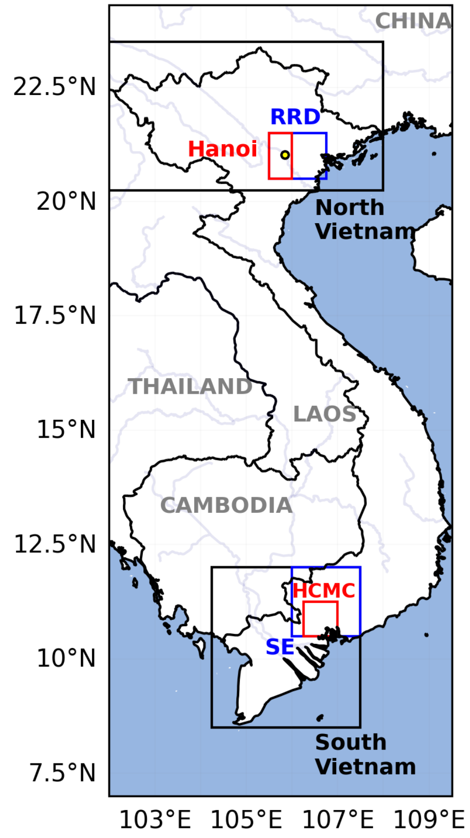

FIGURE 1 | Map of the region of Vietnam, highlighting the areas of study of Table 1. Black line boxes cover the North and South of Vietnam, blue boxes display the Red River Delta (RRD) and Southeast (SE) boundaries whereas red regions limit the municipalities located around Hanoi and HCMC city, which are located in the red dots.

Figure 1 shows the selected study regions, with boundary details given in Table 1. Following Main et al. (2024), we selected a domain between 100°–110° E and 5°–25° N to represent the whole region of Vietnam, with three further sub-areas of decreasing size in both north and south Vietnam. In the northern region we have North Vietnam, Red River Delta, and Hanoi whereas in the south we have South Vietnam, southeastern region (SE), and HCMC. Each of the north/south sub-areas contains either Hanoi or HCMC so we can explore the difference of skill between regional and municipal levels around the cities of study. It is also important to mention that when we refer to the North/South of Vietnam we are referencing the region specified in Table 1, as it includes part of the sea and land that are beyond Vietnam's borders.

TABLE 1 | Geographical limits of the areas of study.

Area	Latitude range	Longitude range
North Vietnam	20.25°–23.5° N	102°–108° E
Red River Delta	20.5°–21.5° N	105.5°–106.75° E
Hanoi	20.5°–21.5° N	105.5°–106° E
South Vietnam	8.5°–12° N	104.25°–107.5° E
Southeast	10.5°–12° N	106°–107.5° E
HCMC	10.5°–11.25° N	106.25°–107° E

The period of study chosen for this study is the Vietnam rainy season (May–October) between 2001 and 2020 so it is consistent with prior DART studies (Main et al. 2024).

2.2 | Verification Data: ERA5 Reanalysis

ERA5 is the 5th generation of ECMWF reanalysis, and consists of the combination of observations in the upper air/near surface around the globe with short term forecasts to obtain an accurate representation of the state of the atmosphere with global coverage (Hersbach et al. 2020). ERA5 data used here has a spatial resolution of 0.25° (~28 km) and a temporal resolution of 6 h for 1940–present. Because of its spatial and temporal completeness, ERA5 was chosen as the verification data in this study. Here we selected data of daily time step of time 00Z, which corresponds to the time after dawn (7 am Vietnamese time) when mosquitoes are more active looking for hosts (Main et al. 2024).

The humidity analysed in the study is relative humidity; nonetheless, relative humidity is not available in ERA5, so we estimated it by selecting the variables: 2 m dew point temperature (K), 2 m temperature (K), and surface pressure (hPa) and following Equation (1) (Wallace and Hobbs 2006).

$$r = \frac{e(T_d)}{(e_s(T))} \tag{1}$$

where r is relative humidity, $e(T_d)$ is the saturation vapour pressure for dew point temperature, and $e_s(T)$ is the saturation vapour pressure for the current temperature T.

2.3 | Re-Forecast Datasets

ECMWF ensemble prediction model is a state-of-the-art NWP model with atmospheric, oceanic, land surface, and sea-ice components. Re-forecast data used in this study comes from the version Cy47r3 of the model, which has an atmospheric resolution of T_{Co639} (~18 km), 91 vertical levels, and uses ERA5 data as initial conditions. Full documentation of the configuration and physics of the model can be found in the ECMWF integrated forecasting system (IFS) documentation (ECMWF 2021a, 2021b, ECMWF 2023a).

Re-forecasts, also known as hindcasts, are forecasts initialised at past dates using the latest version of the model, while avoiding the inclusion of future information that might affect the forecast. Unlike the real-time forecasts, the re-forecast keeps the same model version for all starting dates, and so it is possible to perform an unbiased analysis of the model skill at each starting date.

Here, we used the medium-range re-forecast from the ECMWF ensemble forecast hindcast, which was initialised twice per week for every Monday and Thursday corresponding to the dates of 2021, being the first initialization the 04/01/2001 and the last one on the 28/12/2020. The reason to choose this version of the model is to keep the analysis consistent with the prior analysis made by Main et al. (2024) and ensure that the skill assessment is done in the same conditions as the prior study.

The ensemble has 11 members (10 perturbed ensemble members +1 control member), a spatial resolution up to 0.125° (~15 km), a forecast length of 10 days with a timestep of 6 h. More information about the re-forecast data is available in ECMWF (2021b) (Table 1c).

3 | Methodology and Metrics

3.1 | Bias Correction Technique

Raw data from the NWP tend to deviate from observations as we advance further in the forecast; hence, it is common to post-process raw NWP forecasts in order to reduce their biases so the data can be useful for impact-based forecasting. In the weather and forecast community, quantile mapping (QM) techniques are one of the most used bias correction techniques as they outperform other methods such as shifting or scaling (Azmat et al. 2018; Fang et al. 2015; Teutschbein and Seibert 2012; Worku et al. 2019). In QM, the cumulative distribution function (CDF) of the target data is calibrated to the CDF of the reference data by interpolating quantile points from target to the verification dataset (Cannon et al. 2015). In this study, we used ERA5 as the verification dataset and the re-forecast as the dataset to correct.

For this study we applied QM following the methodology of Main et al. (2024), which is defined in Equation (2).

$$X_{\mathrm{corr}\,m,p}(t) = F^{-1}_{m,o}\left\{F_{m,p}\left[X_{m,p}(t)\right]\right\} \tag{2}$$

where $X_{m,p}(t)$ is the forecasted value to be adjusted in time t, $F_{m,p}$ the CDF function of the re-forecast data distribution, $F_{m,o}$ the CDF function of the observation distribution and $X_{\mathrm{corr}\,m,p}$ the bias-corrected forecast value. The QM correction was done only taking into consideration the rainy season (May-Oct) for every grid point of the dataset and for each lead time separately. This is, we select daily data from the re-forecast corresponding to a specific lead time (1 to 10), and then apply QM using observational data with the same dates that the one contained in the re-forecast, this way the QM correction is lead time-dependent. The reason to perform the correction only considering the rainy season and not the full year is to have a better calibration of the re-forecast data for this season. Also, as in Main et al. (2024), when applying QM we excluded the target year to avoid the introduction of false skill (cross validation).

