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Oman Provisional Climate Normal Based on the Observation from 2010 to 2021

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Abstract

Climate normal calculation over Oman is a key challenge due to scattered and inconsistent ground observations. Based on the available observations record to calculate the normal, the study derives the Provisional Climate Normal. The data from selected stations in this project have been tested and investigated by using the quality check and missing data evaluation. It is found that ERA-5 is the best reanalysis data in temperature as the correlation coefficient is higher compared to ERA-5 land and MERRA-2 which explains the reason for choosing ERA-5 data to calculate the regression model to fulfil the missing data. By using MODIS data, the Urban Heat Island Index (UHI) shows that Sohar and Muscat stations have the greatest UHI effect and Rustaq has the negative UHI trend. Regarding the interpolation, the project used different interpolation methods to calculate the provisional climate normal for Oman, showing that different variogram fitting models must be used for different months for Kriging interpolation. The final results show that all the interpolation methods struggle to predict the air temperature during summertime due to a complex spatial contrast and distribution, except GWR which shows a well-predicted dataset by which it can be said that the GWR is the best performing method for the temperature over Oman.

Keywords

Climate Normal, GWR, Urban Heat Islan Index, Reanalysis

1. Introduction

Calculating the climate normal for an entire country is a crucial project to have a complete picture of the seasonality and climate variation of the temperature. The project is designed to use the reliable statistical techniques to accommodate the geographical disparity between the stations as well as the data spars within the station's observation. Based on the World Meteorological Organisation (WMO), the climate normal is defined as "period averages computed for a uniform and relatively long period comprising at least 3 consecutive ten-year period" as follows: 1/1/1901 to 31/12/1930 …. etc." [1]. However, there is another type which is known as Provisional Climate Normal. According to the WMO manual, The Provisional climate normal is defined as "period averages computed for a uniform period comprising consecutive ten-year period" [1]. In terms of the temporal resolution, there are two types of the climate normals which are the annual normal and monthly normal. The annual normal is calculated from the monthly normal and the monthly normal is calculated from the daily data [1]. The WMO guide to calculate the climate normal is restricted to the following rules: the monthly normal should be tested by "3/5 rule" which means that if there are 3 consecutive months of missing data or 5 months of missing data during the entire period, it is stated as a missing value. In other words, if July is missed in 3 consecutive years or in 5 years, it is stated that July is missed. Regarding the daily data, the "3/5 rule" is applied. The climate normal is affected by different factors. The main factors are 1) stations' spatial distribution, 2) statistical tools estimations and limitations, 3) Data quality level and gaps and 4) the Urban Heat Index (UHI). The UHI is one of the strongest factors as the urbanisation expansion is approaching and subsuming the weather stations network. Urban Heat Island Index is defined as the temperature difference between Urban and Rural Areas [2]. The UHI is used as an indicator for the effect of altering the land surface properties including tarmac and concrete areas as well as the effect of anthropogenic emissions. Such a factor can be tested by satellite data retrieval for Land Surface Temperature (LST) to calculate the temperature difference between the urban and rural or urbanization-free areas. The urbanisation of deserts can lead to a decrease in the LST due to green areas' expansions [3]. The UHI is a complex phenomenon with non-uniformed impacts [4]. The other factors which are related to the quality control are also tested by using statistical methods such as the Homogeneity tests, which indicate check points outlies or data to be checked manually. One of the challenges is to handle the missing data using different techniques. Handling the missing data is a critical aspect of data analysis, and the methods employed depend on the nature of the missing data, such as missing at random (MAR), missing completely at random (MCAR), and missing not at random (MNAR). Weather stations often encounter missing data, which can be related to observed data with seasonality or redundancy, making MAR methods suitable in these cases. The Last Observation Carried Forward (LOCF) & Next Observation Carried Backward (NOCB) are involved by carrying the last available observation forward or the next observation backward in the time series; Linear Interpolation which works well for time series data with trends but may not be suitable for seasonal data, as it does not capture the seasonal variations [5]. This combination method is effective for data with both trend and seasonality, ensuring accurate imputation. Additionally, the Mean, Median, and Mode are also effective for data Imputation. Mean imputation reduces variance in the dataset and is useful when the missing data is MCAR or

MAR. Also, the Linear Regression is a method which assumes a linear relationship between variables used in the regression equation, although such a relationship may not always exist. One of the best data to apply the Linear Regression method to is the ERA-5 data as the second dataset along with the ground stations data. The ERA-5 reanalysis dataset, developed by the European Centre for Medium-Range Weather Forecasts (ECMWF), stands as a comprehensive resource providing detailed meteorological information, especially concerning temperature, through a combination of satellite observations, climate weather stations, and numerical weather prediction models. This dataset adeptly compensates for missing local station data, blending model predictions and global observations coherently by leveraging the laws of physics [6].

As the data complexity increases, other advanced techniques to treat the missing data include Multiple Imputation K-Nearest Neighbours (K-NN) [7]. Multiple Imputation by Chained Equations (MICE), Time Series Missing Value Imputation (imputeTS), Probabilistic Principal Components Analysis (PPCA) and Random Forest (missForest). To evaluate the quality of predictions made by these imputation methods, the Taylor's diagram is often used. It visually compares the predictions of imputed values with the observed values, aiding in the selection of the most accurate imputation method for a specific dataset. The Interpolation is a method that uses a statistical model to estimate unknown values from known values. Several techniques are applied to evaluate Inverse Distance Weighted (IDW), Nearest Neighbour (N-N), Angular Distance Weighted (ADW), and Ordinary Block Kriging interpolations, such as cross validation, R-square, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). IDW, also well known as Simple Inverse Distance Weighted interpolation (SIDW) which is one of the oldest spatial prediction models that calculate the predicted value based on inverse distance from the nearest known value [8]. The effect of distance on the weight is determined by the power parameter. The basic and fundamental theory for spatial autocorrelation and neighbourhood effect is derived from the first law in geography for Waldo Tobler which claims that "Everything is related to everything else, but near things are more related than distant things", that is referred to as basic concept of inverse distance weighted interpolation [8]. The Angular distance weighted interpolation, also known as directional interpolation, takes into consideration the angle and the distance between known data points to calculate the weight needed in the interpolation. The N-N is the simplest interpolation which determines the intensity of the nearest neighbour pixel to predict the unknown pixel values rather than calculating the weight. Kriging is also well known as geospatial interpolation. In early 1950, Kriging was discovered in a mining field by D.G. Kriging [8]. Ordinary kriging is the basic type of kriging method. Kriging interpolation is a developed version of inverse distance interpolation [8]. In an intuitive manner, calculating the weight should be in an objective way to consider the actual spatial autocorrelation [8]. Consequently, semi-variogram was discovered by Matheron and his colleagues to discover the variation between neighbors [6]. Kriging is a superior interpolation model if the data is normally distributed, stationary, and it has no trend. Failing to meet this criterion could lead to interpolation failure. Additionally, Thin Plate Spline (TPS) is also one of well-known models, which is a mechanical spatial prediction model using the smoothing and interpolation. It is considered a polynomial method because it can be fed by multiple parameters [8]. Additionally, the Geographically Weighted Regression (GWR) is used for non-stationary parameters or variables along with the dependent variables [9]. It allows for a more sophisticated level of modelling such that it can involve the distance from the sea, Digital Elevation Model (DEM), slopes and other geographical factors which cannot be rectified over space by ordinary regression models [10].

