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REVIEW

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# Testing the suitability of Marginal Distribution Sampling as a gap-filling method using some meteorological data from seven sites in West Africa

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## Abstract

Meteorological data are useful in many fields related to climate change studies and their use often requires them to be continuous. To date, marginal distribution sampling (MDS), which consists of filling a missing value with an average of the data that are found in similar meteorological conditions over a flexible time window, is widely adopted in the FLUXNET community. In this work, we evaluate the performance of MDS at diurnal and monthly scales for the incoming shortwave radiation (Swin), relative humidity (RH), vapour pressure deficit (VPD), air and soil temperatures (Tair, Tsoil) acquired across seven sites in West Africa. The criteria tested are the MDS's ability to (i) fill gaps while reducing the error rate, (ii) represent proper variability within data and finally (iii) ensure homogeneity between its output and original data. We found during the daytime that MDS is adequate for filling gaps in Swin when both reducing error rate and a good representation of variability are targeted. If the goal is to have a small error rate, then this approach is recommended for all investigated variables except VPD. During nighttime, MDS is satisfactory to minimize the error when filling gaps in Tair, Tsoil and RH while to represent their variabilities it becomes more sensitive to the rate of missing data. At a monthly scale, the gap-filled data are consistent with the original ones for all variables attributable to data size and a wider sliding window that allows more data under similar conditions to be considered.

**KEYWORDS**

artificial gap, continuous data, gap filling, Marginal Distribution Sampling, meteorological data, West Africa

## 1 | INTRODUCTION

Continuous meteorological observations are needed in many studies and investigations in climate science and related disciplines. These data play a major role in the studies related to climate change (Tumenjargal et al., 2020; Zhang et al., 2011), global earth surface modelling (Zhao et al., 2012), data assimilation (Bauer et al., 2015; Dee et al., 2011), evaluation of satellite and reanalysis data (Boilley & Wald, 2015; Escobar et al., 2014; Palmer & Blanchard, 2021) and for several other scientific issues related to weather services (Bliefernicht et al., 2022; Galle et al., 2018). Furthermore, modelling studies oriented towards the identification of the impact of such processes depend greatly on meteorological data, which may be the drivers for predicting system properties. In fact, meteorological time series allow the identification of cycles and patterns repeated over time in such a way that, if properly combined with other observational data, can help in the task of predicting and validating future trends (Bayma & Pereira, 2018). These time series should preferably be temporally continuous; however, missing values are often present, making them sometimes impossible to be directly used. These missing values are due to various causes, including sensors malfunction, servicing and repairs and efficiencies in records storage and transmission (Hui et al., 2004; Vuichard & Papale, 2015).

Several methods have been developed to fill out discontinuities in meteorological time series, such as Marginal Distribution Sampling (MDS; Reichstein et al., 2005) and the Mean Diurnal Variation (MDV) approach developed by Falge et al. (2001), interpolation using classic statistical models as linear regression, Singular Spectrum Analysis (SSA; Schoellhamer, 2001; Vautard et al., 1992) and artificial intelligence-based algorithms (Körner et al., 2018), to name some. MDS has been proven in its ability to fill gaps in the eddy covariance data (Kim et al., 2020; Mahabbati et al., 2021), although they generally have more gaps than weather data. MDS consists in replacing the missing value for a time '*t*' by the average of the data under similar meteorological conditions. An advantage of the MDS method lies in its ability to take environmental variables into account, using a sliding time window adapted to the gap rate when searching for similar data to fill in (Reichstein et al., 2005). Furthermore, by using a limited number of input variables, the method remains simple while showing good performance. Linear interpolation from adjacent time steps is often used for small gaps (<3 half-hourly missing data) and assumes linearity between adjacent values, but the performance of this hypothesis remains questionable (Mwale et al., 2012). MDV is also an interpolation method based on temporal autocorrelation of data. SSA is a data adaptive non-parametric method that decomposes a given time series into smaller components based on Singular Value Decomposition (SVD). Further, SSA was developed to be capable of filling data gaps within time series based on the characteristics derived from available data samples (Kondrashov et al., 2010; Schoellhamer, 2001). The challenge with it lies in the appropriate selection of matrices to accurately reconstruct the various components of the time series. Artificial intelligence-based methods, such as random forest, neural networks, Support Vector Machine (SVM), gradient boosting (Körner et al., 2018) and Bidirectional Long Short-Term Memory I, (Hanoon et al., 2021; Katipoğlu, 2021; Xie et al., 2021), have in common to improve their outputs by minimizing the error values. However, in seeking to minimize error as much as possible, preservation of the variance of data is not always guaranteed (Beguería et al., 2019). In addition, these artificial intelligence algorithms require a huge amount of computational time, and model outputs remain so far very difficult to explain (Breiman, 2001; Coutinho et al., 2018). Using nearby stations could also be an option but this requires the sites to be very close to each other.

To date, however, no unique filling methodology exists in the literature to be recommended as a standard to deal with the missing data issue. This is because performances of the respective gap-filling techniques depend on the type of site, the type of variables, the length of the gaps and the time of day (Alavi et al., 2006; Lucas-Moffat et al., 2022; Park et al., 2015; Zhu et al., 2022). Because of this and because MDS is the gap-filling routine that has been chosen by FLUXNET in its flux computation processing chain (Pastorello et al., 2020), giving it much visibility, we test in this work, for the first time in the West African region, the suitability of the MDS algorithm to fill gaps in meteorological variables. To the authors' knowledge, this topic has never been covered in West Africa while continuous time series can be used to understand the climate variability and change in this region. Data for five meteorological variables namely: incoming shortwave radiation (Swin), air temperature (Tair), relative humidity (RH), vapour pressure deficit (VPD) and soil temperature at 10 cm (Tsoil) acquired above seven sites spread over the West African region in Benin (Dangbo, Bellefoungou and Nalohou), in Niger (Banizoumou) and Mali (Agoufou, Bamba and Kobou) were used. To achieve this aim, three scenarios have been tested. For each meteorological variable at each site, artificial gaps were injected into the half-hourly data according to a different percentage of gaps taken in block (25%, 50% and 100%) at diurnal scale and in extreme months (dry and wet). Next, the performance of MDS has been evaluated at two scales (diurnal, monthly) with three metrics being the Percent Bias (PBIAS), the Root Mean Square

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Error (RMSE)–observations standard deviation ratio (RSR) and the Differential Shannon Entropy (DSE). The technique and scenarios included in this study can be tracked on any other location and their performances can be compared with the findings of this work.

The manuscript has the following structure. In Section 2, a brief description of the sites and data used are presented. The methodology that includes MDS as well as the three metrics used to evaluate the performance of MDS are shown in Section 3. Section 4 gives the results obtained and finally the outcomes of the study are discussed. Section 5 summarizes the main findings of this work and ends with a conclusion.

## 2 | SITES AND DATA DESCRIPTION

### 2.1 | Sites description

The meteorological data used in the current study originates from seven different sites (Figure 1) acquired in three West African countries (Benin, Niger and Mali). Following the latitudinal ecoclimatic gradient of the region, these sites can be classified in two/three main climate categories: the subequatorial (Dangbo) and Sudanese (Nalohou and Bellefoungou) sites of Benin, the Sahelian sites of Niger (Banizoumou) and Mali (Agoufou, Bamba and Kobou).

The Dangbo site (lat. 6.6014° N, long. 2.5465° E) is located within the Institute of Mathematics and Physics, at Dangbo's village. The station was installed in October 2020 above a small maize and cassava field. The climate in this region is a tropical savanna according to the Köppen climate classification; it is also called ‘tropical equatorial climate’ (Judex et al., 2009) or a subequatorial climate and is characterized by two rainy seasons and two dry seasons. The average annual rainfall varies between 1200 and 1400 mm (Vissoh et al., 2012) and mean temperature is about 27°C (Ouranos & Oxfam, 2020). Over the study period, average air temperature is about 27 ± 2.8°C for an incoming shortwave radiation of 188 $W/m^2$.

The Nalohou site (lat. 9.74° N, long. 1.60° E) is located in a cultivated area that consists of crops alternating with fallows, while the Bellefoungou site (lat. 9.79° N, long. 1.72° E) lies in a woodland open clear forest with perennial vegetation (Mamadou et al., 2016). These two sites are located 13 km apart in the Donga catchment. The climate is Sudanian type in the northern region of Benin, characterized by a succession of wet and dry seasons separated by two transitional periods (Mamadou et al., 2014). Mean precipitation amount in the region is 1230 mm over the period 1950–2010 (Mamadou et al., 2016) and more than 70% of the annual rainfall fall between July and October (Le Lay & Galle, 2005). Mean annual temperature is about 25°C (Galle et al., 2018).

