* P and L denote Page and Line, respectively.

Reviewer #1:

General comment:

The idea of this paper is to use copulas in order to capture the dependence between site-measured and remotely-sensed data. Yet, there is a major problem with the approach suggested by the authors as described in this paper. Unless wrongly understood, marginal distributions and copulas are fitted on the basis of only four data points, as for each time step a copula and marginals are fitted on data of 4 stations. How valid can such an approach be?

1- We want to emphasise on the problem definition as:
   - P1, L23, the problem is defined as: Weather stations are often sparse and usually located at irregular positions. If their data are used for crop growth simulations, then their results at unvisited locations are likely to be uncertain.
   - P2, L4 to L8, we added further explanations as: Due to the coarse spatial resolution of weather forecasted gridded data, there is an apparent mismatch between measurements obtained from weather stations and weather forecast data. In this study, unvisited locations are grid points which do not contain an observation due to the relatively low number of weather stations in the study area. In order to obtain unbiased values, a bias correction method should be applied for these grid points before using the weather forecast data.

2- We were able to increase the number of stations to eight stations and use the historical data at each day to deal with low number of observations as:
   - P11, L29-31 and P12, L1-4: Eight weather stations (Table 2) were selected because they had a long range of air temperature measurements available and were well spread over the study area. Minimum and maximum distances between stations are 13 and 78 km, respectively (Figure 3). For all weather stations, the daily minimum and maximum air temperatures are available for the periods 1-30 June 2004 to 2014. The quality of measurements and number of missing values, however, differ at each stations (Table 2). Daily air temperature is determined by averaging the minimum and maximum temperatures at each weather station.
   - P12, L10-13: To analyse the temporal variability of dependence structure, which is modelled by copula's parameter, the proposed bias correction methods are applied separately at each day in June 2014. Due to lack of availability of daily air temperature measurements in 2014 over the study area, copulas and marginal distributions are fitted to the eleven years series of the daily air temperature data.
   - P4, L29-32 and P5, L1-2: goodness of fit test is done for copulas and p.values are listed in Table 4.

Furthermore, notations are not straightforward and unambiguous. For instance, u_1 and u_2 are sometimes used to indicate a value (e.g. in equation4), sometimes a variable (e.g. in equation 8). Similarly, p_{u_1} is sometimes used to indicate a variable (equation 4), sometimes a function (e.g. p.5, line 4: The conditional quantile p_{u_1} . . .). This hinders the reader to understand the approach followed by the authors.

- Notations are improved. As suggested by the reviewer, we now use capitals to indicate variables, and small letters to indicate values.

2 Specific comments

• I would suggest to use capitals to indicate variables, and small letters to indicate values.

- As suggested by the reviewer, we now use capitals to indicate variables, and small letters to indicate values.

• I would suggest to remove the superscript t in the naming of the copulas. This is confusing, as it is only fairly late in the paper that it becomes clear where the t comes from.

- The superscript t in the naming of the copulas is removed.

• Why not using the general notations e.g. $C_{12}(u_1, u_2)$ and $F_{2|1}(u_2|u_1)$ for copulas and conditional distributions, respectively?

- P4, L7: The nations of conditional copulas are based on the literature. Conditional copula is shown as $C_{u_2}(u_1)$ in (Nelsen 2006).

• What is the definition of a bivariate conditional copula? By taking the derivative of a copula to one of its variables, one ends up with a conditional distribution function, but is this function a copula?

- A bivariate conditional copula is the derivative of a bivariate copula (bivariate joint distribution) to one of its variables. The "bivariate" specifies that the joint distribution has two variables and it is not multivariable. This terminology is based on the (Gräler, 2014).
- P4, L6: This reference (Gräler, 2014) is inserted into the text.

• Equation (4), u1 and u2 are treated as values whereas they are treated as variables in Equation (8).

- P4, L7: As suggested by the reviewer, we use capitals to indicate variables, and small letters to indicate values. The notations of conditional copulas, however, are based on the literature. Conditional copula is shown as $C_{u_2}(u_1)$ in (Nelsen 2006).