2. Project's Approach and Problems to Be Addressed

This project has used several techniques to approach the most robust based outcomes. The homogeneity test is used to examine the degree of harmony in the preprocessing and postprocessing data. According to WMO guide, it is accepted to use satellite or postprocessing data, such as reanalysed data to fill the missing data [1]. Therefore, the reanalysis data has been used to fulfil the gaps besides statistical methods such as linear regression. One of the main issues is the urbanisation expansion which affects the readings from the stations. To address this problem, the project used LST to examine the degree of effect of UHI on the stations' locations.

3. Study Area

This project focuses on the Sultanate of Oman, which is located in the southeastern part of the Arabian Peninsula and Western Indian Ocean. The entire area of the country is 309.500 km^2 and most of Oman is covered by deserts. The highest mountain peak is around 3000 m high in Jabal Shams. The climate of the country is predominantly arid with some semi-arid parts. the Sultanate of Oman has borders with UAE from the Northwest, Saudi Arabia from the west, and Yemen from the southwest (**Figure 1**).

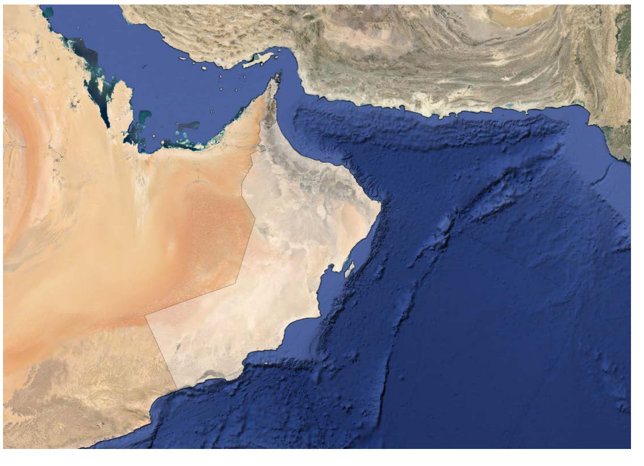


Figure 1. Oman's Map with political boarders according to the National Survey Authority. (the boarders shapefile is from Oman National Survey Authority and the base map is from ESRI Satellite view.)

4. Dataset

The project has used five datasets to calculate the provisional climate normal as shown by Table 1.

Table 1. Summary of the datasets used in the project including weather ground stations, Reanalysis data and satellite data.

Data source	Spatial resolution	Temporal resolution	Range	Source
Ground weather stations	-	Hourly	2010-2021	Directorate General of Meteorology-Oman
ERA-5	31 km	Hourly	2010-2021	Copernicus Climate Change Service Climate reanalysis
ERA-5 Land	9 km	Hourly	2010-2021	Copernicus Climate Change Service Climate reanalysis
MERRA-2	50 km	Daily	2010-2021	NASA-GMAO reanalysis product
MODIS-Terra	1 km	8 Days	2000-2021	Earth Data

1) Ground weather stations

The ground observations are taken from the Directorate General of Meteorology in Oman which consists of 34 stations distributed all over the country with temporal resolution of 1 hour for 12 years (2010-2021).

2) ERA-5

ERA5 dataset, with a spatial resolution of approximately 31 km, is ideal for investigating local temperature patterns and anomalies. It provides temperature data across various pressure levels, with a specific focus on 1000 hPa, aligning with surface temperature usage.

3) ERA-5 land

This study utilized both ERA5 and ERA5-land datasets. ERA5-land, focusing on a higher detailed 9 km resolution specifically on land data, distinguishes itself from ERA5, which encompasses both land and water surfaces. Despite this disparity, both datasets share an impressive high temporal resolution, measured hourly. ERA5-Land considers land surface variables, excluding oceanic parameters, and heavily relies on surface-based observations and land surface models, emphasizing surface features. In contrast, ERA5 employs satellite and weather models from various levels, offering a comprehensive view of the entire atmosphere.

4) MERRA-2

MERRA-2 is an improved version of MERRA-1 data that gives a comprehensive view of the atmosphere. It is a reanalysis dataset produced by NASA Global Modelling and Assimilation Office (GMAO). It is widely used in climate studies and considered as one of the most consistent and high-quality records and long-term data. The spatial resolution of MERRA2 covering the globe is 50 km horizontal resolution and includes ranges of vertical levels, thus making it capable of conducting climate studies. However, MERRA-2 has all the essential weather variables with multiple dimensions, allowing different research and analyses conducted due to such features. Mainly temperature data were used in Oman provisional climate normal research.

5) MODIS-Terra

The Moderate Resolution Imaging Spectroradiometer (MODIS) has been used for different applications, including the dynamics and processes occurring in the lower atmosphere, land and ocean. The instruments view the earth surface every 1 to 2 days, but the temporal resolution of 8 days is needed to have the scan in the same place. The available spatial resolutions from MODIS are 250 m, 500 m and 1000 m. The study used MODIS Terra to monitor and assess the changes in the Land Surface Temperature (LST).

5. Methodology

5.1. Tools

The project used different tools to acquire robust outputs and minimize the errors. The programming languages used are Python 3.9 and R 4.4.2, and the software used are QGIS (3.22) and SAGA (9.1) after the initial filtering of the data by using EXCEL, the programming languages have been used for data extraction and manipulation as well as the statistical analysis. For instance, Python has been used to manipulate and clean up the satellite data as well as download the ERA-5 data. A variety of R packages have been used as the final stride for data visualization and interpolation. The project heavily relies on R language to examine kriging interpolation pre-requirements before applying the method as well as other interpolation models.

5.2. Data Collection and Selection Method of Weather Stations

The common period of studying the climate normal is 30 years, but unfortunately most of Oman's ground stations are less than 30 years of age and the majority have 10 to 20 years of records. Based on WMO manual, the climate normal can be divided into 2 types; first one is the classic climate normal and the second is provisional climate normal. The second type is the most suitable option, because it needs at least 10 consecutive years of observations, which is available from a wider range of the stations distributed all over the country. However, the stations are not well distributed in the southern part of the country, particularly in Al Wusta and Dhofar governorates. The distribution in the southern governorates is scattered where most of the persisted stations in Dhofar are along the coast. This is another challenge that interferes from a systematic way of choosing stations' locations (**Figure 2**).