The Niger site is located in a Sahelian zone in Banizoumbou (lat. 13.5311° N, long. 2.6613° E). Banizoumbou lies in a rural and agro-pastoral area located 60 km from Niamey. This site is located 200 m altitude and received an average yearly rainfall of 509 mm over the period from 1994 to 2005 (Laouali et al., 2012). In Niger, we have generally two seasons: a dry season from October to May and a rainy season from June to September with a mean annual temperature of 29.2°C from 1950 to 2010 (Leauthaud et al., 2017). The area has a typical semiarid tropical climate.

In Mali, meteorological data acquired in Agoufou (lat. 15.34° N, long. 1.48° W), Bamba (lat. 17.1° N, long. 1.4° W) and Kobou (lat. 14.7° N, long. 1.5021° W; Mougin et al., 2009) have been used for testing the MDS gap-filling performance. All these three sites are located in the Gourma region of eastern Mali, between the Sahelian and Saharo–Sahelian transition zone, near the Niger River and bordering Burkina Faso (Mougin et al., 2009). The region experiences one rainy season extending from June to September with 370 mm the higher rainfall and one dry season (October–May). Gourma has mean annual temperature of 30.2°C (Galle et al., 2018).

All study sites (except that of Dangbo) are part of the African Monsoon Multidisciplinary Analysis–Coupling of the Tropical Atmosphere and Hydrological Cycle (AMMA–CATCH) observatory (Galle et al., 2018; Lebel et al., 2009). The Dangbo site that has been installed within the framework of the Assessment of Surface Ecosystem Exchanges in West Africa (ASEEW@) project thanks to the Organization of Women in the Developing World (OWSD).

### 2.2 | Data used

Table 1 summarizes the main characteristics for each location. Variables of interest are: incoming shortwave radiation (Swin), RH, VPD, air temperature (Tair) and soil temperature (Tsoil or T_soil_10cm).

Before the implementation of the method used, the rate of missing data on a yearly basis according to each variable of interest was calculated using the imputeTS package (Moritz & Bartz-Beielstein, 2017). Figure 2 shows the distribution of gaps over the study period and for each site. The rate of missing data ranges from 0% to 75%, and soil temperature is the gappiest. In addition, we also assessed the percentage of gaps in each year at different times of the day (night, morning and afternoon) for each variable of interest. We present in Figure 3, and the rates of these gaps for only one site while the others are provided in Figures S1–S6. It is worth

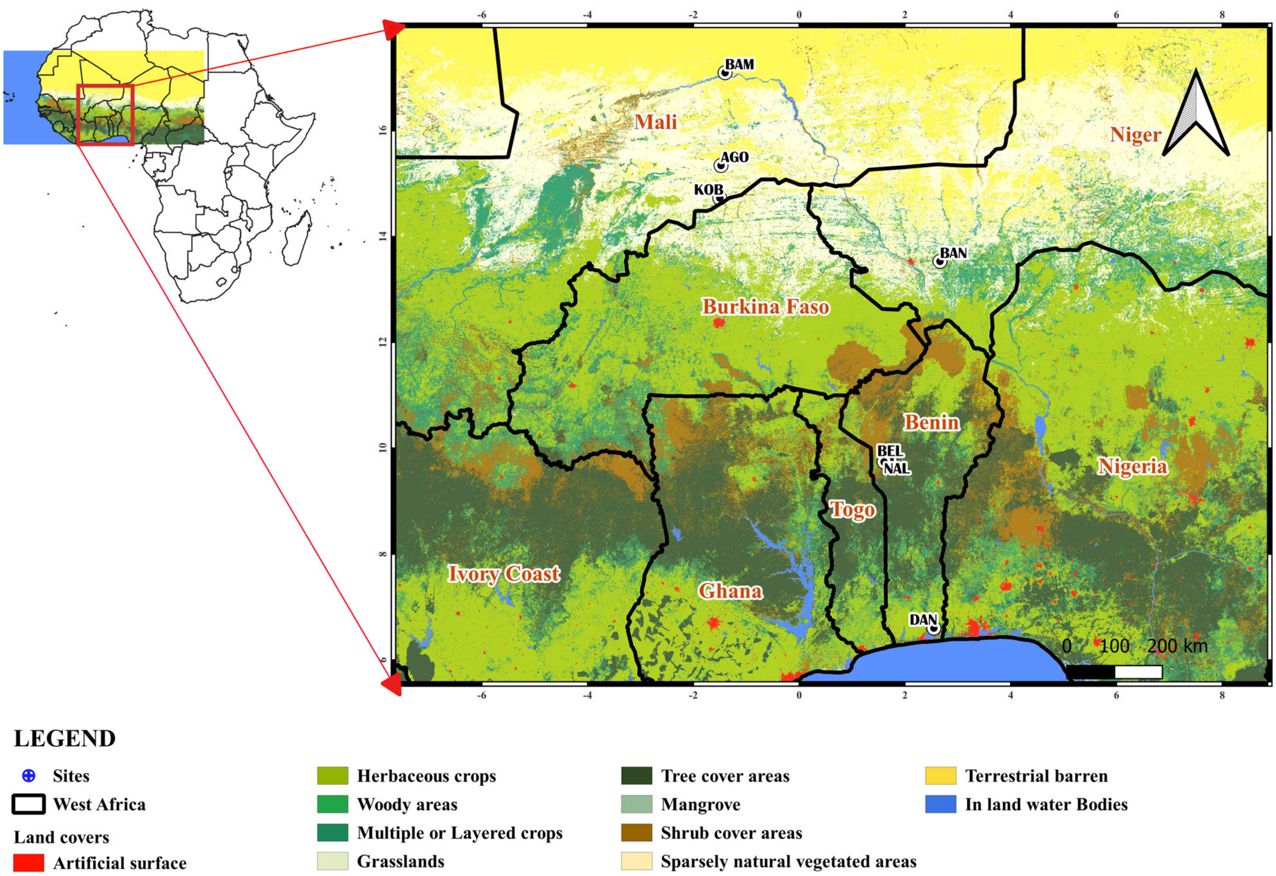



**FIGURE 1** Land cover map of the study area and location of meteorological stations: Dangbo (DAN), Nalohou (NAL), Bellefoungou (BEL), Kobou (KOB), Agoufou (AGO) and Bamba (BAM).

**TABLE 1** General characteristics of selected stations in West Africa.

| Station name | Acronym | Latitude (°) | Longitude (°) | Elevation (m) | Starting date | Ending date | Period test | Variables |
|---|---|---|---|---|---|---|---|---|
| Dangbo | DAN | 6.6 | 2.54 | 50 | 1 December 2020 | 22 June 2022 | May 2021–May 2022 | RH, Swin, Tair, Tsoil and VPD |
| Nalohou | NAL | 9.74 | 1.6 | 449 | 1 January 2006 | 31 December 2018 | 2008 | RH, Swin, Tair, Tsoil and VPD |
| Bellefoungou | BEL | 9.79 | 1.72 | 445 | 1 January 2006 | 31 December 2018 | 2008 | RH, Swin, Tair, Tsoil and VPD |
| Banizoumbou | BAN | 13.53 | 2.66 | 200 | 1 January 2006 | 31 December 2015 | 2013 | RH, Swin, Tair, Tsoil and VPD |
| Kobou | KOB | 14.7 | 1.5 | 250 | 1 January 2008 | 31 December 2011 | 2010 | RH, Swin, Tair and VPD |
| Agoufou | AGO | 15.34 | 1.48 | 290 | 1 January 2005 | 31 December 2011 | 2010 | RH, Swin, Tair and VPD |
| Bamba | BAM | 17.1 | 1.4 | 250 | 1 January 2005 | 31 December 2010 | 2006 | RH, Swin, Tair and VPD |

Abbreviations: RH, relative humidity; VPD, vapour pressure deficit.

noting that there is generally more missing data at night. In Table 1, one can also find the longest gap-free periods selected as the 'MDS period' or 'year test'. This 'period/year' test must encompass 12 consecutive months without gaps for all variables of interest and can also coincide with a normal calendar year (from January to December).