It is important to highlight that quantile mapping techniques assume that the climate is stationary, which is not necessarily true. As we are focusing the analysis in a short period (~20 years), assuming stationary climate should not be an issue. Also, in this study the weather forecast model makes predictions up to 10 days, and bias with ERA5 is assessed for that 10-day period, so we do not expect a considerable drift in that period. As such, we consider that each point used to assess bias to be stationary.

Hereafter raw re-forecast data refers to re-forecast data straight from the model ensemble, and corrected re-forecast data refers to data which was post-processed using the QM technique.

3.2 | Climatology and Persistence as Reference Forecasts

Using ensemble forecasting for predicting the evolution of a continuous variable requires use of probabilistic, continuous metrics. In the weather and climate community, forecast skill is often compared against a reference forecast. Here, climatology and persistence are used as a baseline. A forecast is (relatively) skilful compared to the climatology when the forecast can outperform the predictive skill of a distribution obtained from combining the observations of prior years. On the other hand, the forecast is more skilful than persistence when it outperforms the predictive skill of the distribution based on the day before the initialization of the forecast.

In order to construct a climatological reference forecast at each grid point for each day of the year, we selected daily values from ERA5 at each grid point for each year in the study period. Each year is considered a single ensemble member, with the target year excluded so we can avoid the introduction of artificial skill (cross validation).

Persistence, on the other hand, was constructed by using the value 1 day prior to the initialization of the re-forecast and it is usually chosen as a reference forecast for short-range forecasts (Murphy 1992). However, in tropical climates the weather conditions persist for several days; hence, persistence can be used for longer timescales (Bombardi et al. 2020). In order to confirm that the weather conditions are sufficiently stable to use persistence as a reference, we measured the temporal autocorrelation of the analysed variables between 1 and 10 days by lagging the data against itself and then averaging the value per day.

3.2.1 | Rank Histogram and Cramér-Von Mises Test

Reliability is a quality of the forecast which measures the degree of statistical consistency between each class of the forecast against the observation distribution. A forecast is considered reliable when the forecasted probability of observing a specific event is in agreement with the real frequency of the event; hence the observation and forecast distributions are practically indistinguishable from each other (Hamill 2001).

The reliability of the forecast is tested by constructing the rank histogram. This is done by first measuring the rank of the observation within $M+1$ values, M being the ensemble members. The frequency of occurrence of each rank is then calculated and plotted on a histogram sorted from lowest to the highest rank. If the probability of observing each rank in the forecast follows a uniform distribution, the forecast is reliable as the ensemble forecast has the same variance as the climatology (Hamill 2001). On the other hand, deviations from uniformity in the rank distribution highlight a weakness of the forecast. For example, overpopulation of the first/last rank indicates that the forecast has a consistent bias and underestimates/overestimates the real value of the observation, whereas a U-shaped histogram indicates that the forecast underestimates the observed variability (overconfidence). As in Main et al. (2024), the rank histograms are tabulated using forecast-observation pairs for each grid point within the areas of interest and for each lead forecast day.

The Cramér-von Mises (CvM) test, which is a non-parametric goodness of fit test (Cramér 1928; Smirnov 1936), is applied to test whether the ensemble from the re-forecasts follows a similar distribution as the observations. The discrete form of CvM is described in Equation (3) (Elmore 2005):

$$W = N^{-1} \sum_{i=1}^{k} Z^{2}{}_{j} p_{j} \tag{3}$$

where $Z = \sum o_i - \sum e_i$, with o_i being the observed number of counts in bin i, e_i the forecasted values in bin i, N the total number of samples and p_i the probability of having an observation landing in any cell. The CvM test assumes that the distributions are independent, which is not totally true for reanalysis and reforecast data, hence, here the test is used to calculate the significance if they were independent, providing an estimate of the lower bound of significance.

3.2.2 | Continuous Ranked Probability Skill Score

The continuous ranked probability score (CRPS) is a probabilistic metric that comes from the generalisation of the ranked probability score, and assesses the risk of surpassing a specific threshold when these thresholds are continuous (Jolliffe and Stephenson 2012). CRPS provides a measure of how good the forecasts are in matching observed outcomes, when CRPS = 0, the forecast is wholly accurate and when CRPS = 1, the forecast is wholly inaccurate. The CRPS is measured as in Equation (4).

$$\text{CRPS} = \int_{-\infty}^{\infty} \left[F(x) - H(x-y)\right]^2 dx \tag{4}$$

where y is the observation, x the forecast and H the Heaviside action, which is 0 when $x < y$, and F the cumulative density function obtained using ensemble forecast.

The CRPS score obtained from the forecast is compared against a CRPS measured using a reference forecast (CRPS_{ref}) by way of the continuous ranked probability skill score (CRPSS). CRPSS assesses whether the forecast skill improves or worsens compared to a reference forecast and is measured by Equation (5).

$$\text{CRPSS} = 1 - \frac{\text{CRPS}}{\text{CRPS}_{\text{ref}}} \tag{5}$$

When CRPSS > 0, the forecast is more skilful than the reference, with CRPSS = 1 indicating perfect forecast skill whereas when CRPSS = 0 the forecast is as skilful as the reference.

CRPSS was calculated for each grid point for the different lead times in order to observe the performance of the forecast in different subsets of the North and South regions of Vietnam.

4 | Results

4.1 | Humidity Climatology Patterns in Vietnam

Figure 2 shows the intermonthly percentile distribution for relative humidity in North and South Vietnam. Both regions show extremely wet conditions, with a mean relative humidity of ~90% in the North and between 80% and 90% in the South. It is also worth commenting that the interannual variability in the northern region is smaller compared to the South, especially during the rainy season, where humidity values oscillate between 85% and 100% for the whole year, whereas the southern region manifests some seasonal variability (November–April relative humidity often ranges between 65% and 98%, whereas between May and October it mainly goes between 80% and 96%). Dengue incidence is the highest during the rainy season (see Section 1.2), which is when we observe the highest values of humidity. From now on, all results will focus only on the rainy season.

Figure 3 represents the mean relative humidity in Vietnam during the rainy season. We observe very wet weather conditions, with values near the saturation limit in most of the country (between 85% and 95%) with the exception of the eastern south-eastern coast of the country, where relative humidity is slightly lower (between 75% and 85%). Also, mean humidity is higher in the northern region compared to the south, as expected from results from Figure 2.