Figure 2. The selected stations for the project.

As mentioned previously, most of the stations do not meet WMO standards of calculating the provisional climate normal in terms of the missing data. Hence, it is decided to use ERA-5 reanalysis to accommodate the missing data as it is described instead of rejecting them, based on the statistical test, the ERA-5 has the best correlation coefficient values with the observations compared to the other reanalysis models. The chosen stations have the fewest occurrence of 3 consecutive days of missing data. Fortunately, some stations are located in a very critical location on mountain summits which are crucial to correct the interpolation over the high elevation areas. Also, the Homogeneity test has been applied to eliminate any outliers in the data. The observation from the chosen stations have the best correlation with ERA-5 except Salalah which is chosen instead of Salalah_1 because it has been relocated in 2015 as the airport area got reconstructed. In summary, the chosen stations have the least error fraction in the data, located in critical locations and have high correlation with ERA-5 to fulfil the missing data with a miner effect. Then, the study used the reanalysis data to establish the correlation between reanalysis data and ground station observations. Such comparative analysis enabled to identify the most strongly correlated reanalysis dataset. Subsequently, the best-correlated reanalysis dataset was utilized to develop an optimal regression model for the study. While ERA5 includes both land and ocean data, ERA5-land, offering detailed land surface variables at a 9 km spatial resolution, provides invaluable for localized climate analysis. Both datasets, with a similar temporal resolution, are powerful tools to conduct comprehensive climate studies, each providing unique insights into temperature variations and trends at different scales. The study concentrated on daily temperature data extracted by averaging the available hourly data, which, although granular, enables a nuanced analysis of daily temperature cycles. This fine-grained temporal resolution allows for an examination of short-term temperature fluctuations and their long-term impacts. The MERRA-2 dataset which is a combination of satellite data, weather observation, atmospheric models and other simulation techniques to make a coherent dataset over 2010-01-01-2022-12-01 11:29Z of Averaged Map of 2-meter air temperature daily mean of 0.5 × 0.625 deg. The domain used in Oman provisional climate normal project is the region 50.5811E, 16.5088N, 61.875E, 27.0557N. The reanalysis data have been used in the regression model which is defined as a statistical technique used to analyse the relationship between a dependent variable and one or more independent variables. The linear regression is used, where the relationship between the variables is assumed to be linear. The general form of a linear regression model with one independent variable can be represented by Equation (1)

$$Y = \beta_0 + \beta_1 X + \varepsilon \tag{1}$$

Y is the dependent variable.

X is the independent variable.

β_0 is the intercept (the value of Y when $X = 0$).

β_1 is the coefficient for the independent variable X (represents the change in Y for a unit change in X).

ε represents the error term, which accounts for the variability in Y that cannot be explained by the linear relationship with X.

Regression models are estimated using various techniques, such as the least squares method, which minimizes the sum of squared differences between the observed and predicted values of the dependent variable. Building a regression model is crucial to assess the performance using metrics like mean squared error (MSE), root mean squared error (RMSE), coefficient of determination (R2 score), and others, depending on the specific problem at hand. Additionally, techniques like cross-validation can be employed to evaluate the model's generalizability to unseen data [5].

5.3. Urban Heat Island (UHI)

Regarding the UHI effect, the project relies on satellite LST product from MODIS. The radiometric skin temperature is calculated by the satellite-based instruments. It is derived from the longwave radiation emitted from the underlying surface within an instantaneous field of view (FOV), after corrections for atmospheric and surface emissivity effects [11]-[13]. The UHI effect is better to be studied via satellite because it provides a high spatial resolution, complete coverage and continuality calibrated data. The data represent the average of each pixel. In other words, the data represent the skin temperature of the entire pixel as an averaged skin temperature. The way it is used to investigate the possibility of UHI effect is to check the history of urbanization expansion using satellite images. The focus is on locations where the urbanisation expansion is profound within the last 21 years. As the terrain is not uniformed or coherent over Oman, it is not scientifically justifiable to choose a single type of soil such as rocks lands or deserts to compare with the targeted urbanised Areas. Alternatively, find places where the microclimate is almost similar, including temperature, wind patterns and other meteorological parameters. Additionally, soil properties such as soil type, albedo, emissivity and others were considered while investigating the chosen stations. The steps of the process are the following:

1) The selected location to compare with should have the same soil characteristics such as albedo (emissivity-brightness-absorption) and texture.

2) The two locations should be within the same microclimate to avoid significant changes, which includes the elevation and main weather condition as well as the geography

3) Using MODIS TERRA to investigate the effect of urban heat island effect since 2000, because the urban expansion has rapidly expanded since 2000.

4) All selected stations have observations for more than 10 years.

The UHI is calculated as described by Equation (2)

$$\mathrm{UHI}_{skin} = T^{u}_{skin} - T^{r}_{skin,\mathrm{LC}} \tag{2}$$

UHI_{skin} is the skin-level, T^{u}_{skin}, is the skin temperature averaged from all urban pixels for a given region, and $T^{r}_{skin,\mathrm{LC}}$ is the skin temperature averaged from all rural pixels in the region for a specific Land Cover (LC).

5.4. Homogeneity Test

The project used RHtestV4 [14], which is considered as the best homogeneity test as documented and tested by [15]. The test requires a specific format to run correctly. The test was run before the regression model and after the implementation of the regression model to investigate the performance of the data processing method using R language.

5.5. Interpolation

5.5.1. Inverse Distance Weighted (IDW), Angular Distance Weighted (ADW) and Nearest Neighbour (N-N)

These methods are applied to the data using SAGA software as described in the introduction. The study relied on the cross-validation technique to evaluate the performance of each method.

5.5.2. Kriging

The kriging interpolation is considered as a superior interpolation method due to several criteria that any data should be examined through to apply this method. The study examines the distribution of the data to check if the data is normally distributed or not. There are three methods to check the normality of the data which are 1) histogram, 2) density curve and 3) normal Q-Q for all the data of selected stations. The next test is the so-called stationarity. This test is conducted to check the similarity of stations mean, variance and auto-correlation. In other words, all stations have constant statistical properties. The assumption of stationary data in kriging interpolation is critical for the accuracy of the geostatistical model. Non-stationary data could lead to over/underestimated for the values. The other test is Voronoi map, also known as Thiessen polygon maps, which uses polygon boundaries to represent regions with similar characteristics. It was not originally designed to examine the stationarity of data. However, it can be a useful tool to visualize data pattern and spatial distribution. Voronoi map uses colour coding to identify regions with trend and variability based on the values of each data point. Variation in region size, shape, and colour could conclude with non-stationary data. The additional test is the regression model which is highly significant when using kriging interpolation and it might lead to under/over estimation for the predicated values. Choosing a proper order of regression model will identify the spatial relationships between point data superbly. Semivariogram cloud is a visualization tool in a scatterplot distribution for data to examine spatial autocorrelation. This can discover any trend, anomalies, and special pattern in data which affect the final result in kriging interpolation. It points out how the distance can affect the variance of the specific variable. Semivariance can be calculated using the following equation:

$$\gamma(h) = \frac{1}{2N} \sum_{i=1}^{n} \left[z(x_i) - z(x_i + h) \right]^2 \tag{3}$$

$\gamma(h)$ is semivariance gamma, h is the lag distance, N is the number of pairs.