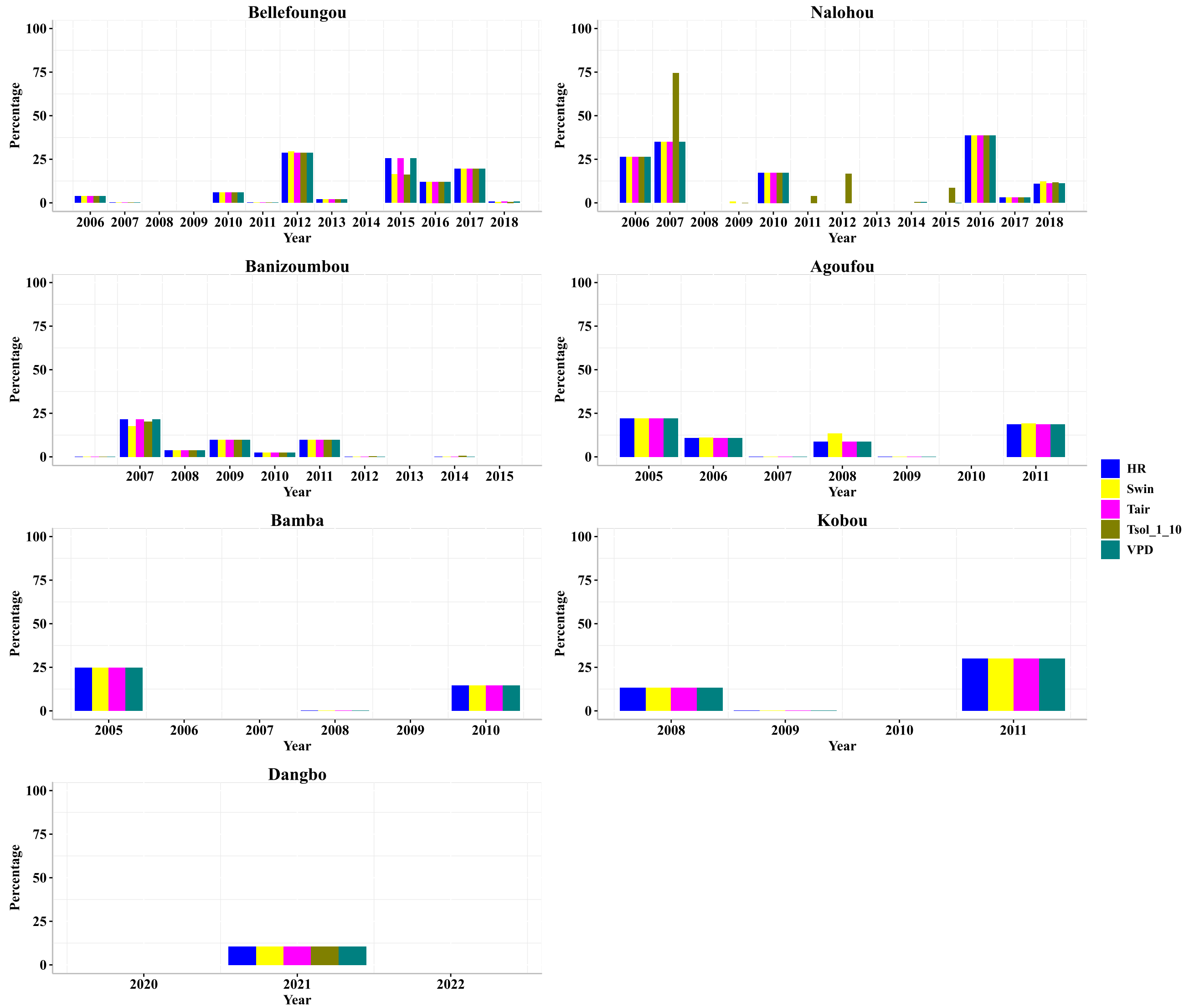



**FIGURE 2** Percentage of gaps over study period and per sites for relative humidity (RH; blue colour), incoming shortwave radiation (Swin; yellow), air temperature (Tair; magenta), soil temperature (Tsoil_1_10; green) and vapour pressure deficit (VPD; forest-green).

# 3 | METHODOLOGY

## 3.1 | The MDS method

Many methods exist in recent literature to fill gaps in meteorological data, but the most common method used in the FLUXNET network is MDS, originally proposed by Reichstein et al. (2005) and for turbulent fluxes. MDS is based on the construction of a look-up table around each half-hourly single gap. Its fundamental hypothesis is that 'for a short time window (7–14 days) and under similar meteorological conditions, the measured data should be similar' (Falge et al., 2001). Herein, similarity can be defined as meteorological variables that characterize mostly the study site, the variable to be filled and, finally, variables that do not deviate, in the time windows considered from a certain set threshold. Reichstein et al. (2005) considered the global radiation, air temperature, VPD with thresholds of 50 W/m$^2$, 2.5°C and 500 Pa, respectively, as targeted meteorological variables. On this basis, the MDS algorithm was developed using two other existing methods for different cases. When there is no meteorological 'data' for a half an hour, a temporal auto-correlation is done on adjacent days, and the average is taken and used to fill the gap: this approach is called the mean daily variation (MDV; Falge et al., 2001). The window of the adjacent day should be short enough to avoid influences of vegetation development. The window often considered is 14 days. In cases where meteorological variables are present, the missing data (at a half an hour) are filled by averaging the variable calculated over a window of '*n*' consecutive days, for similar

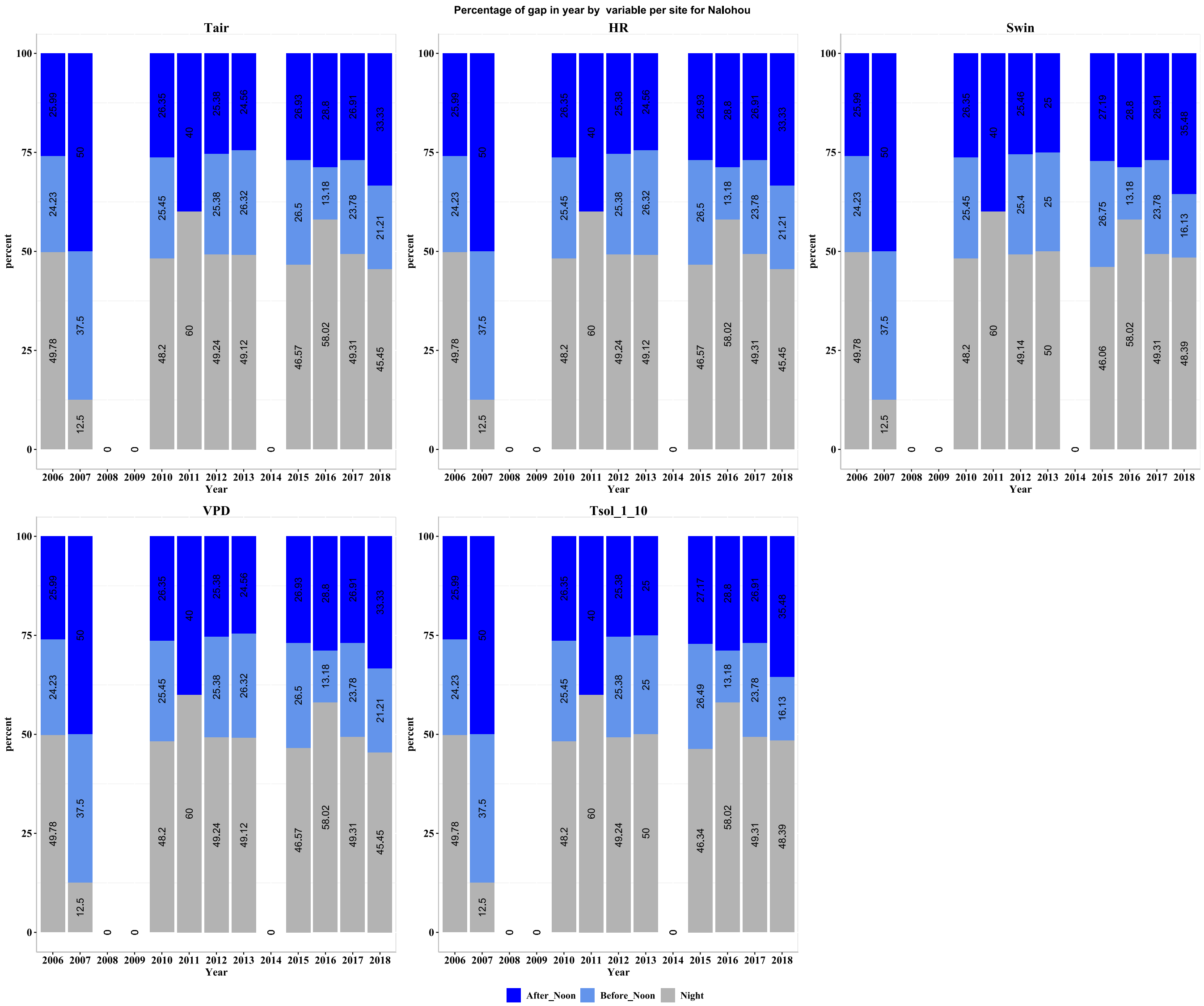



**FIGURE 3** Percentage of gaps for each variable according to the year and day periods: Night (grey), Before Noon (cornflower blue) and After Noon (blue) at Nalohou site. RH, relative humidity; VPD, vapour pressure deficit.