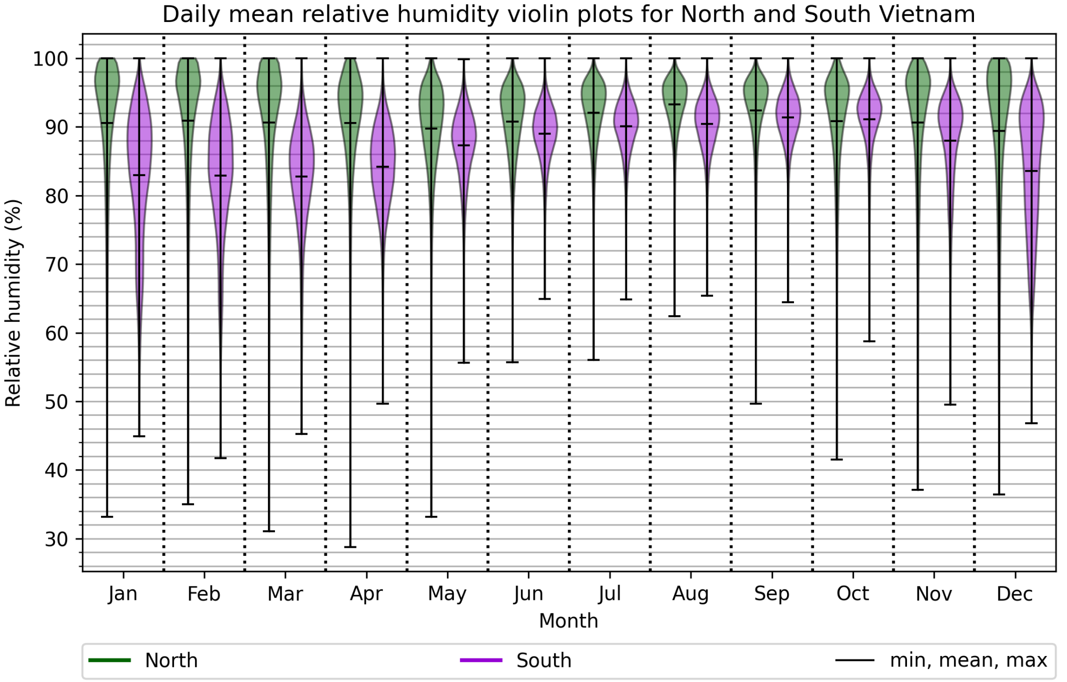

FIGURE 2 | Inter-monthly distribution of relative humidity for north and south Vietnam from ERA5 between 01/01/2001–31/12/2021.

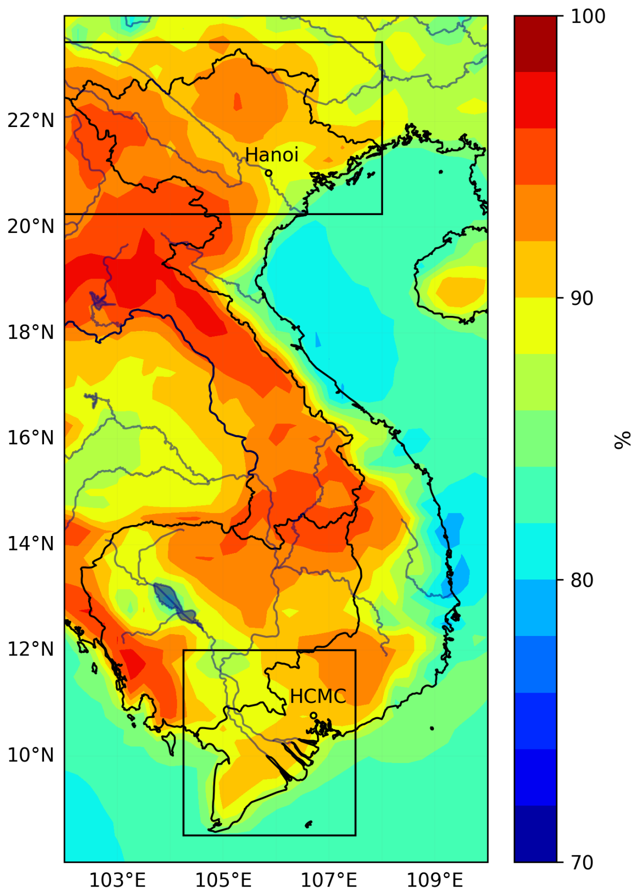

FIGURE 3 | Mean relative humidity during the rainy season using ERA5 data between 2001 and 2020.

Figure 4 shows the lagged autocorrelation of relative humidity during the 10 lead days forecast during the rainy season. Results show a high autocorrelation in North Vietnam and Red River Delta in lead day 1 (~0.8), decreasing up to 0.6 the 6th lead day and then it barely changes until the 10th lead day. In Hanoi the autocorrelation follows the previously described pattern, but with slightly lower values. In South Vietnam we start with an autocorrelation value of 0.7 on the first lead day, and then gradually decrease to ~0.55 by the 10th lead day. By contrast, in the Southeast region and HCMC we start with higher autocorrelation values (near 0.9 at 1st lead day and near 0.8 by the 10th lead day). These results show that relative humidity in Vietnam has high autocorrelation and that persistence can be used as a reference for forecast skill up to 10 days in advance in both regions.

4.2 | Bias Between Raw Re-Forecast Data and ERA5

Figure 5 shows the relative humidity relative bias between raw re-forecast data and reanalysis data for the whole region of Vietnam during the rainy season. In the north-west area, the bias is slightly positive (between 0% and 2%) and remains constant with lead time. Near Hanoi, the bias is slightly negative at 1st lead day (between −1% and 0%), and this increases with lead time up to −2%. In the central region, there is a small positive bias (between 0% and 2%, which remains constant until the end of the forecast). In the south–south-east region, where HCMC is located, there is a mainly positive bias ranging between 3% and 4%, which slightly increases with lead time.