$z(x_i)$ is the value of specific variable at some sampled location.

$z(x_i + h)$ is the neighbor value at distance $x_i + h$ [6].

The next kriging pre-test is known as the experimental semivariogram. It is a fundamental concept for accurate interpolation using Kriging method. It simplifies selecting the optimal variogram model which is defined as a tool that described the relationships between semvariance and lag distance. For the best result, smaller semivariance is expected at shorter distance, and stable semivariance anticipated at longer distance [6].

5.5.3. Thin Plate Spline (TPS2D, TPS3D)

The TPS 2D, 3D has been applied to the data by using the so-called TPS package in R. The difference between the TPS2D and TPS3D is that the elevation is considered in the 3D type. The cross-validation is used to evaluate the performance of the interpolation methods.

5.5.4. Geographically Weighted Regression (GWR)

The Geographically weighted regression (GWR) is used for non-stationary parameters or variables along with the dependent variables. The so-called GWR package in R is used to apply the technique to the data. Additionally, the study considers different variables in the process, such as the distance from the sea, DEM, roughness, slope and aspects and these options allow GWR to perform such sophisticated modelling level comparing to the ordinary least squares regression (OLS).

6. Results

6.1. Missing Data Investigation

It is found that the missing data in the observations network varies. Unfortunately, the missing data represent a significant proportion of the entire data, which means that the WMO restrictions cannot be applied without further processing, such as the regression models to fulfil the observation gaps. The Linear regression was used instead of other methods which were mentioned in the introduction because they depend on the available data within the datasets to perform a statistical gab filling instead of dynamic gab filling by using the reanalysis data. **Table 2** shows the missing data in all selected stations. The stations with a significant missing data percentage have been investigated further to check whether it is possible to fulfil the gabs with the ERA-5 or not such as Fahud, Qarnalam, Khasab_2, Marmul and Saiq_2. The data from ERA-5 showed a high correlation with the stations exceed 90% as shown by **Figure 4**. Some stations which are located in very critical locations have been used after applying the regression test, such as Saiq stations. Most of the stations with significant portion of missing data have faced administrative issues as well as logistic reasons as shown in **Table 2**.

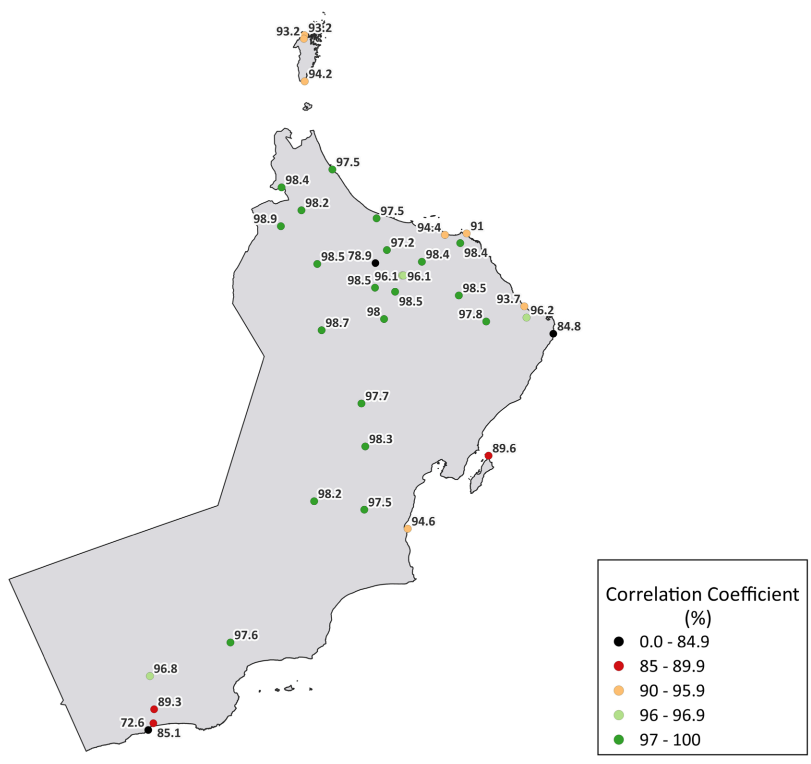
Table 2. Missing data percentage of the selected weather stations from 2010 to 2021.

Station	Missing Data %	Station	Missing Data %
Adam	6.04	Qarnalam	31.69
Al Amrat	2.38	Ras Al Hadd	3.56
Bidiyah	3.94	Rustaq	8.95
Buraimi	7.85	Saiq_2	23.88
Dhank	12.51	Saiq_1	17.98
Diba	7.05	Salalah	2.55
Duqm	7.81	Samail	2.51
Fahud	35.40	Sohar	3.50
Ibri	10.72	Sunaynah	0.34
Khasab_1	5.07	Sur	6.44
Khasab_2	24.30	Suwaiq	6.09
Marmul	34.77	Thumrait	2.11
Masirah	1.94	Zamaim	17.20
Muscat	3.87	Ibri	4.30
Nizwa	9.54	Bahla	1.30
Qairoon Hairiti	3.01	Hima	2.90
Qalahat	0.78	Yalooni	6.20

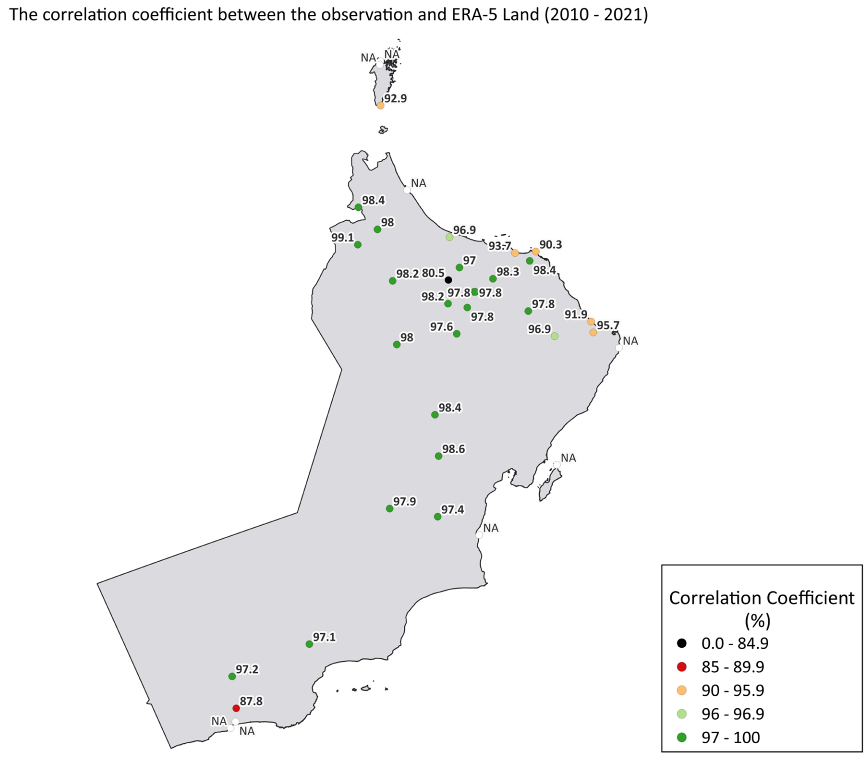
6.2. Reanalysis Correlation with the Ground Stations