meteorological conditions: this is the look-up table (Falge et al., 2001). In some cases, one of the meteorological variables may be missing. Moreover, the length of window considered may not be sufficient to obtain a sufficient number of points for averaging. Therefore, the algorithm is run again but for a larger window to obtain the required number of points. A noteworthy fact, as demonstrated by several authors (Papale et al., 2006; Park et al., 2015), is that the temporal window defines the gap-filling quality. It is worth noting that several authors (Moffat et al., 2007) have demonstrated the inability of MDS in filling gaps longer than 2 weeks. On the other hand, MDS has shown poor performance for gaps occurring at night (Moffat et al., 2007; Reichstein et al., 2005). In this study, the offline version of the MDS algorithm in R (R Core Team, 2017), under the package REddyProc (Wutzler et al., 2018), which provides more advanced setting abilities, is used to test the consistency of the MDS for the selected meteorological variables and at diurnal and monthly scales. This offline version allows changing the variables used to create the look-up tables and define the similar meteorological conditions. It also permits authors to alter the variable range.

## 3.2 | Strategies for evaluating MDS at diurnal scale and for extreme months

The evaluation of the MDS across studied sites has been done at diurnal scale and for extreme months (dry and wet). From the 'year' or 'period' test corresponding to the year or the period without gaps for all variables analysed, we identify in each month the 'day test' by comparing the monthly diurnal cycle relative to all days of the month. The 'day test', which is further retained for each variable, is the day with the smallest Euclidean distance $D(x,y)$ between the monthly diurnal cycle and all days of the month. By this way, we assume that the 'day test' is more or less representative of the target month for the variable concerned. The Euclidean distance is expressed as:

$$D(x,y) = \sqrt{\sum_{i=1}^{n=48} (y_i - x_i)^2}, \tag{1}$$

with $y_i$ and $x_i$ denoting the half-hours of the mean monthly diurnal cycle and the day of the month, respectively.

Afterwards, given that most of the previous studies have highlighted that performance of gap-filling methods vary between day and night (Moffat et al., 2007), and to make our analysis more thorough, we split the 'day test' data (48 values) for each variable into three parts: BeforeNoon (BeN), AfterNoon (AfN) and Nighttime (NiT). To identify accurately the time intervals, days and nights are identified by using the sunrise and sunset times as described by Ham (2015). In fact, this method divides the Daylength ($\omega$; Equation (2)) by 2 and then adds or subtracts the solar noon ($\alpha$) given in Equation (3).

$$\omega = \frac{\pi \times \cos^{-1}(-\tan(\phi)\tan(\delta))}{6}, \tag{2}$$

where $\delta = 0.409 \times \sin\left(\frac{2\pi N}{365}\right) - 1.39$ is the sun's declination angle, $\phi$ is the latitude and $N$ is the day of the year.

$$\alpha = 12 - \frac{E}{60} - \frac{\beta - \theta}{15}, \tag{3}$$

where $E = 9.87\sin(2B) - 1.5\sin(B)$ is the time equation, $\beta = 15 \times t_z$ is the local time meridian, $t_z$ is the time zone, $\theta$ is the longitude and $B = \frac{2\pi(N-81)}{364}$.

The BeN samples are taken between the beginning of the sunrise and noon, while the AfN samples are taken between 1 PM and the time of sunset. After this categorization of the 'day test' data, and for each part of the day test, artificial gaps were introduced by blocks of 25%, 50% and 100% and then the gap filling was performed at diurnal scale using the MDS algorithm. These percentages were chosen to be close as much as possible to the real situation where one may have 25%, 50% or 100% of consecutive gaps in the data for the period of the day considered. Indeed, the block of gaps were inserted continuously to ensure that all samples for each part of the day (BeN, AfN and NiT) were considered. For example, in the case where half of the data in the NiT period is missing meaning that 50% of artificial gaps are introduced (corresponding to 12 consecutive half hours) in the first part of the night, the MDS algorithm is then used to fill these missing values. Afterwards, we ran the gap-filling algorithm for the next 12 half hours of data. By this way, the number of MDS simulations is dynamic and relies on the rate of gaps injected in block. For each gap scenario, an average of the MDS simulation outputs (four, two and one in the case of 25%, 50% and 100% of gaps were introduced, respectively) and their associated standard error ($\varepsilon$) rate are finally computed for each variable of interest.

For extreme months, we identify from the 'period test' or 'year test' one dry and one wet months. The dry month is the month of the dry season during which air temperature is the highest, while the wet month is the month of the wet season with the lowest value of air temperature. The idea is to test the ability of the MDS to fill gaps in data at monthly scale based on half-hourly data. Similar to what had been described earlier at diurnal scale, three gap scenarios were tested (25%, 50% 100%) and for each scenario, dynamic simulations were done yielding to the computation of the average values of gap-filled data as well as associated errors. This allows the generation of differently located random gap scenarios for each case tested.

## 3.3 | Evaluation of MDS performance

The performance of the MDS method is evaluated using three different metrics. They are the PBIAS, the RMSE–observations RSR and the DSE. We preferred these metrics due to their high accuracy and efficiency compared to bias, mean square error and entropy (Bennett et al., 2013; P. Gupta & Christopher, 2008; Moriasi et al., 2007; H. J. Wang, Riley, & Collins, 2015). Combining these three metrics allows more insight relative to closeness, homogeneity and variance explanation between original data and those gaps filled using the MDS approach.

### 3.3.1 | Percent bias

According to H. Gupta et al. (1999), the deviation of data being evaluated, which is called PBIAS, allows examining the model's ability to overestimate or underestimate the measured data except that it removes the mean effect of observed data in its evaluation. Positive values indicate an underestimation, while negative values indicate an overestimation of the model. A model is accurate to the measured data when the PBIAS is between 0% and 25% (Abbaspour et al., 2015; Moriasi et al., 2007). PBIAS is calculated as:

$$\mathrm{PBIAS}=\frac{\sum_{i=1}^{n}(x_i-y_i)*100}{\sum_{i=1}^{n}x_i}, \tag{4}$$

with $y_i$ sample of output of model, $x_i$ a measured sample and $n$ represents the length of data.

### 3.3.2 | RMSE–standard deviation ratio

The RMSE–RSR is used instead of the classical RMSE because RSR combines both an error index described with the RMSE and the additional information recommended by Legates and McCabe (1999). With this combination, RSR incorporates the advantages of error index statistics and includes a scaling/normalization factor so that the resulting statistic and reported values can be applied to various output responses (Verma et al., 2020). RSR is the normalized version of the RMSE by standard deviation (Moriasi et al., 2007). A low value of RSR (close to 0) expresses a low amplitude of the errors and a good suitability to the observed data (good explanation of the variance). Moriasi et al. (2007) suggested a criterion to evaluate the model performance for different ranges of RSR:

- If $0 \leq \mathrm{RSR} \leq 0.5$, model has very good performance
- If $0.5 < \mathrm{RSR} \leq 0.6$, model has good performance
- If $0.6 < \mathrm{RSR} \leq 0.7$, the model is satisfactory
- If $RSR > 0.7$, the model is unsatisfactory.

$$\mathrm{RSR}=\frac{\sqrt{\sum_{i=1}^{n}(x_i-y_i)^2}}{\sqrt{\sum_{i=1}^{n}(x_i-\overline{x})^2}}, \tag{5}$$

with $y_i$ sample of output of model, $x_i$ a measured sample, $\overline{x}$ average of measured samples and $n$ representing the data length.