• line 9, page 4: s refers to a location: there is no s in Equation (4).

- P4, L9, this is removed. The definition of s and t is moved to P4, L2.

• line 13, page 4: Empirical marginal distributions u1 and u2: not clear. Are u1 and u2 marginal distributions here?

- P4, L13, this line is revised as: Empirical marginal quantiles u_1 and u_2.

• lines 16-18, page 4: not clear, what is meant.

- P4, L16-18, this sentence is revised as suggested by reviewer #3: Extreme values that possibly exist in the observations, however, are prevented from occurring at unvisited locations after this transformation.

• line 19, page 4: I doubt that fitting a polynomial to 4 data points to obtain a marginal distribution is correct. Furthermore, how is this done in the fitting as it requires a positive slope everywhere and its maximum value should be one.

- We were able to increase the number of stations to eight and use the historical data at each day to deal with low number of observations as: P11, L29-31 and P12,L1-4: Eight weather stations (Table 2) were selected because they had a long range of air temperature measurements available and were well spread over the study area. Minimum and maximum distances between stations are 13 and 78 km, respectively (Figure 3). For all weather stations, the daily minimum and maximum air temperatures are available for the periods 1-30 June 2004 to 2014. The quality of measurements and number of missing values, however, differ at each stations (Table 2). Daily air temperature is determined by averaging the minimum and maximum temperatures at each weather stations.
- P12, L10-13: To analyse the temporal variability of dependence structure, which is modelled by copula's parameter, the proposed bias correction methods are applied separately at each day in June 2014. Due to lack of availability of daily air temperature measurements in 2014 over the study area, copulas and marginal distributions are fitted to the eleven years series of the daily air temperature data.
- P4, L19, spline is used for fitting marginal distribution instead of a polynomial, as suggested by the reviewer #3.

• line 3, page 5: conditional quantile pu1 : not clear what is meant.

- P5, L3, we revised this sentence as: when the conditional quantile $p_{u_1|u_2}$ in Eq. (4) is predicted, it is used to derive the marginal quantile,… .

• line 27, page 5: F1, F2: not explained

- P5, L27, we revised this sentence as: where F_1 and F_2 are marginal distribution function of the measurements from weather stations and weather forecasts, respectively. The marginal distribution functions are spatially stationary during each moment t in time.

• line 5, page 6, Equation (7): notations are not clear

- P6, L6-9, the definition of notations is added as: where $\hat{z}_{1(mean)}$ is the mean value of the variable $\hat{Z}_1$, $E[|]$ is conditional expectation operator, Z_1 and Z_2 are measurements and forecasted variables, respectively, u_1 and u_2 are marginal quantiles of the variables Z_1 and Z_2, F_1 is marginal distribution function of the measurements from weather stations, and c is the conditional copula density function. The marginal distribution functions and copula are spatially stationary during each moment *t* in time.

• line 11, page 6, Equation(8): ct(u1|u2) = ct(u1, u2): not clear why.

- P6, L10, we revised it as: it can be shown that (see Appendix 1)
- P20, L18-28, we now show the proof in the appendix 1 as: In the case of constructing bivariate copulas, it can be shown that: $c(U \le u|V = v) = c(U, V) = \frac{\partial^2 C(U,V)}{\partial U \partial V}$, where $c(U \le u|V = v)$ is conditional density and $c(U, V)$ is joint density distribution. In copulas, marginals (U, V) are uniformly distributed i.e. *f(U)=f(V)*=1, *F(U)=U* and *F(V)=V*, where f and F are density and cumulative distribution functions, respectively (Kuipers and Niederreiter, 2012). The conditional cumulative distribution is given as (Nelsen 2006): $C(U \le u|V = v) = \frac{\partial C(U,V)}{\partial V}$. The conditional density distribution is derivative of cumulative distribution to its variable: $c(U \le u|V = v) = \frac{\partial}{\partial U}\left(C(U \le u|V = v)\right) = \frac{\partial}{\partial U}\left(\frac{\partial C(U,V)}{\partial V}\right) = \frac{\partial^2 C(U,V)}{\partial U \partial V}$. In addition, the joint density distribution is derivative of cumulative distribution to its variables: $c(U, V) = \frac{\partial^2 C(U,V)}{\partial U \partial V}$.