Accounting for Oman geography and stations distribution, the ERA-5 results correlated with a high level of confidence (84.8% - 98.5%) performing better in the rural area than coastal areas. As mentioned in [16], ERA-5 temperature data correlated well with the ground stations. However, coastal, more tropical, regions as shown by **Figure 3(a)**. The mean temperature estimation introduces risks such as underestimating the temperature data and many times does not account for heat mortality [16]. So, the high results of correlation are optimal, moreover, but risk relating on using 100% real data. The comparison between ERA-5 land and ground stations data shows high correlations on the daily cycle (**Figure 3(b)**) with the highest correlation coefficient value in Ibri 98.1% and temperature difference of 0.99˚C higher in ground station data. Regarding MERRA 2, the analysis resulted in the least correlated reanalysis dataset with the observations of higher value 97% in Ibri and 0.08˚C higher in ground station data (**Figure 3(c)**). The comparison between the reanalysis data shows that MERRA-2 has the lowest correlation over Oman despite the distance from the sea or the elevation. Oman provisional climate normal project with different correlation coefficient values reflected the study by [17] where ERA5 had better estimated values than ERA5-Land which concludes that ERA5, ERA5-Land, then MERRA-2, respectively yielded better estimations of mean square error, the absolute value of error, correlation between actual and predicted value, which agrees with [18].

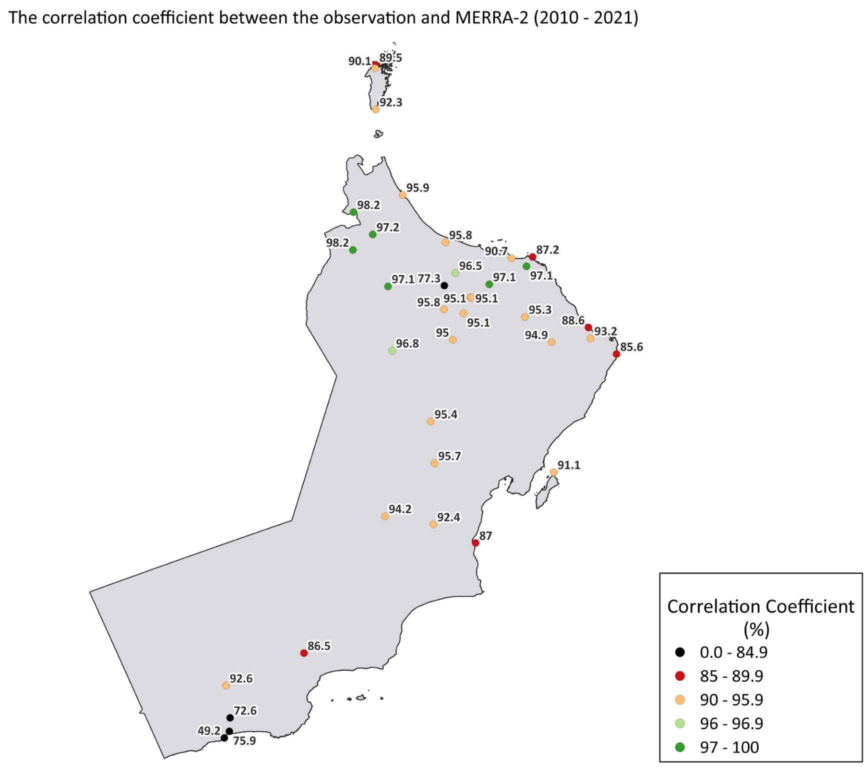
The correlation coefficient between the observation and ERA-5 (2010 - 2021)



(a)



(b)



(c)

Figure 3. Correlation coefficient between the observations and and ERA-5 data (a), Correlation coefficient between the observations and and ERA-5 land (b) and Correlation coefficient between the observations and MERRA-2 (c).

6.3. Homogeneity Test of Pre-Processed Data and Post-Processed Data

Table 3. Homogeneity test of the temperature of all stations before and after handling the missing data by using a regression model based on ERA-5 data.

Station	H.T For Pure Observations (Number of Checkpoints)	H.T For Treated Data (Number of Checkpoints)	Station	H.T For Pure Observations (Number of Checkpoints)	H.T For Treated Data (Number of Checkpoints)
Adam	0	0	Nizwa	0	0
Al Amrat	0	0	Qairoon Hairiti	1 (20200421)	1 (20200421)
Bahla	0		Qalhat	0	0
Bidiyah	0	0	Qarnalam	0	0
Buraimi	0	0	Ras Alhad	3 (20140521, 20150815, 20200526)	3 (20140521, 20150815, 20200526)
Dhank	0	0	Rustaq	0	0
Diba	2 (20150131, 20210113)	0	Saiq_1	0	0
Duqm	3 (20101118, 20150618, 20160703)	2 (20101118, 20160703)	Saiq_2	0	0
Fahud	0	0	Samail	0	0
Ibra	0	0	Salalah	4	0
Ibri	0	0	Sunynah	0	0
Khasab_1	2 (20140929, 20210116)	2 (20140929, 20210116)	Sur	0	0
Khasab_2	0	2 (20150129, 20210116)	Suwaiq	0	0
Sohar	2 (20150129, 20210117)	2 (20150129, 20210117)	Thumrait	0	0
Marmul	1 (20180607)	0	Zamaiam	0	0
Masira	2 (20100515, 20140521)	2 (20100515, 20150416,) 1 Unclear (20160324)	Yalooni	0	0
Muscat	2 (20141119, 20210206)	2 (20141119, 20210205)	Haima	0	0