Based on model evaluation studies in which both PBIAS and RSR have been used (Carlos Mendoza et al., 2021; Moriasi et al., 2007), we define the general performance rating used in this study to evaluate the consistency of the MDS in Table 2.

**TABLE 2** Categorization of percent bias (PBIAS) and root mean square error–standard deviation ratio (RSR) intervals according to the performance of the marginal distribution sampling (MDS).

| Performance of the MDS | PBIAS | RSR |
|---|---|---|
| Very good | PBIAS $\leq +10\%$ or PBIAS $\leq -10\%$ | $0 < \mathrm{RSR} \leq 0.50$ |
| Good | $-15\% <$ PBIAS $\leq -10\%$ or $10\% <$ PBIAS $\leq 15\%$ | $0.50 < \mathrm{RSR} \leq 0.60$ |
| Satisfactory | $-25\% <$ PBIAS $\leq -15\%$ or $15\% <$ PBIAS $\leq 25\%$ | $0.60 < \mathrm{RSR} \leq 0.70$ |
| Bad | $-50\% <$ PBIAS $\leq -25\%$ or $25\% <$ PBIAS $\leq 50\%$ | $\mathrm{RSR} > 0.70$ |

### 3.3.3 | Differential Shannon Entropy

Shannon entropy, a formalism originally from information theory (Guizzo, 2003), is a measure of the homogeneity of information contained in numerical data.

Let us consider a set of finite samples $(x_1,x_2,\ldots,x_n)$ of a measurable function or variable $X$ associated with a probability distribution $p:(x_1,x_2,\ldots,x_n)\longrightarrow\mathbb{R}_+$, such as $p(X=x_i)=\frac{x_i}{\sum_{i=1}^{n}x_i}$ and $\sum_{i=1}^{n}p(X=x_i)=1$, the entropy of the distribution (SE) that is the amount of information provided by the variable is defined as:

$$\mathrm{SE}(p)=\frac{-1}{n}\sum_{i=1}^{n}p(X=x_i)\log_2 p(X=x_i). \tag{6}$$

According to Godden and Bajorath (2001), DSE is an effective metric that can serve to augment differential expression whenever one seeks to measure differences in homogeneity rather than mere differences in magnitude. Therefore, it is used herein to compare differences in information content and variance of variables between the gap-filled and the non-gap-filled data. Calculating the entropy difference between the observed data samples and the entropy of the gap-filled data means thus comparing the information (or homogeneity) of the two data. This allows accounting in different manner the quality of the gap filling performed. Using DSE calculations, relative information content of these two data can be

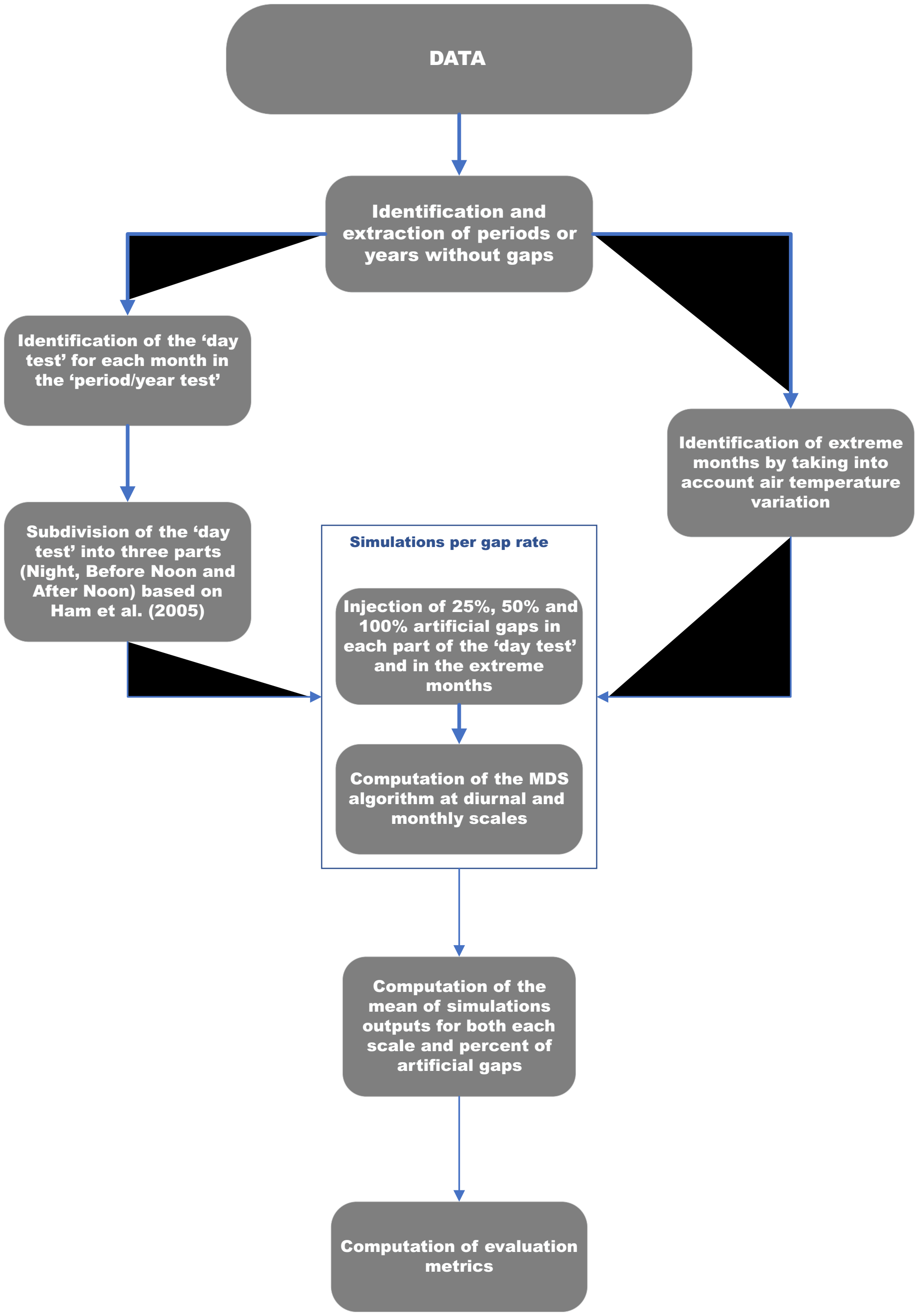



**FIGURE 4** Diagram showing the different steps of the methodology used in this study. MDS, marginal distribution sampling.

quantified, even if differences are subtle. DSE is written as follows:

$$\mathrm{DSE} = \left|\mathrm{SE}_i - \mathrm{SE}_p\right|, \tag{7}$$

with $\mathrm{SE}_i$ entropy of the test data and $\mathrm{SE}_p$ that of data in which gaps are filled. DSE ranges in [0, 1]. For values close to 1, there is a greater heterogeneity and for values close to 0, there is a greater homogeneity. In this work, DSE is calculated using the EntropyExplorer package of R (K. Wang, Phillips, et al., 2015). The methodology followed in this work is summarized in Figure 4.