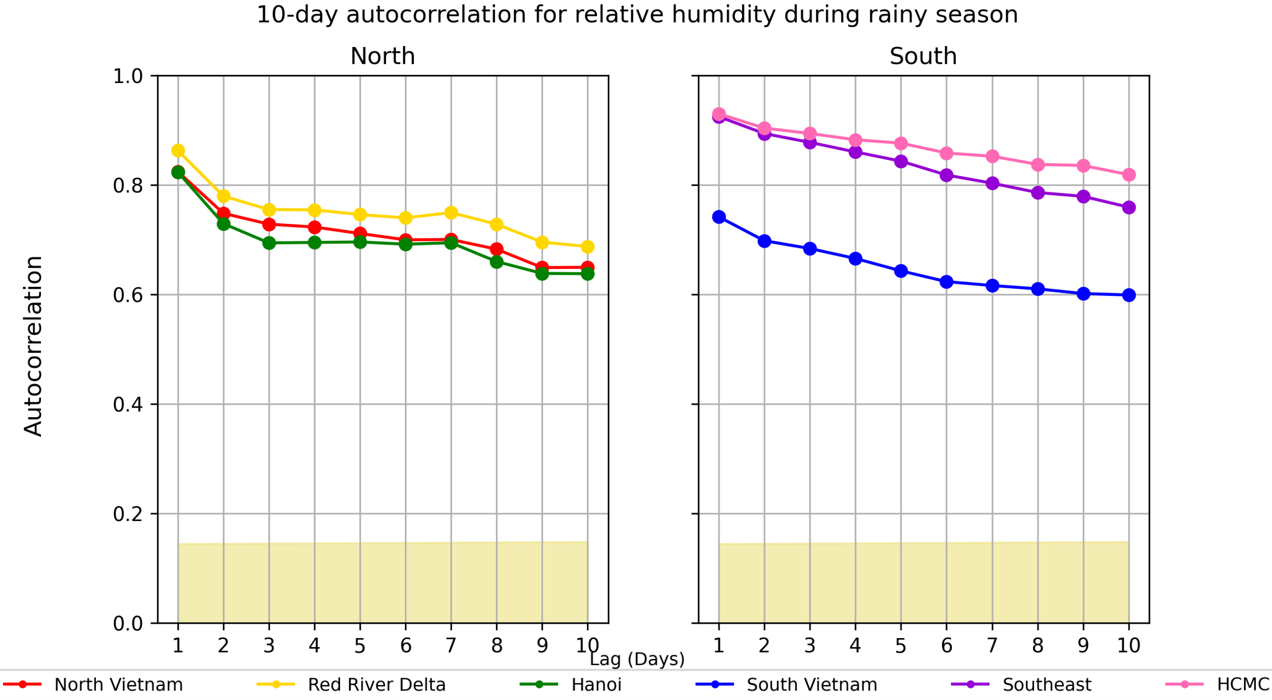

FIGURE 4 | ERA 5 temporal autocorrelation of relative humidity for the first 10 days of the forecast during the rainy season (May–October). The yellow region shows where autocorrelation is no longer significant (using a 95% confidence interval).

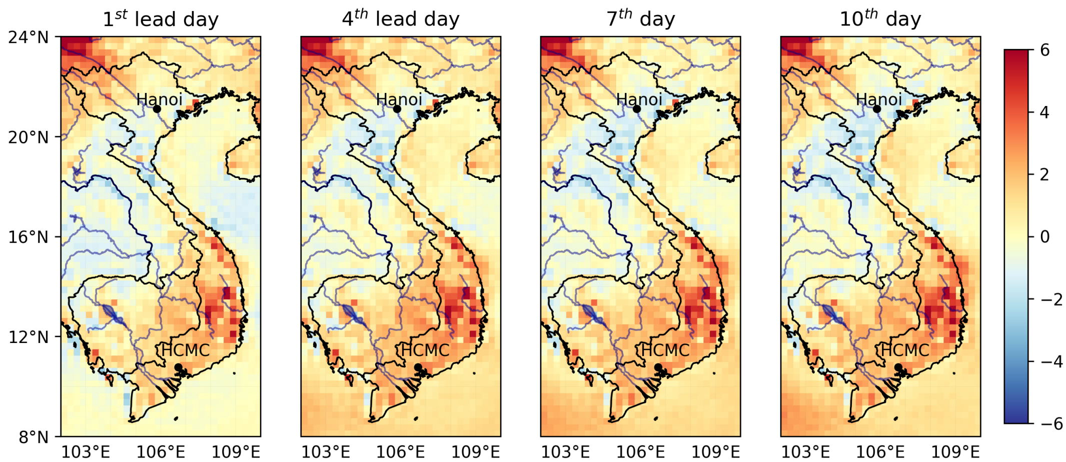

FIGURE 5 | Relative bias of relative humidity between raw re-forecast and ERA5 during the rainy season (May–October).

Results from Figure 5 show that in the south and north-west part of Vietnam relative humidity is slightly overestimated, whereas in the area around Hanoi it is slightly underestimated. The overestimation in relative humidity in most of the regions might be related to the existence of the cold bias between ECMWF model predictions and observations, which was also observed in prior studies (Main et al. 2024; Haiden et al. 2022). As relative humidity was estimated in this study using surface pressure, 2 m dew point, and 2 m temperature, it is possible that lower values of temperature might lead to an overestimation of relative humidity, as the air is closer to the saturation rate. It is also worth mentioning that areas where the relative humidity bias is the highest correspond to mountainous regions (North mountains highlands in the north-west of the region and the highland Tay Nguyen in central Vietnam).

These results highlight that raw re-forecast data for relative humidity does not deviate greatly from observations; nonetheless, even if the bias is low, it is still possible to have an unskilful and unreliable forecast. Therefore QM was applied to reduce the bias between re-forecast and observations, and then we compared the results between raw and calibrated re-forecast.

It is also important to highlight that although QM can reduce the bias between re-forecast data and the observations, prior studies concluded that QM techniques struggle at correcting extreme values located at the tails of distribution (Cannon et al. 2015; Main et al. 2024). Figure S1 shows the percentile bias for relative humidity between corrected re-forecast data and ERA5 per different lead times, and we observe that the