It is shown that most of the stations have a better homogeneity test, compared to pre-processing statge as shown in Table 3. However, there are some limitations in the test in some stations, such as Salalah and Salalah_1 stations, because the fluctuation is expected during the summertime due to the effect of monsoon winds. The cloudiness during this period plays an important rule, because the cloud cover can persist for a while, but there are days of clear skies. This fluctuation in the cloud cover affects the temperature where the changes can cause a sudden increase in the temperature. Regarding the performance of the test before and after the data processing, there are 23 stations with no checkpoints even with the missing data as shown in Table 3. By and large, the regression model has improved the homogeneity of the data except for Khasab_2. The test is the first phase of the data selection strategy along with missing data percentage. Fahud has an accepted homogeneity test, but the missing data is significant which represents 35% of the data (Table 2). The homogeneity test of Salalah_1 does not show any change which is expected because the outlier from the test is due to a meteorological factor not the missing data. However, there is another station 13 km away in the port which has better homogeneity test after the regression model. Additionally, Salalah station is relocated due to a new airport construction. Another important point is the effect of the regression model which can be a misleading approach. This issue appeared in Jabal Shamas which had been disconnected for almost 55% of the entire period. Once the regression model is applied, the homogeneity test gave zero checkpoints which is an expected output because the reanalysis data after the regression model filled the gabs. The reanalysis data went through a complex process of correction and calibration which means that the data is homogenized. The stations in Table 3 were chosen according to the results of two tests of missing data and Homogeneity test.

6.4. Urban Heat Island (UHI)

Table 4. Homogeneity test of the temperature of all stations before and after handling the missing data by using a regression model based on ERA-5 data.

Station	Trend	P-Value	Tau	Slope	Station	Trend	P-Value	Tau	Slope
Adam	increasing	6.29E−05	0.1653128	0.0016085	Qarnalam	no trend	0.1357559	−0.061643	−0.0003535
Al Amrat	no trend	0.24133	0.0484	0.00069	Ras Al Hadd		No Data		
Bidiyah	no trend	0.3930625	−0.0617978	−0.0008065	Rustaq	decreasing	0.0361	−0.0865	−0.0014
Buraimi	no trend	0.2796971	−0.0446768	−0.0005879	Saiq_2	increasing	0.00087	0.137	0.00241
Dhank	no trend	0.7866991	0.0112052	7.15E−05	Saiq_1	decreasing	0.0129	−0.10263	−0.0004581
Diba	no trend	0.377	0.0369	0.000811	Salalah		No Data		
Duqm	decreasing	0.0011819	−0.1930717	−0.0042646	Samail	decreasing	0.0079774	−0.1096036	−0.0004115
Fahud	decreasing	0.0085912	−0.1085667	−0.0004	Sohar	increasing	1.15E−13	0.3065733	0.0031897
Ibri	no trend	0.733	0.01411	0.0002395	Sunaynah	decreasing	0.0055789	−0.1145005	−0.0008972
Khasab_1	increasing	0.0347049	0.0872508	0.0018588	Sur	increasing	1.44E−09	0.2499424	0.0016822
Khasab_1	increasing	0.0072361	0.1109575	0.0007257	Suwaiq	no trend	0.2840611	−0.0442735	−0.0001522
Marmul	no trend	0.669002	−0.0176864	−0.0002802	Thumrait	decreasing	1.15E−10	−0.2662749	−0.0024432
Masirah	no trend	0.792607	0.0108884	0.0001899	Zamaim	increasing	0.0008613	0.1376599	0.0004167
Muscat	increasing	0.00087	0.13745	0.0024174	Ibra	decreasing	8.37E−05	−0.1624899	−0.0004428
Nizwa	no trend	0.3095	0.04199	0.0004	Bahla	increasing	1.05E−05	0.181991	0.0003879
Qairoon Hairiti	no trend	0.3151401	0.0416776	0.0023593	Hima	increasing	0.0237097	0.0934439	0.0001834
Qalahat	no trend	0.8315	0.0088	0.000137	Yalooni	no trend	0.3471532	0.0388582	0.0001874

Fortunately, not all stations have been affected by UHI phenomena due to the urbanisation expansion. Table 4 illustrates the stations with the possibility of UHI. It is noticed that there is a significant fluctuation in the last 5 years in the temperature which can be an indication of active urbanisation and land use changes. Also, it can be due to climate variability during the period of interest or any changes in local scale such as plantation, deforestation and others. It is known that MODIS satellites have not been modified or upgraded with new instruments. This profound change in the LST indicates a significant change or it is significant enough to alter the LST behaviour. The data showed that the effect is clear in some areas. As mentioned previously, the stations in open spaces in desert area such as Marmul and Thumrait have not been affected by the other factors. Such stations are hard to be investigated as the surface has not been changed to check whether there is a change or not. The UHI effect is clear in big cities and residential areas like Muscat, Sohar, Saiq and Sur. There are stations which are a way from the urban expansion, such as Ibri, Al Amrat and Diba. However, there is a negative trend in the UHI effect in some stations such as Rustaq, Nizwa, Sunynah and Samail. The effect of vegetation is clear in Rustaq station as the Palm trees farms have been expanded since 2000 and Nizwa is more likely to be affected by the same factor, but further investigation is needed. The pixel covers Salalah area is affected by the edge between the sea surface and the land as shown in Table 4.

6.5. Interpolation

6.5.1. IDW, ADW and N-N

As mentioned before, the study used SAGA software to evaluate the performance of IDW, ADW and N-N. Table 5 shows that Angular distance weighted is the best performing method with higher R value and smaller RMSE. The IDW and ADW are closer to each other compared to N-N which has a higher RMSE value despite the R values which are not significantly different from the other two methods. All methods struggled with the summertime as it is shown in Table 5 when the greatest RMSE values were calculated compared to other seasons.

6.5.2. Thin Plate Spline and Geographically Weighted Regression (GWR)

The TPS shows different performance in different months as Table 6 shows. The performance of TPS without the elevation is worse in winter months as well as March and November. However, it works much better during the rest of the months. The maximum R value gained by TPS 3D is 0.86 for January which is much better than TPS 2D which has R of 0.020. The improvement is clear during November, December and February where the accuracy is increased by more than 300%. This is a significant difference, but during the rest of the months, TPS2D is much better with a maximum R of 0.878 in August which is more accurate than the results from TPS 3D which have R of 0.75. During the months of increasing temperature, the TPS 2D works better comparing to the months when the temperature drops. However, the comparison between the months shows that TPS3D is not significantly inaccurate during the months when TPS 2D is higher. The greatest difference is less than double in May. By and large, the winter months seems to be highly affected by the elevation where the interpolation of the rest of the months does not improve by using the elevation. The exact reason behind the negative effect of Digital Elevation Model is unclear during the analysis even if the relation between the temperature and DEM is well-established. In contrast, the GWR shows a good performance even in summertime. It considers all the possible variables by which the results can differ. The distance from the sea and topography are involved in the model. The highest recorded RMSE from GWR is in August with 1.5 C which is much lower than the rest of the models. In March the GWR records the lowest R, but the RMSE is the best among the interpolation models.