# 4 | RESULTS AND DISCUSSION

## 4.1 | Performance of MDS at diurnal scale

The heatplots of the three metrics used to evaluate the performance of MDS at diurnal scale are displayed in

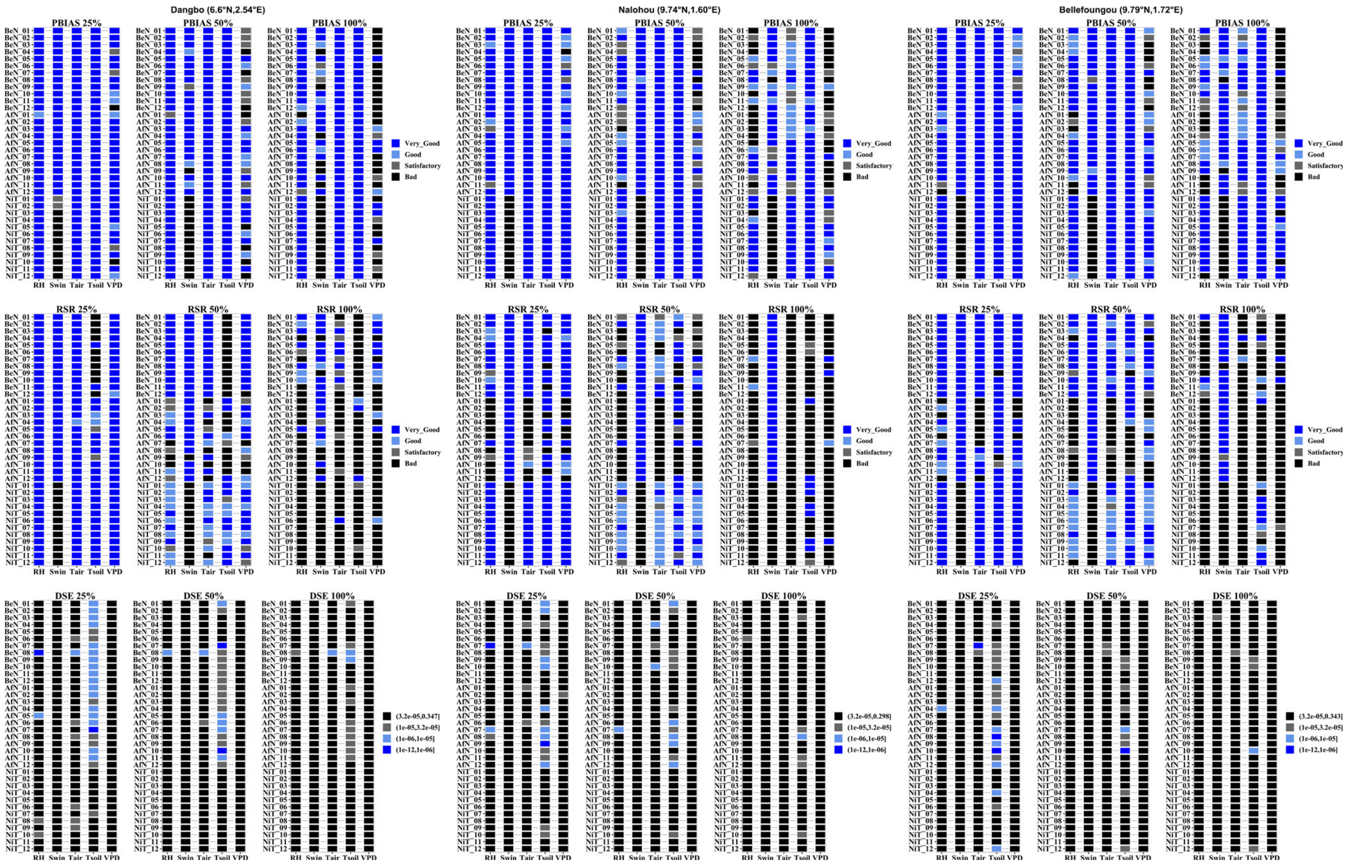


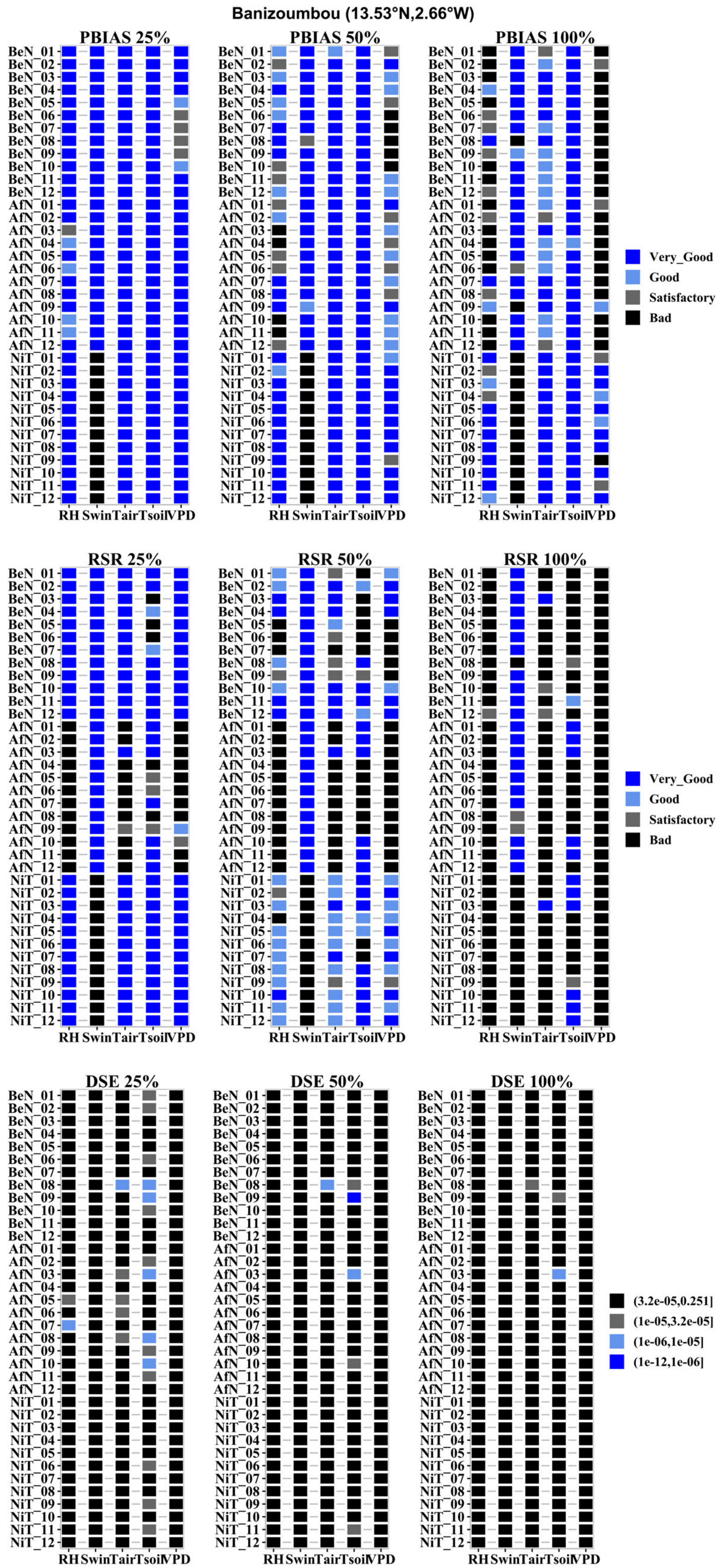

**FIGURE 5** Representation of metric outputs for each missing data scenario in Benin sites at the diurnal scale. From left to right: Dangbo, Nalohou and Bellefoungou. From top to bottom: percent bias (PBIAS), root mean square error–standard deviation ratio (RSR) and differential Shannon entropy (DSE) for each scenario (25%, 50% and 100%, respectively).

Figures 5–7. Metrics vary significantly across sites with the increase of artificial gap rates.

For all sites and in the AfN on average, the PBIAS values reveal that the gap-filled data are consistent with those measured for all variables except the VPD where magnitude of error increases with the percentage of gaps (Figures 5–7). In the same time, we noticed a very good explanation of the variance with the RMSE–observations RSR for the incoming shortwave radiation (Swin) that ranges between 0 and 0.5 ($0 \leq \mathrm{RSR} \leq 0.5$) whatever the percentage of gaps injected or the sites considered, while for the other variables, RSR values are worse regarding both day test and missing values (especially for Tair and Tsoil). Note that the MDS representativity for the Swin's variance is more obvious for sites located further north (Figures S7–S9). This suggests that using MDS reproduces well the variability of Swin in the AfN regardless of the considered site and the gap rate inserted (Figures 5–7). As expected, when the percentage of gaps reaches 100% in this case, the performance of MDS decreases. Previous work done by Zhu et al. (2022) had also shown that the performance of MDS decreases with increasing gap rate but for carbon dioxide ($CO_2$), latent heat (LE) and sensible heat (H) data from 94 FLUXNET2015 sites. Using MDS to gap-fill Swin data, therefore, could be suggested if one is looking for both representativity of the variability and low error magnitude for this time slot. In case of only low error magnitude is targeted, MDS is thus suitable for all analysed variables except VPD (Figures 5–7).