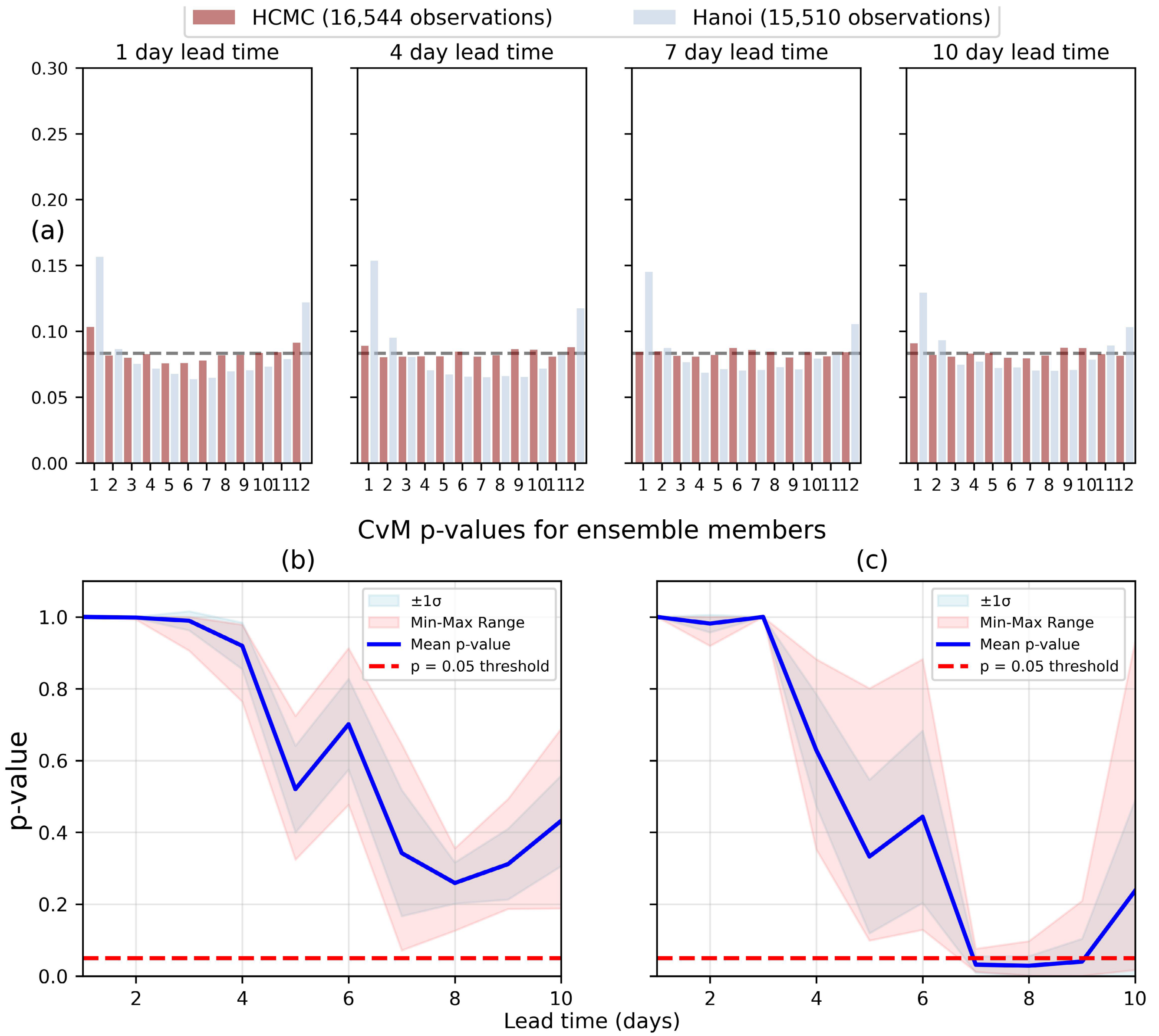

FIGURE 6 | Rank histogram distribution (a) of relative humidity in Hanoi (grey) and HCMC (light red) for lead days 1, 4, 7, and 10 and Cramér-von Mises (CvM) *p* values spread during different lead times for HCMC (b) and Hanoi (c).

percentile bias is the highest for extremely low values of relative humidity (values between 0 and 5th percentile). On the other hand, for extremely high relative humidity (between percentiles 95 and 100th), it also shows some bias, although it is much smaller compared to the lowest values of humidity, and it increases with lead time. Oppositely, percentiles located in the middle of the distribution (between percentiles 10 and 90th), the bias is close to 0.

4.3 | Rank Histograms

Figure 6a shows the rank histogram for corrected re-forecast relative humidity data for several lead days at HCMC (light red) and Hanoi (grey), and Figure 6b,c shows Cramér-von Mises *p* values spread during different lead times for HCMC and Hanoi. In Figure 6a, histogram data from HCMC show a very uniform distribution for the whole forecast period. On the other hand, for Hanoi the re-forecast data displays a slight tendency to overconfidence in the initialization of the forecast (slight overpopulation of first and last rank and relatively lower frequency for intermediate ranks), implying that the forecasted values of humidity in Hanoi tend to be lower compared to the observations, although as we advance in lead time the histogram flattens, and by day 10 the distribution is near uniformity.

Figure 6a (and the equivalent raw re-forecast Figure S2) shows that applying the QM correction to the re-forecast data flattens the rank histogram and increases the reliability of the forecast. The shape of the rank histogram distribution from Figure 6 is similar to that observed in fig. 10 of Main et al. (2024), where the re-forecast of 2 m temperature also tended to be slightly overconfident in the region of Hanoi even after the QM correction, whereas results in HCMC are closer to uniformity.

In Figure 6b,c, we show the *p* values obtained for the CvM test between corrected re-forecast ensemble members for forecast lead times 1–10 against observations in HCMC and Hanoi, respectively. In the case of HCMC (Figure 6b), the *p* values are far from the 5% significance level for lead days 1–10. Hanoi (Figure 6c) has similar results to HCMC for lead days 1–6, although *p* values decrease faster. However, for lead days 7–8 the *p* value drops to below the 5% significance level, and by days 9–10 most ensemble members are above the mentioned significance level. This means that in Hanoi, most of the ensemble members start deviating from observations after a week, but as the forecast advances some ensemble members "stabilise," remaining similar enough to observations at the 9–10th lead day.

We also performed the CvM test between raw re-forecast ensemble members and observations, but independently of the region and lead day *p* values were always below 0.05 for every lead day (not shown).

Hence, re-forecast data corrected with the QM technique shows increased reliability compared to the raw data, and this is manifested as a smoother and more uniform rank distribution. Also, after the QM correction in most of the lead times, a great proportion of the ensemble members follow a distribution close to observations up to the 10th forecast lead day, confirming that the correction helped to improve the reliability of the forecast.

4.4 | CRPSS

Relative humidity CRPSS for both North and South Vietnam is represented in Figure 7 using persistence (red line) and climatology (blue line) as a reference in the land areas of North and South Vietnam. See composite CRPSS maps in Figures S3 and S4 for values over the ocean, which are excluded here as they are not relevant to Dengue prediction and have lower overall scores.

In Figure 7, North Vietnam CRPSS scores using persistence as reference start at around 0.5 at 1st lead day, and then gradually decrease until they reach values below 0.2 at the 10th lead day. In the areas of Red River Delta and Hanoi city, we have the same tendency although with higher scores (~0.6 on the 1st lead day and 0.2 on the 10th lead day) and less variability. By contrast, CRPSS with climatology as a reference shows higher scores in all the northern regions, starting with values around 0.7 at the 1st day of the forecast and decreasing monotonically to 0.6 at the 10th lead time.

For the South Vietnam region (Figure 7 lower row), the CRPSS obtained using persistence shows a low score since lead day 1 (~0.3), and slightly decreases with time reaching values ~0.2 at 10th lead time, showing similar results in the Southeast and HCMC areas. By contrast, CRPSS obtained with climatology as reference in South Vietnam has a higher score and variability compared to those obtained using persistence as reference