Table 5. RMSE and R of IDW (left), ADW (Middle) and N-N (Right) from the cross validation.

Month	IDW	ADW	N-N
January	RMSE -> 1.85 R -> 0.80	RMSE -> 1.79 R -> 0.81	RMSE -> 2.83 R -> 0.76
February	RMSE -> 1.74 R -> 0.81	RMSE -> 1.68 R -> 0.82	RMSE -> 2.8 R -> 0.76
March	RMSE -> 1.72 R -> 0.81	RMSE -> 1.65 R -> 0.82	RMSE -> 2.83 R -> 0.76
April	RMSE -> 1.98 R -> 0.80	RMSE -> 1.88 R -> 0.81	RMSE -> 3.15 R -> 0.76
May	RMSE -> 2.28 R -> 0.79	RMSE -> 2.18 R -> 0.80	RMSE -> 3.50 R -> 0.76
June	RMSE -> 2.63 R -> 0.74	RMSE -> 2.53 R -> 0.75	RMSE -> 3.60 R -> 0.75
July	RMSE -> 3.01 R -> 0.75	RMSE -> 2.90 R -> 0.76	RMSE -> 3.93 R -> 0.78
August	RMSE -> 3.09 R -> 0.74	RMSE -> 2.99 R -> 0.75	RMSE -> 3.97 R -> 0. 77
September	RMSE -> 2.51 R -> 0.77	RMSE -> 2.41 R -> 0.78	RMSE -> 3.53 R -> 0.77
October	RMSE -> 1.77 R -> 0.85	RMSE -> 1.67 R -> 0.86	RMSE -> 3.00 R -> 0. 78
November	RMSE -> 1.78 R -> 0.84	RMSE -> 1.69 R -> 0.85	RMSE -> 2.95 R -> 0.78
December	RMSE -> 1.77 R -> 0.85	RMSE -> 1.84 R -> 0.81	RMSE -> 2.88 R -> 0.77

Table 6. The comparison between TPS2D (mid-left column), TPS 3D (mid-right column) and GWR (Right) using correlation coefficient (R) values and Root Mean Squared Error (RMSE).

Month	TPS 2D	TPS 3D	GWR
January	RMSE -> 2.67	RMSE -> 1.2	RMSE -> 0.55
	R-> 0.0200	R-> 0.86	R-> 0.83
February	RMSE -> 2.49	RMSE -> 0.985	RMSE -> 0.67
	R-> 0.25	R-> 0.86	R-> 0.61
March	RMSE -> 2.16	RMSE -> 0.9899	RMSE -> 0.95
	R-> 0.0429	R-> 0.672	R-> 0.04
April	RMSE -> 2.218	RMSE -> 1.4	RMSE -> 0.54
	R-> 0.575	R-> 0.3	R-> 0.72
May	RMSE -> 2.597	RMSE -> 1.97	RMSE -> 0.66
	R-> 0.7045	R-> 0.42	R-> 0.86
June	RMSE -> 2.64	RMSE -> 2.45	RMSE -> 1.02
	R-> 0.836	R-> 0.65	R-> 0.76
July	RMSE -> 3.05	RMSE -> 3.00	RMSE -> 1.36
	R-> 0.86	R-> 0.725	R-> 0.86
August	RMSE -> 3.0	RMSE -> 2.99	RMSE -> 1.5
	R-> 0.878	R-> 0.75	R-> 0.82
September	RMSE -> 2.77	RMSE -> 2.35	RMSE -> 1.2
	R-> 0.81	R-> 0.68	R-> 0.82
October	RMSE -> 2.1	RMSE -> 1.2	RMSE -> 0.51
	R-> 0.67	R-> 0.6	R-> 0.92
November	RMSE -> 2.4	RMSE -> 1.07	RMSE -> 0.75
	R-> -0.3178	R-> 0.865	R-> 0.68
December	RMSE -> 2.7	RMSE -> 1.07	RMSE -> 0.65
	R-> -0.07	R-> 0.84	R-> 0.78

6.5.3. Kriging

1) Kriging with the same variogram fitting model

All Kriging interpolation methods show different performance in different months which indicates the instability in the data characteristics, such as the spatial differences and trends (Table 7). When the same variogram fitting model was used, it reveals that the Universal kriging (UK) is the best among the kriging models in wintertime as well as November based on the RMSE and R. However, it is shown that Simple kriging (SK) is much better in summertime. In springtime, SK and OK are the best among the kriging models. Moving to the Ordinary Kriging (OK), it has the best performance in October in terms of R, but the SK is better in terms of RMSE. Regardless of the best performance, it is illustrated in Table 7 that the accuracy of Kriging interpolation methods is the worst in summertime when the RMSE exceeded 3˚C which indicates that the cross-validation test shows that the predicted values are as great as 3˚C. The performance in winter and spring is much better than the summertime. By and large, the OK and SK are better than UK in terms of the accuracy of the prediction based on the cross validation.

Table 7. The comparison between OK (second-column), SK (third-column) and UK (far right column) using correlation coefficient (R) values and Root Mean Squared Error (RMSE).

Month	Ordinary	Simple	Universal
January	RMSE -> 1.916 R-> 0.0279	RMSE -> 1.949 R-> 0.031	RMSE -> 0.9696 R-> 0.8675
February	RMSE -> 1.436 R-> -0.107	RMSE -> 1.486 R-> -0.0931	RMSE -> 0.66 R-> 0.829
March	RMSE -> 0.946 R-> -0.0198	RMSE -> 1.024 R-> 0.0143	RMSE -> 0.9636 R-> -0.4
April	RMSE -> 1.137 R-> 0.505	RMSE -> 1.184 R-> 0.53	RMSE -> 1.88 R-> -0.201
May	RMSE -> 1.81 R-> 0.62	RMSE -> 1.82 R-> 0.635	RMSE -> 2.88 R-> -0.422
June	RMSE -> 2.99 R-> 0.600	RMSE -> 2.99 R-> 0.608	RMSE -> 4.046 R-> -0.648
July	RMSE -> 3.989 R-> 0.6454	RMSE -> 3.99 R-> 0.647	RMSE -> 5.15 R-> -0.6975
August	RMSE -> 4.11 R-> 0.6427	RMSE -> 4.11 R-> 0.644	RMSE -> 5.3 R-> -0.7178
September	RMSE -> 2.746 R-> 0.6549	RMSE -> 2.74 R-> 0.65	RMSE -> 3.945 R-> -0.655
October	RMSE -> 1.360 R-> 0.5806	RMSE -> 1.317 R-> -0.5741	RMSE -> 2.17 R-> -0.386
November	RMSE -> 1.360 R-> -0.217	RMSE -> 1.42 R-> -0.2075	RMSE -> 0.699 R-> 0.84
December	RMSE -> 3.749 R-> -0.07119	RMSE -> 1.96769 R-> -0.117	RMSE -> 0.98 R-> 0.8470

2) Kriging with the best variogram fitting model

The investigation of using a fixed variogram model and the best fitting model shows that the performance of OK and UK has been improved significantly in terms of the correlation coefficient but not in terms of the RMSE generally (Table 8). The RMSE of all kriging models shows a significant increase in the error, but not in all cases. For instance, the UK shows the worst performance in summertime with RMSE of up to 5.15˚C, however, the best fitting model decreases the error and increases the correlation coefficient. The UK in wintertime when the best performance is found, shows even a higher correlation coefficient, but the RMSE has increased slightly. Moving to the OK which shows the same improvement as the UK but with a different magnitude. The increase in RMSE is greater for OK which exceeded 1˚C in January and the increase is between 0.2˚C and 1˚C except for September and October when the reduction in the error exceeded 40% in October. On the other hand, SK has been affected negatively with a decrease in RMSE and correlation coefficient especially from April to September.