During the night period (NiT) accounting for 24 half-hourly values, the MDS algorithm performed poorly according to PBIAS and RSR obtained values for all percentage of artificial gaps in the incoming shortwave radiation ($25\% \leq \mathrm{PBIAS} \leq 50\%$; $-50\% \leq \mathrm{PBIAS} \leq -25\%$) and $\mathrm{RSR} > 0.7$ with a greater overestimation during the transitional night hours (from day to night and vice versa; Figures S7–S9). Overall, when looking at the obtained results for the Tair, VPD and RH (Figures 5–7), we noticed a good representativity in terms of magnitude ($\mathrm{PBIAS} \leq 10\%$ or $\mathrm{PBIAS} \geq -10\%$) of the NiT data. Sites located in the south of the study area (especially Dangbo) have some months (September, October and November) during which the magnitude of the gap-filled VPD is not well consistent with original data meaning that MDS fails for these months. Over the studied sites, where

**FIGURE 6** Representation of metric outputs for each missing data scenario in Banizoumbou site at the diurnal scale. From top to bottom: percent bias (PBIAS), root mean square error–standard deviation ratio (RSR) and differential Shannon entropy (DSE) for each scenario (25%, 50% and 100%, respectively).




measurements of soil temperature are available (Nalohou, Bellefoungou, Banizoumou and Dangbo), consistent values of PBIAS and RSR were observed from January to December and especially at Dangbo. Besides, results demonstrated that MDS explains well the variability of RH whatever the site considered. Indeed, during the NiT, RH is

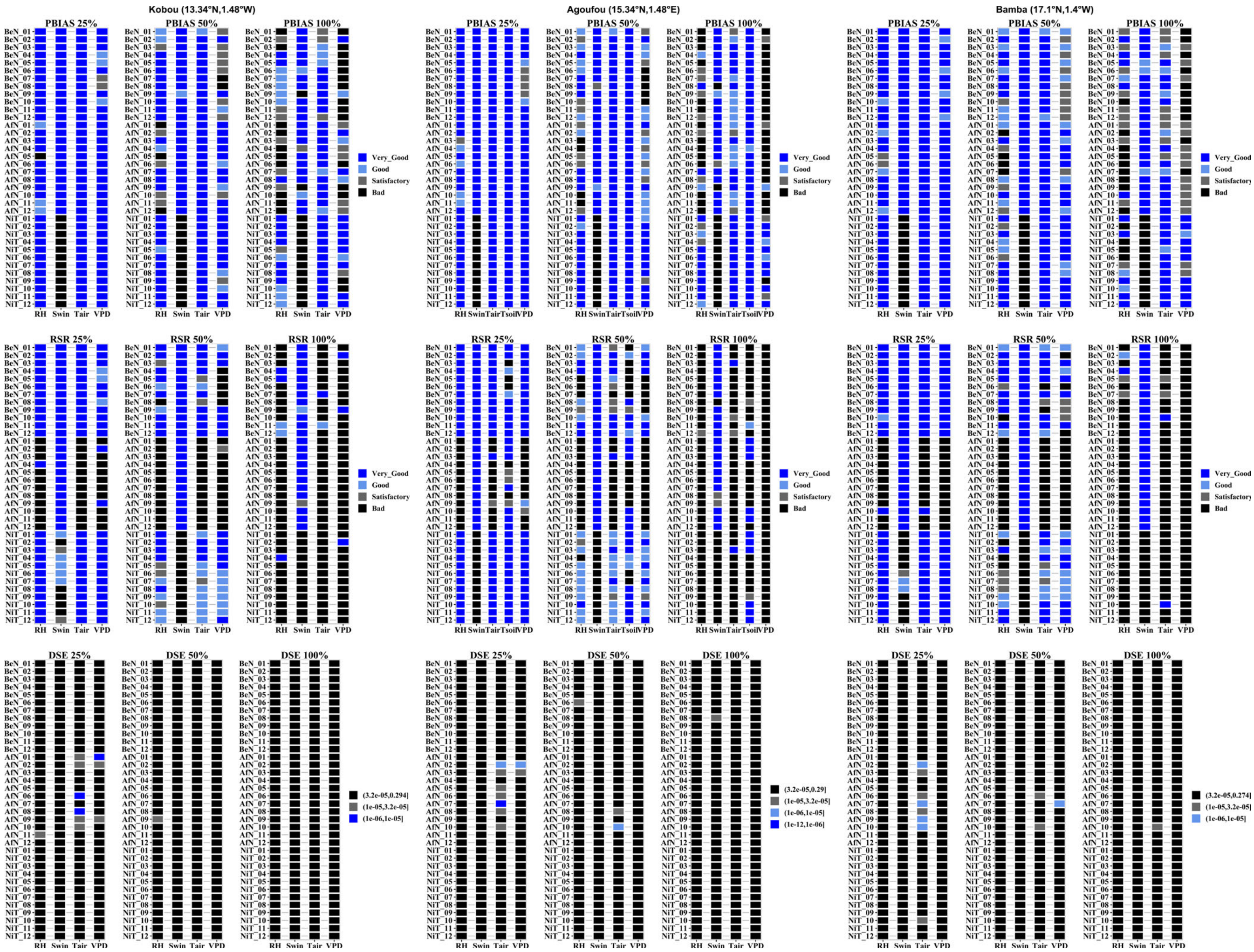



FIGURE 7 Representation of metric outputs for each missing data scenario in Mali sites at the diurnal scale. From left to right: Kobou, Agoufou and Bamba. From top to bottom: percent bias (PBIAS), root mean square error–standard deviation ratio (RSR) and differential Shannon entropy (DSE) for each scenario (25%, 50% and 100%, respectively).

higher and incoming shortwave radiation is low and does not vary enough. In addition, the atmospheric surface layer is mainly stable with lower friction velocity and wind speed (Hounsinou et al., 2022; Mamadou et al., 2014). Consequently, the mixing of air particles would not be efficient at all and from one half hour to another, little difference is observed in data (Figures S7–S9). This could explain the fact that MDS represented well the variability of RH. Also, explanation of the variance by MDS for all variables seems to be highly sensitive to percentage of missing values especially during the night hours. Finally, MDS represents Tair, Tsoil, RH and VPD well in terms of magnitude, while in terms of variability, it is more sensitive to percentage of missing data during NiT.

From 6:30 AM to 11:30 AM, MDS outputs are mostly unsatisfied $(25\% \le \mathrm{PBIAS} \le 50\%; -50\% \le \mathrm{PBIAS} \le -25\%)$ relative to VPD observation data regardless of the site considered and the percentage of gap filling, followed by an unsatisfactory representation of the variance; the latter increases with the rate of missing data (Figures 5–7). On the other hand, for the same period and across all sites, the differences between observed and simulated for others variables (Swin, Tair and Tsoil) are generally lower ($\mathrm{PBIAS} \approx 0$). As in the AfN, MDS explains here also well the variance for Swin. Finally, soil temperature has RSR site-to-site variations according to the percentage of missing data.

Figures 5–7 represent DSE and give more insights into the internal variability of the meteorological fields (RH, Swin, Tair, Tsoil, VPD) investigated. It should be noted that the DSE magnitude is very far from 0 whatever the site considered as well as for all time slots. By taking into account the DSE meaning, one can attribute this result to a degree of heterogeneity between MDS outputs and observation data. However, it should be noted that