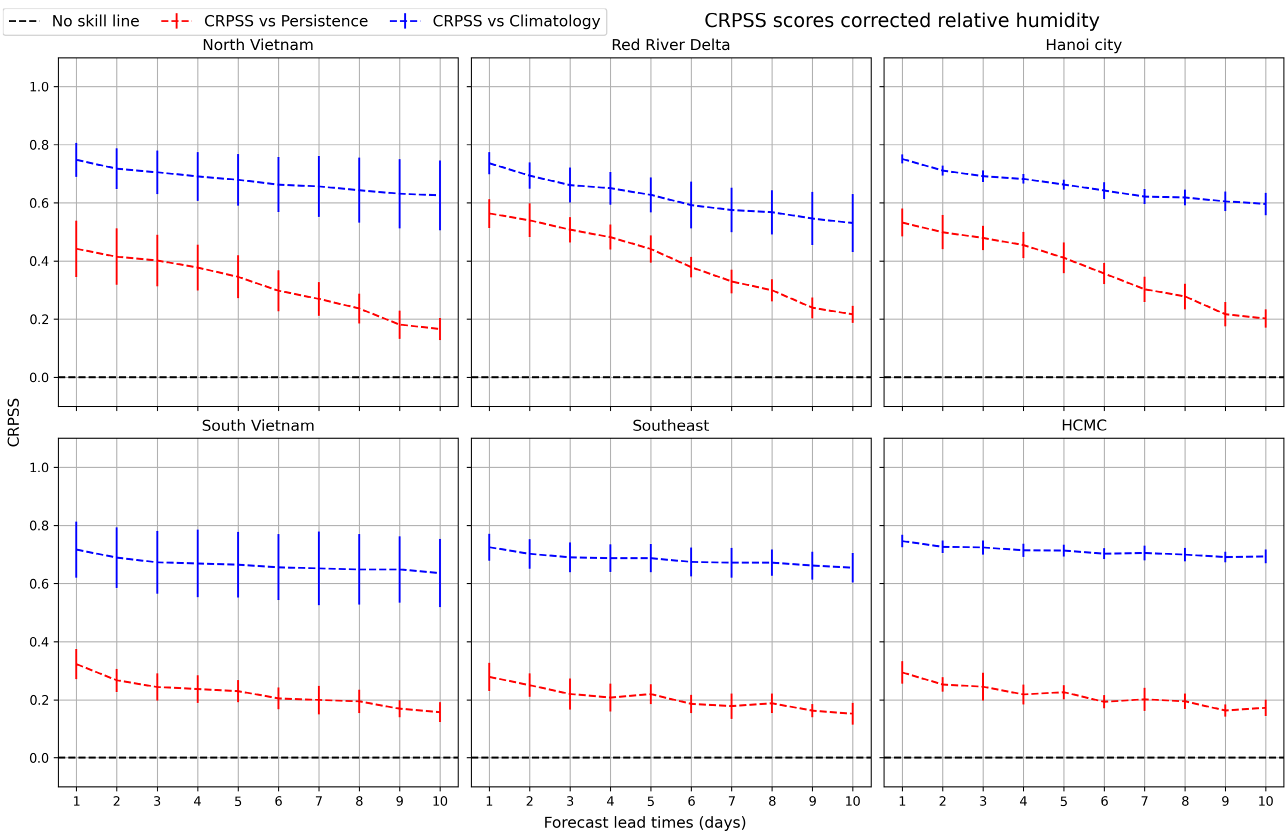

FIGURE 7 | Mean CRPSS for corrected relative humidity for the northern (up) and southern (down) regions of Vietnam during the rainy season. The blue/red line shows the CRPSS obtained when using the persistence/climatology as a reference whereas the black dash line shows the lower limit in which the forecast is considered skilful.

(scores start near 0.8 at lead day 1 and finish near 0.6). It is also worth noting that, even though the relative humidity forecast skill is lower in the southern region, the decrease in skill with lead time is considerably slower compared to its northern counterpart for both forecasts of reference. Also, it is interesting to note that the variability of CRPSS decreases as we go from bigger to reduced spatial areas.

Figure S5 shows the same information as Figure 7, but for the raw re-forecast data. There we see that results from Figure S5 are similar to Figure 7, but with slightly lower skill and increased variability. Hence, QM correction slightly increases the skill of the forecast and reduces forecast uncertainty.

It is worth noting that climatology does not work well as a reference for relative humidity, as exemplified by the high CRPSS scores in both North and South Vietnam (see Figure 7). Conversely, CRPSS scores obtained using persistence as a reference have much lower values compared to those obtained with climatology. The high autocorrelation in relative humidity (Figure 4) makes persistence the most challenging reference forecast, especially in the southern region. Nevertheless, results show that correcting the re-forecast dataset improves CRPSS scores up to 10 days in advance, regardless of which reference forecast is used.

We also measured the CRPSS variability for relative humidity during different months (Figures S6 and S7). When we use climatology as a reference (Figure S6), results are very similar to Figure 7, with barely any inter-monthly variability. Conversely, when using persistence as a reference (Figure S7), there is higher inter-monthly variability, and results change with regions. In the northern regions, skill is higher in September–October and lowest in August–May. By contrast, for the southern regions, October and September are the months with lowest skill, with CRPSS values reaching 0 by the 10th lead day. May is the month with the highest skill: CRPSS values are stable (~0.4) by the 10th lead day. This shows that persistence is the hardest reference to beat during the rainy season in South Vietnam, as the weather conditions in the tropics are much more stable compared to those in the subtropics. Hence, we expect that relative humidity forecast would be less skilful compared to persistence by the 10th day of forecast during the last month of the rainy season in South Vietnam. This does not mean that the forecast of relative humidity is unreliable during those months, as it is still much more skilful than the climatology (Figure S6), but that it will be less skilful than the persistence, which is a hard reference to beat in South Vietnam due to the high correlation of humidity in the southern region, as we saw in Figure 4.

The results obtained with CRPSS scores are consistent with those obtained by Main et al. (2024) for 2 m temperature; this is, the highest skill score is obtained at the beginning of the forecast and gradually decreases while still remaining skilful after 10 days. Nonetheless, unlike Main et al. (2024) who showed climatology to be the most challenging reference for cumulative precipitation, here we obtained a clear difference in skill depending on the reference forecast chosen with persistence being the toughest reference to beat, specially in the southern region.

The relative humidity forecast skill is lower in the southern region (Figure 7), one possibility that explains the difference between North and South Vietnam is that one of the variables used to measure relative humidity may not be well represented in the tropics, thus hindering the capability of the model to forecast relative humidity. To assess this we analyse CRPSS values for each of the weather variables used to derive relative humidity, namely 2 m temperature, 2 m dew point temperature and surface pressure (see Section 2.2). We focus on the latter two of these variables since the 2 m temperature verification is contained in Main et al. (2024).

Prior to the calculation of CRPSS for 2 m dew point and surface pressure, we verified that persistence is a valid reference for both 2 m dew point and surface pressure by measuring the autocorrelation across different lead times in the same manner as Figure 4 (Figure S8). In that Figure S8, we observe that autocorrelation values across the two variables are greater than 0.75; hence, both surface pressure and 2 m dew point have high enough autocorrelation to use persistence as a forecast of reference.

Figure 8 shows the CRPSS score for surface pressure for all regions of study using persistence and climatology as reference. Independently of the area or reference forecast, CRPSS scores for surface pressure show good skill at the initialization of the forecast (~0.6 in the northern regions and ~0.7 in the southern region) and by the 10th lead time we reach values of 0.2 (0.4) when using the climatology (persistence) as a reference. Results obtained are similar between North and South regions.

In Figure 9, we represented CRPSS per lead time for corrected values of 2 m dew point temperature. In North Vietnam, CRPSS values at the beginning of the forecast start at ~0.6 independent of the forecast of reference, but as we advance in time, results differ. For example, when we use CRPPS with climatology as a reference the score reaches 0.2 at the 10th lead day, whereas CRPSS using persistence, the skill is higher and more stable, having values around 0.4 at the 10th lead day of the forecast. Results for smaller sections of the North region (Red River Delta and Hanoi) are similar to those observed in North Vietnam but with less variability. The behaviour of 2 m dew point temperature in the North region is similar to 2 m temperature in Main et al. (2024), although here the difference between persistence and climatological references is more noticeable, with the climatological reference being the hardest to beat.

In the southern regions (Figure 9 lower row), the CRPSS scores at the beginning of the forecast are low (~0.3) for both reference forecasts, gradually decreasing to values between 0.2 and 0 at the 10th lead day. In addition, skill scores for 2 m dew point temperature in the southern region are significantly lower compared to the northern region. This tendency is also observed for 2 m temperature in Main et al. (2024), but skill scores obtained here are lower compared to the latter, reaching scores of near 0 by the 10th lead day.