• line 15, page 6: marginal quantile ˆu1: not clear

- P6, L15, this sentence is revised as: the empirical marginal quantiles of the bias-corrected variable.

• line 18, page 6: empirical marginal quantile ˆu1 equals u2 or 1−u2: not clear why.

- P6, L17-18, this sentence is revised as: Therefore, after applying EP, the empirical marginal quantiles of the bias-corrected variable equals the empirical marginal quantiles of the forecasted variable u_2 or $1 - u_2$ (see Appendix 2).
- P21, L1-10, we now show the proof in the appendix 2 as: Let (x_1, y_1), (x_2, y_2), …, (x_n, y_n) be a set of observations for variables X and Y. If $x_1 > x_2$ and $y_1 > y_2$, the pair is concordant. If $x_1 > x_2$ and $y_1 < y_2$, the pair is discordant. When the number of concordant pairs is more (or less) than discordant pairs, the dependence between X and Y is positive (or negative) (Nelsen 2006). The conditional expectation is defined as: $[x|\, y] = \int_x X.f(X \le x|Y = y)dX = \int_0^1 (F)^{-1}(U).c(U \le u|V = v)dU$. The conditional expectation is either an increasing or a decreasing function of the conditioning variable i.e. if $x_1 > x_2$ then $E[x_1|\, y] > E[x_2|\, y]$ (Dodds et al., 1990). Therefore, after applying conditional expectation, the empirical marginal quantiles of predicted variable X^{prd}: $\{E[x_1|\, y_1], \dots, E[x_n|\, y_n]\}$ equals the empirical marginal quantiles of Y i.e. v or $1 - v$ in the case of positive or negative dependence.
- P18, L23-24, the new reference (Dodds et al., 1990) is added to the "Reference" list.

• line 7, page 7: generating independent variates u2: isn't u2 known? This is after all the conditioning value, or not?

- P7, L4-6, further explanations are added as: As mentioned in the Sect. 2.2, in the copula-based bias correction methods, when the conditional quantiles are predicted, they are used to obtain the bias-corrected values at unvisited locations. Simulation of conditional quantiles is one procedure to predict conditional quantiles.

• page 7, paragraph 2.3.4: this paragraph is not clear

- P7, L4-17, this paragraph is revised as: As mentioned in the Sect. 2.2, in the copula-based bias correction methods, when the conditional quantiles are predicted, they are used to obtain the bias-corrected values at unvisited locations. Simulation of conditional quantiles is one procedure to predict conditional quantiles. In the simulation of conditional quantiles, realizations of the random variable $\hat{Z}_1$ are obtained by generating independent variates u_2 and $p_{u_1|u_2}$ uniform on [0,1]2 (Salvadori et al. 2007; Nelsen 2006). These variates are used in Eq. (9) to obtain samples $\hat{u}_1$. These samples are transformed to obtain realizations of the random variable $\hat{Z}_1$ by applying the inverse transformation of the marginal distribution in Eq. (10). The number of samples in the simulations, however, influences the simulation of conditional quantiles. In the simulation procedure, a choice for either the mean, or the median or the mode of a simulation provides a single value $\hat{z}_1$ as a realizations of the random variable $\hat{Z}_1$. In the literature, the mean value of the simulations is considered as a single realization (Laux et al. 2011; Vogl et al. 2012). When choosing large number of the samples in the simulation and one chooses either the mean or the median of the simulations as a single value, the mean or median are equal to the mean value as derived from the conditional copulas using expectation predictor explained in Sect. 2.3.2 and or the median value as derived using median predictor explained in Sect. 2.3.3 (Mao et al. 2015).

• page 7-8: the explanation of the methods BCQM-type I and BCQM-type II is not clear. What and how many copulas are fitted, what is then done with these copulas. What is meant with "Substituting the quantiles p_{u2} for p_{u1}".