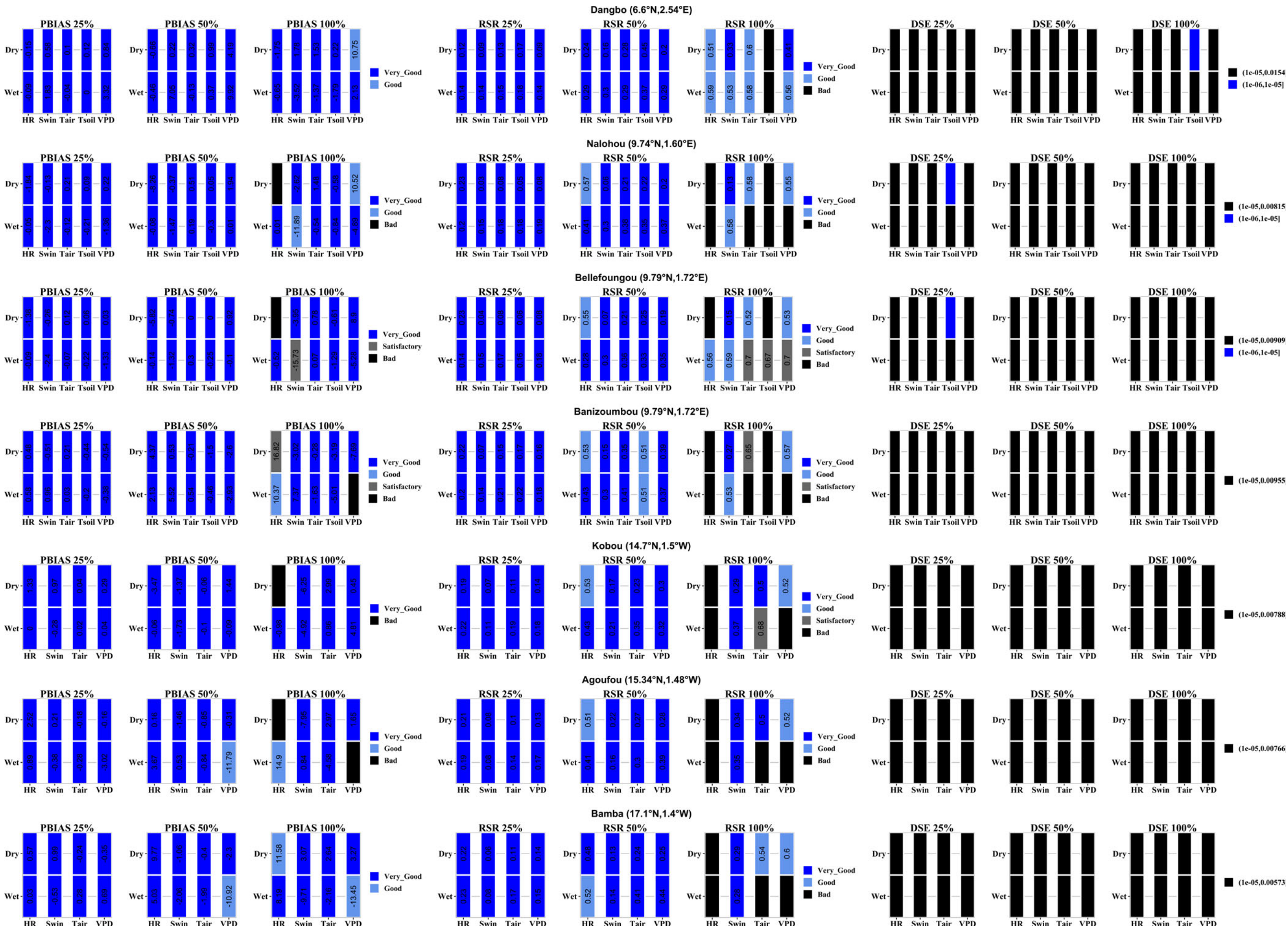



**FIGURE 8** Representation of the three metric outputs for each missing data scenario and for all sites at the monthly scale. DSE, differential Shannon entropy; PBIAS, percent bias; RSR, root mean square error–standard deviation ratio.

for the sites located further south (Dangbo and Nalohou), DSE is close to zero in the before noon hours and during the month of July and August for RH and Tair, regardless of the artificial gap rate considered. In addition, this metrics seems to be less sensitive at diurnal scale to the percentage of missing values and thus may not be a relevant metric to properly appreciate the results.

## 4.2 | Performance of MDS at monthly scale

The variance representativity and low error magnitude for both dry and wet months (Figure 8) are suitable over all sites and for all variables analysed (RSR > 0.2). This is probably due to the length of data involved compared to the diurnal cycle and thus a greater variability in atmospheric, terrestrial and energetic processes at a monthly scale. Hence, the amount of available data under the same meteorological conditions increases, which would facilitate the reduction of error magnitude and allows a good representation of variability. When the sliding windows of MDS are wider and can allow the detection of several data under similar meteorological conditions, the quality of MDS is poorly flagged, as pointed out by Wutzler et al. (2018). This is reflected by the DSE values which are less close to 0 (more heterogeneous) for the gap-filled data of VPD and Swin whatever the season. When looking at the homogeneity of data, it has been found that MDS ensures a greater homogeneity for Tair (DSE very low) whatever the site, period and gap rate.

When looking at the values of RSR and PBIAS for each variable and each site, some specific features can be highlighted. Indeed, the MDS outputs tend to be overestimated (negative values of PBIAS) for the RH data during dry months at the Benin sites (Figure 8). In contrast, they are underestimated (positive values of PBIAS) during the dry months at the Mali and Niger sites. Besides, it is obvious that sites characterized by sub-equatorial and Sudanian climates are more humid compared to sites located within the Sahelian climate. Therefore, the results obtained with the PBIAS at monthly scale and during dry months suggest that if the aim is to create unavailable data of the RH, then the use of MDS would underestimate or overestimate the values depending on the climate considered. During the wet months, PBIAS values for air and soil temperatures are closer to zero at the sites in Benin, while for the sites in Mali, they are closest to zero for RH and Tair. Finally, regarding the RSR and for both dry and wet months, Swin is the variable for which MDS preserves the best variance regardless of the site and the percentage of gap considered.

## 5 | SUMMARY AND CONCLUSION

The Marginal Distribution Sampling (MDS) method has previously shown good performance in gap filling of eddy covariance data but evidence of its ability to fill gaps in meteorological data remains less documented nowadays. In this study, we investigated the performance of MDS at fine scales (diurnal and monthly) of five meteorological variables collected from seven sites in West Africa. For this purpose, artificial gap scenarios (25%, 50% and 100%) were performed within different parts of the day (BeforeNoon [BeN], AfterNoon [AfN] and Nighttime [NiT]) and on extreme temperature (dry and wet) months. Our results show that MDS is able to fill the missing data in air and soil temperatures (Tair, Tsoil), relative humidity (RH), vapour pressure deficit (VPD) and incoming shortwave radiation (Swin), with a low error rate during the day (BeN and AfN) but with a good representation of the variability for Swin and RH (especially in BeN for RH) whatever the site. However, at night, the representation of the variability by MDS is sensitive to the gap rates especially for Tair and VPD. The representation of the variability is poor at night for Swin while it is good for RH whatever the site considered. This difference between the variability representation of Swin and RH is related to the fact that during the night, Swin values are low and vary weakly compared to those of RH, due to the absence of short-wave solar radiation at night, and one could assume Swin $\sim 0\,\mathrm{W/m^2}$ at night. In the same period, we notice a good performance of MDS in terms of reduction of error magnitude for Tair and Tsoil whatever the site considered and the rate of missing data. At the monthly scale, MDS shows a good performance whatever the target variable for all sites considered. At this scale, the variability of the data is greater and the time window of MDS is wider. This allows considering more data under the same meteorological conditions, thus facilitating the achievement of both a low error rate and good variability. However, the quality of the gap filling remains low for Swin and VPD. It should be noted that DSE reveals the heterogeneity between data and is not very sensitive to the gap-filling rate for Swin and VPD. Also, MDS would over- or underestimate RH values depending on the type of climate considered (Subequatorial, Sudanian or Sahelian) during dry months. These various subtleties brought out by our study should be taken into account in order to improve how to assign a flag quality during the gap filling of meteorological variables thanks to the MDS algorithm. The used codes and obtained outputs in this study are available on the GitHub repository: GitHub.

## AUTHOR CONTRIBUTIONS

**Djidjoho Renaud Roméo Koukoui:** Conceptualization (equal); formal analysis (equal); investigation (equal); methodology (equal); writing – original draft (equal); writing – review and editing (equal). **Ossénatou Mamadou:** Conceptualization (equal); funding acquisition (supporting); methodology (equal); project administration (lead); resources (lead); supervision (lead); validation (lead); writing – original draft (equal); writing – review and editing (equal). **Miriam Hounsinou:** Conceptualization (equal); investigation (supporting); validation (equal); visualization (equal); writing – review and editing (equal). **Basile Kounouhéwa:** Funding acquisition (supporting); project administration (lead); supervision (supporting); writing – review and editing (lead).

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## CONFLICT OF INTEREST STATEMENT

No conflict of interest.

## DATA AVAILABILITY STATEMENT

AMMA-CATCH Data: doi: 10.17178/AMMA-CATCH.all. The data of the Dangbo site can be obtained upon request to Ossénatou Mamadou (ossenatou.mamadou@imsp-uac.org).

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## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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