In Main et al. (2024), both persistence and climatology acted as a similar benchmark for measuring forecast skill for temperature; here we found that for relative humidity persistence is the hardest reference to beat, whereas for 2 m dewpoint and surface

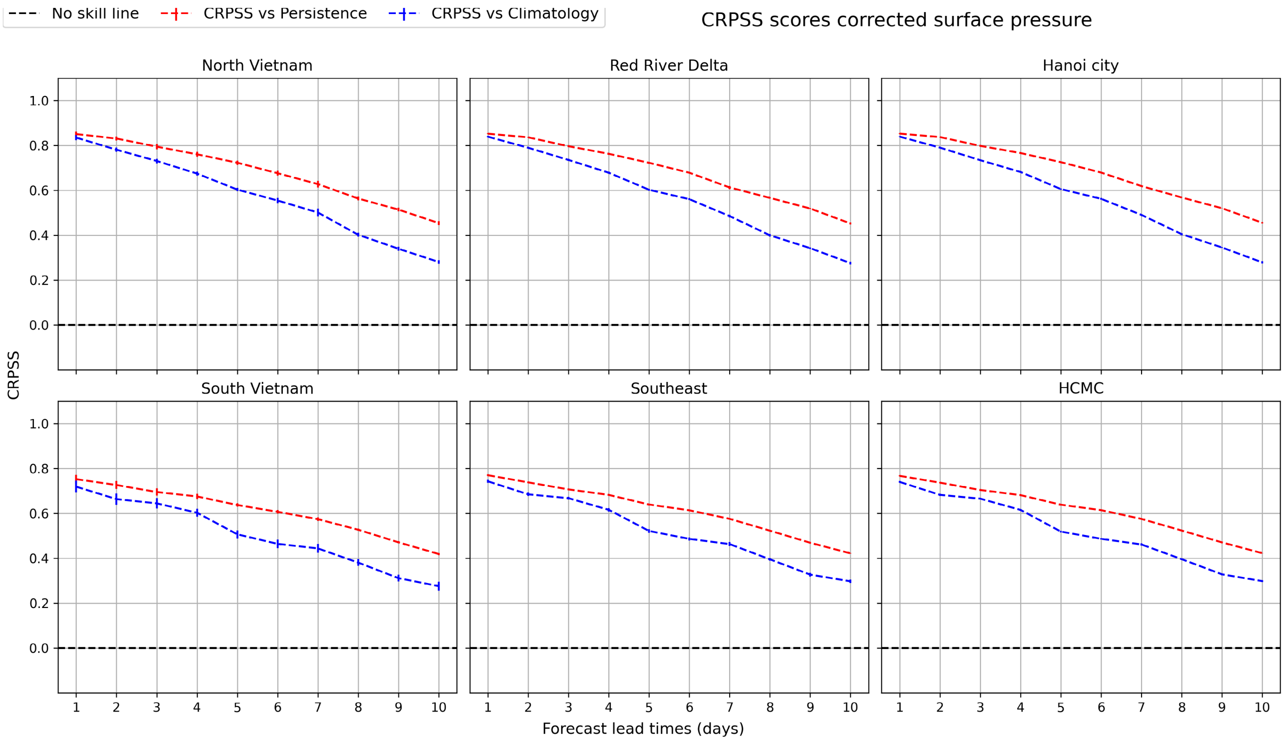

FIGURE 8 | Mean CRPSS for the northern (up) and southern (down) regions during the rainy season for surface pressure. The blue/red line shows the CRPSS obtained when using the persistence/climatology as a reference.

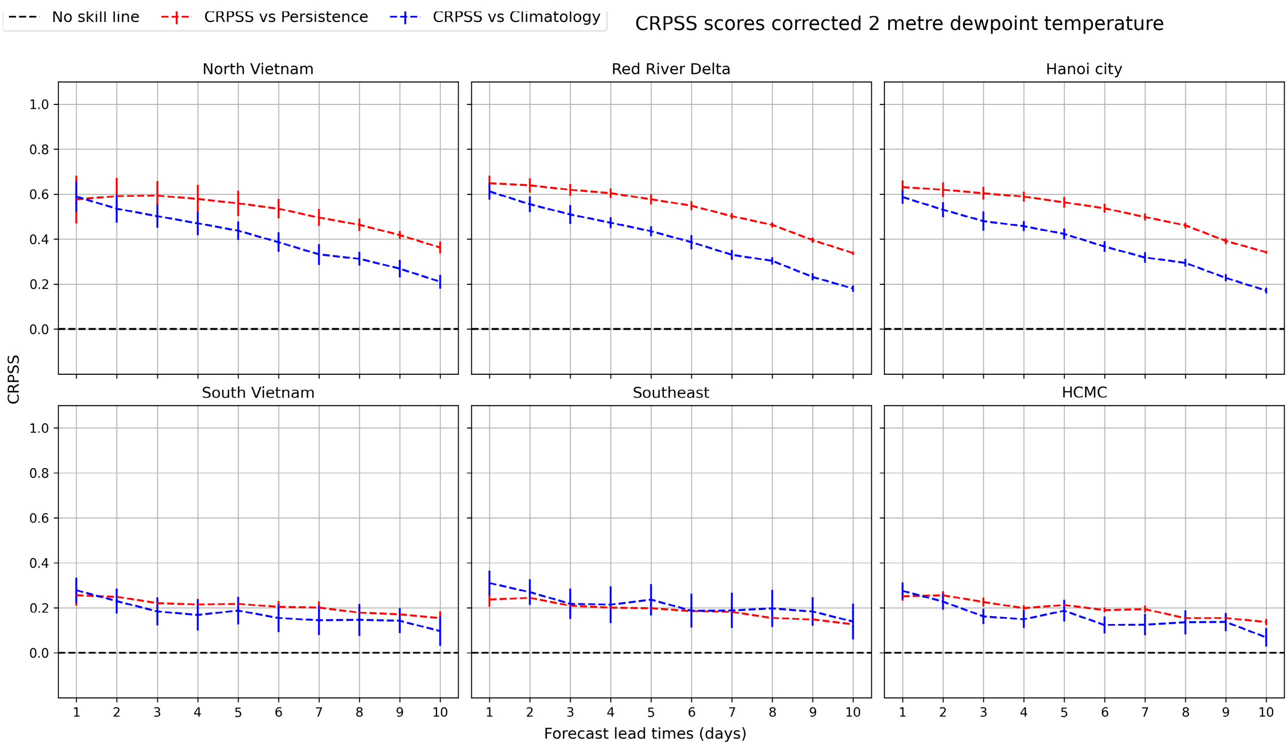

FIGURE 9 | Mean CRPSS for the northern (up) and southern (down) regions during the rainy season for d2m. The blue/red line shows the CRPSS obtained when using the persistence/climatology as a reference, respectively.

pressure it is the opposite. In Figure S9, we display the percentile distribution of relative humidity for the whole year; there we see that relative humidity has fairly low variability during the rainy season, which makes climatology a hard reference to use for relative humidity, whereas for variables with larger annual cycles such as 2 m temperature, 2 m dewpoint and surface pressure it acts as a harder (and therefore more informative) benchmark. By contrast, persistence is a harder benchmark to beat for relative humidity, especially in the southern region of Vietnam, as we saw in Figure 4.