- P7, L24-L29 , P8, L1-25, and P9, L1-3, the explanation of these two methods is completely revised.
- P7, L21-22, we added Figure 1 to show the quantile mapping in the BCQM methods.

• line 2, page 8: How can the influence of land cover be captured by taking R into account? If the elevation (value of e_s) is kept constant, data with an equal value of R are located on a circle.

- P8, L2-3, this sentence is removed.
- P7, L26-27, the variable R is replaced by the elevation.

• equations (12) and (13): What is C_{tuR}?

- P8, L6, it is revised as: $C_{u_e}(u_1)$ and $C_{u_e}(u_2)$.
- P8, L10-11, the definitions are added as: $C_{u_e}(u_1)$and $C_{u_e}(u_2)$ are conditional copulas describing dependence between measurements and elevation, and between forecasted air temperature and elevation, respectively.

• Wouldn't it be better (if enough data are available) to fit a multivariate copula or a vine to take into account the dependences between all these variables?

- P5, L16-17, this suggestion is added to the paper as: The combination of covariates in a Vine copula (Aas et al., 2009) might improve the bias correction, but is out of scope of this paper.
- P5, L9-L16, more explanations are added as: The purpose of the bias correction method is to predict the bias-corrected values $\hat{z}_1$ at unvisited locations. This section describes briefly available methods which are quantile mapping, expectation predictor, marginal transformation based on a single quantile, and simulation of conditional quantile. In addition, the newly developed methods are explained and compared to the quantile mapping and expectation predictor . We utilized the concept of bivariate conditional copula to develop new methods for bias correction, as bivariate copulas are well understood and easy to estimate. The flexibility in the determining of the conditional quantiles makes the newly developed methods appealing for spatial variabilities at unvisited locations when low number of observations are available.

• page 9: Quantile search: I don't understand which parameter the authors want to optimize such that the fitness function is maximized.

- P9, L4-28 and P10, L1-11, the explanation of this method is completely revised.

• line9, page 10: how are genetic algorithms applied here?

- P10, L8-11, the paragraph is revised as: There are several methods that lead to the minimization of the fitness function (Burke and Kendall, 2014). In this study, we applied a genetic algorithm for doing the search. Details on this algorithm can be found in the literature (Sastry et al., 2013) and are beyond the scope of this paper. The sample code to implement in R, however, is given in the appendix 3.
- P18,L13 and P19,L33, the references are added.
- P21, L11-17, appendix 3 is added.

• lines 27-28, page 9: the authors refer to previous Sections (2.2, 2.3.5.1, 2.3.5.2) for an explanation. Yet, I don't see any explanation in these Sections.

- P9, L27-28, these lines are removed.
- P9, L4-28 and P10, L1-11, the explanation of this method is completely revised.

• line 22, page10, Equation (18): T?

- P10, L23, the definition is added as: where T is the number of time steps in time series.

• line 24, page 10: A minimum value of the error score indicates for the minimum SMAE. Not clear.

- P10, L23-25, it is revised as: To compare the five bias correction methods based on the SMAE, an error score (ES) is calculated at each weather station (Durai and Bhradwaj 2014). The smallest ES indicates for the smallest SMAE.

• lines 5-6, page 11: not clear

- P11, L5-11 and P11, L1-2, it is revised as: For investigating the performance of each method to reproduce the moments of the marginal distribution; mean, standard deviation (as well as coefficient of variation), skewness and kurtosis, the relative error RE^{m_i} is calculated as:

  $$RE^{m_i,t} = \frac{|m_i^t - \hat{m}_i^t|}{|m_i^t|}, \text{ i=1:5,} \qquad (21)$$

  where m_i^t and $\hat{m}_i^t$ are the ith order moment of the marginal distribution calculated using measurement z_1 from weather stations and bias-corrected values $\hat{z}_1$ at moment t in time. The bias-corrected values $\hat{z}_1$ are predicted where correction functions are estimated using the measurement from weather stations and applied to the same locations (Lafon et al. 2013).