Taking into consideration the results obtained in Figures 7–9 and fig. 13 of Main et al. (2024), the model is fairly skilful at predicting surface pressure for all lead times in all regions, whereas the 2 m dew point temperature forecasts are skilful in the northern region of Vietnam while it declines substantially in the south, showing lower skill compared to the results for 2 m temperature found in Main et al. (2024). Consequently, 2 m dew point temperature seems to be the variable that limits the skill of relative humidity in the southern region. Haiden et al. (2018) found a dry and cold bias between ECMWF model predictions and observations in regions closer to North Vietnam which increases towards lower latitudes. In Figure S10, we estimated the mean bias between 2 m dew point temperature in raw re-forecast data and observations, and we detect a systematic negative bias (between −1.5 and −1 K), thus confirming that 2 m dew point in Vietnam tends to be underestimated in a similar magnitude as the result observed in Haiden et al. (2018). The latter study also suggested that the humidity bias from the ECMWF model is (partly) caused by an overestimation of turbulent mixing in cloudy boundary layers, as well as to an insufficient temperature and dew-point gradient in the lowest 200 m. Taking into consideration that the southern region of Vietnam is located in the tropics (8.5°–12° N) it is plausible to think that relative humidity skill is limited in the tropics because of the incomplete representation of processes that affect humidity, which cannot be fully corrected using QM. We repeated the humidity analysis skill correcting the dew-point temperature before measuring the relative humidity, but it does not improve the results.

5 | Discussion and Further Studies

5.1 | Summary and Discussion

Raw re-forecast data from the ECMWF ensemble prediction model showed a spatially varying bias in predicting relative humidity during the rainy season (May–October) in Vietnam. This bias is not considerably big (up to 4% of relative bias in the South of Vietnam and in regions with high orography, and around −2% in the Red River delta region), but it is enough to affect the reliability of the forecast and consider raw re-forecast data as significantly different from observations.

Corrected re-forecast data show increased reliability compared to raw re-forecast data, and most of the ensemble members follow the same distribution as observations up to 10 days in advance. In addition, corrected re-forecast data also produces skilful forecasts of relative humidity up to 10 days compared to persistence and climatology, although forecast skill seems to be more limited in South Vietnam. From the two forecasts of reference, persistence is the hardest reference to beat, specially in South Vietnam, and this might be linked to the higher autocorrelation values of relative humidity in the tropical regions (see Figure 4), which would also explain why skill decays slower with lead time compared to the northern region. Forecasting relative humidity over smaller regions does not decrease forecast skill and reduces its variability. This is consistent with results from Main et al. (2024): this study concluded that this is likely to be associated with the fact that small scale behaviour is dominated by large-scale dynamics of the monsoon that are well represented in the model.

We analysed the skill of the model at predicting 2 m dew point temperature and surface pressure, and results showed that 2 m dew point temperature forecasts decline substantially in the south, showing lower skill compared to the results for 2 m temperature found in the Main et al. (2024). Therefore, the 2 m dew point might hinder the relative humidity forecast skill in South Vietnam. Haiden et al. (2018) demonstrated that some atmospheric processes in the tropics are not well represented. This includes an insufficient temperature and dew-point gradient in the lowest 200 m, which might compromise model skill at longer lead times. Therefore, a more accurate representation of 2 m dew point temperature in the tropics may increase the model's ability to forecast relative humidity in south Vietnam. Nonetheless it is also important to state that the results displayed here were obtained with the re-forecast data, which has 11 ensemble members whereas the current ECMWF real-time forecasts model has 101 ensemble members available for the first 15 days (see https://www.ecmwf.int/en/newsletter/173/earth-system-science/next-extended-range-configuration-ifs-cycle-48r1). As the operational DART Dengue prediction model will be using real-time forecast, we expect to obtain higher probabilistic skill as it has a higher amount of ensemble members.

It is also possible that global climate modes such as El Niño Southern Oscillation (ENSO) and Madden-Julian Oscillation (MJO) might affect 2 m dew point and 2 m temperature forecast skill. ENSO is the main climate driver which induces the development of heatwaves and cold surges in Vietnam (Pham-Thanh et al. 2024). By contrast, MJO modules cold surges and precipitation in Vietnam (Chen et al. 2004; Le et al. 2024). Hence, identifying how ENSO and MJO affect relative humidity skill might enable us to identify windows of opportunity for having skilful humidity forecasts.

These findings, along with prior results found by Main et al. (2024), verify that the ECMWF's forecasts are able to skilfully predict the temporal evolution of weather variables linked to Dengue development in Vietnam (temperature, precipitation and relative humidity), up to 10 days in advance during the rainy season (May–October), although relative humidity seems to be the most difficult variable out of the three to forecast in the southern region (at least, when compared with persistence as a reference).

Nonetheless, we also have to take into consideration the limitations of this study. The first one is that we assumed that the climate is stationary for the QM correction, as there was no obvious trend that there was a change in climatology for the last few years. Last, even though QM correction improved the reliability and accuracy of the relative humidity forecast, this technique does not perform an effective correction on the extreme values located at the tails of the distribution. This is because the frequency of occurrence of extreme values is low, and the characteristics of the new distribution obtained after the correction are strongly dominated by non-extreme values (Cannon et al. 2015; Zhang et al. 2022).

5.2 | Future Work

The findings of this study together with Main et al. (2024) confirm that the ECMWF weather forecast model is able to skilfully predict the evolution of 2 m temperature, total precipitation and relative humidity in Vietnam up to 10 days in advance. The skill of the ECMWF ensemble model in the extended forecasts for precipitation, 2 m temperature and humidity in the sub-seasonal scale (10–30 days in advance) will be assessed to establish the maximum lead time that can be given in the DART Dengue forecasts for appropriate interventions to be enacted. The bias-correction methodology has been included in the DART data pipeline to pre-process future real-time weather forecast data, and this will be followed by validation and testing of the full real-time DART Dengue forecasting system. The results presented in this manuscript, along with an assessment of the extended range weather forecast (between 1 and 3 weeks in advance), which is currently ongoing, will be key to expanding the time window available for applying mitigation measures that will limit/reduce the spread and damages of Dengue incidence, such as targeting interventions to affected areas, informing the public where future outbreaks are likely to occur, and preparing resources for health services.

Apart from expanding the model skill assessment into the sub-seasonal scale, the impact of modes of climate variability, such as El Niño Southern Oscillation or the Madden-Julian Oscillation on weather forecast skill in Vietnam could be explored. In particular, whether these modes can provide windows of opportunity that enable skilful forecasts between 10 and 30 days in advance, increasing the time of response before future Dengue outbreaks occur so as to improve future healthcare planning.

Depending on location, the spatial resolution of the weather forecast data may cover multiple districts and so increasing resolution through downscaling techniques may help ensure the DART goals of an accurate forecast for urban-district level can be achieved. This is likely to be most important for highly localised fields such as precipitation.

Author Contributions

Iago Pérez-Fernández: writing – original draft, writing – review and editing, visualization, investigation, validation, methodology, software, formal analysis, data curation. **Sarah Sparrow:** conceptualization, funding acquisition, supervision, resources, methodology, writing – review and editing, formal analysis, project administration, investigation. **Antje Weisheimer:** writing – review and editing, conceptualization, investigation. **Matthew Wright:** investigation, writing – review and editing, formal analysis. **Lucy Main:** software, data curation, resources, methodology.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** met70159-sup-0001-Supinfo.docx.