• line 5, page 14: not clear

- P11, L14-16, it is revised as: To compare the five bias correction methods based on the MMRE, an error score (ES) is calculated. The smallest ES indicates for the smallest MMRE.

• Section 3: more info is needed on the data (resolution, correlations,. . .)

- P11, L23, this sentence is added: The crop calendar is listed in Table 3.
- P11, L28-31 and P12, L1-4, information on data from the weather stations is given as: Considering the importance of June in the crop calendar of the study area which is the end of winter crops and beginning of summer crops especially maize, we applied the proposed methods to available dataset of this month. Eight weather stations (Table 2) were selected because they had a long range of air temperature measurements available and were well spread over the study area. Minimum and maximum distances between stations are 13 and 78 km, respectively (Figure 3). For all weather stations, the daily minimum and maximum air temperatures are available for the periods 1-30 June 2004 to 2014. The quality of measurements and number of missing values, however, differ at each stations (Table 2). Daily air temperature is determined by averaging the minimum and maximum temperatures at each weather stations.
- P22, Table 2, this table shows more information on weather stations, now.
- P30, Figure3, this figure shows the location of eight weather stations, now.
- P12, L5-9, information on data from ECMWF is given.
- P12, L10-16, further illustrations are added.
- P13, L3-22, figures 4, 5 and 6 show the bias in values, correlations and the bias in the moments.

• lines 27-30, Section 4.1: how do you define outliers?

- Outlier were responsible for negative temperature in March. Based on our knowledge, negative temperature in March is a strange value in the study area. Aggarwal 2013 defined outlier as : "Outliers are also referred to as abnormalities, discordants, deviants, or anomalies in the data".
- P12, L27-30, this paragraph, however, is removed due to removing data in March. We now limit the implementation to data in June.

• line 28 page 12: "As can be seen": this is not clear to me.

- P12, L28, this line is removed.

• line 2, page 13: there was no need to remove the outliers: what is the purpose of defining outliers if they don't need to be removed?

- P13, L1-2, this paragraph is removed due to removing data in March. We now limit the implementation to data in June.

• lines 17-19, page 16: Is it necessary for the research carried out that observations are separated day by day, in order to remove autocorrelation. In this research, one is only interested in the dependence between observations of the same day. Hence, no dependence between data values at certain time lags is to be taken into account.

- P2, L22-L26, further explanations are added about removing autocorrelation in time series: A bias correction method proposed by Laux et al. (2011) employed bivariate conditional copulas to model dependence between the daily precipitation time series retrieved from a regional climate model and observations at three locations where data is available. In their method, however, a bivariate copula is fitted to daily time series at one location, ignoring the temporal variability of copula parameter as well as spatial dependency. In addition, the fitting is required to remove autocorrelation and heteroscedasticity which may exist in the time series (Laux et al. 2011).
- P3, L2-11, the aim of this study is further explained as: In this study, we aim for:
    - estimating different conditional quantiles at different unvisited locations accounting for the temporal variability of the dependence structure.
    - evaluating these methods' ability to predict the spatial variability of the bias-corrected daily air temperature at unvisited locations.
    - comparing the proposed methods with available bias correction methods, which are quantile mapping, expectation predictor and single quantile predictor.
    - providing a review of these methods for bias correction of the daily air temperature data when a relatively low number of observations are available.

• lines 1-3 page 17: not clear

- P17, L1-3, this is revised as: In BCQM-methods, it is assumed that the dependence structure between the bias-corrected variable and the covariate should obey the dependence structure between the biased variable and that covariate.

• lines 15-16, page 17: "The new methods are beneficial for the local refinement..." : this is not shown in the manuscript

- P17, L11, this sentence is added: From this study, based on the error measures in Table 5 and 7 and the correlation coefficients in Table 6,….

• lines 17-18, page 16: "The new methods are advantageous ..." : this is not shown in the manuscript

- P17, L11, this sentence is added: From this study, based on the error measures in Table 5 and 7 and the correlation coefficients in Table 6,….