Table 8. The comparison between OK (second-column), SK (third-column) and UK (far right column) after using the best fitting model using correlation coefficient (R) values and Root Mean Squared Error (RMSE).

Month	Ordinary	Simple	Universal
January	RMSE -> 2.16 R -> 0.84	RMSE -> 2.359 *R* -> 0.150	RMSE -> 1.156 *R* -> 0.970
February	RMSE -> 1.66 *R* -> 0.89	RMSE -> 2.296 *R* -> 0.017	RMSE -> 0.943 *R* -> 0.960
March	RMSE -> 1.25 *R* -> 0.90	RMSE -> 2.311 *R* -> -0.425	RMSE -> 1.260 *R* -> 0.908
April	RMSE -> 1.44 *R* ->0.90	RMSE -> 2.490 *R* -> -0.313	RMSE -> 2.111 *R* -> 0.816
May	RMSE -> 1.97 *R* ->0.88	RMSE -> 2.743 *R* -> -0.086	RMSE ->3.059 *R* -> 0.681
June	RMSE -> 3.04 *R* -> 0.73	RMSE -> 3.166 *R* -> 0.040	RMSE -> 4.098 *R* -> 0.442
July	RMSE -> 4.00 *R* -> 0.66	RMSE -> 3.809 *R* -> 0.225	RMSE -> 5.052 *R* -> 0.394
August	RMSE -> 4.01 *R* -> 0.63	RMSE -> 3.877 *R* -> 0.268	RMSE -> 4.991 *R* -> 0.377
September	RMSE -> 2.58 *R* -> 0.79	RMSE -> 2.955 *R* -> 0.283	RMSE -> 3.327 *R* -> 0.597
October	RMSE -> 0.88 *R* -> 0.97	RMSE -> 2.260 *R* ->0.283	RMSE -> 1.686 *R* -> 0.885
November	RMSE -> 1.48 *R* -> 0.93	RMSE -> 2.240 *R* ->0.278	RMSE -> 0.601 *R* -> 0.985
December	RMSE -> 2.19 *R* -> 0.84	RMSE -> 2.430 *R* -> -0.026	RMSE -> 1.020 *R* -> 0.967

6.5.4. Final Results

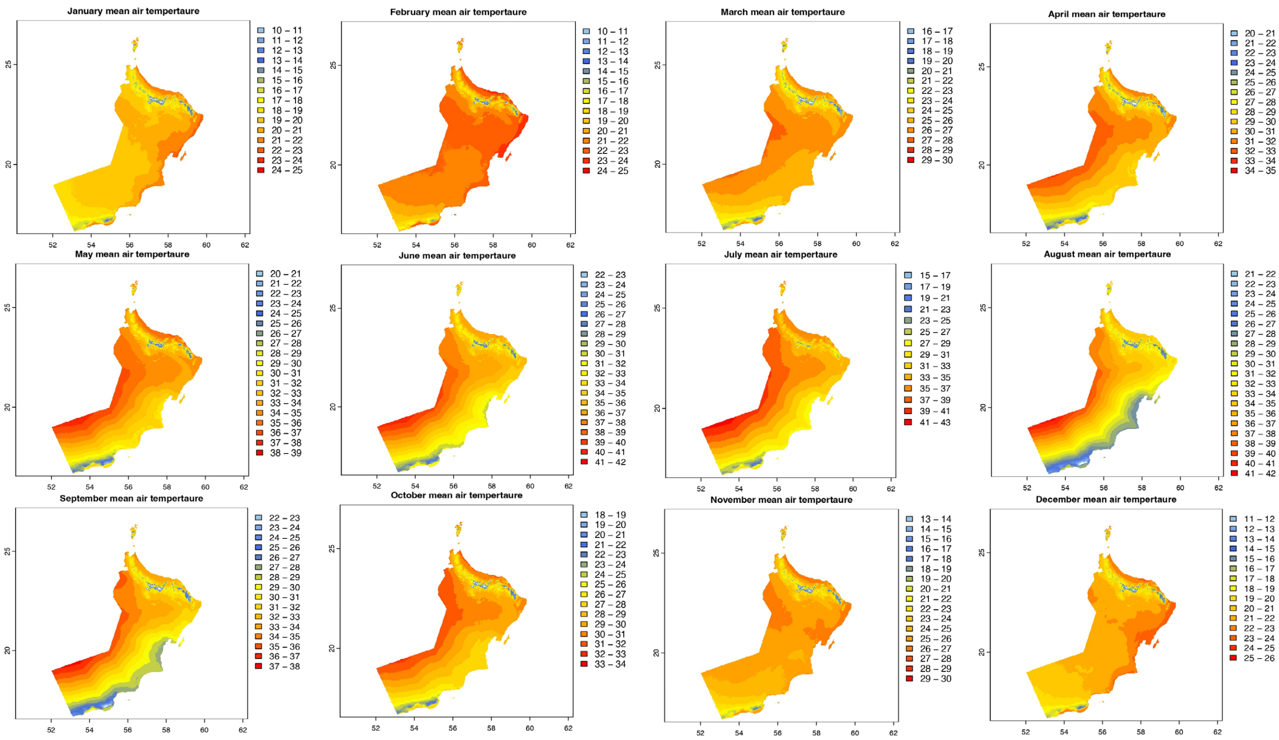


Figure 4. The interpolated monthly provisional climate normal using Geographically weighted regression (GWR) for all months based on the best performing model analysis.

Based on the best performing interpolation method, which is GWR, it is shown that the provisional climate normal of monthly mean air temperature in January varies between 9˚C to 25˚C (**Figure 4**). The mountainous areas with higher altitude have the lowest mean air temperature, conversely, the highest is about 25˚C in the northeast of Oman. The desert mean temperature varies between 19 and 23˚C. In February, the situation is the same with slightly warmer climate which is almost 2˚C warmer than January mean air temperature in some areas. In March, the temperature gets warmer by almost 4˚C to 5˚C in mountainous areas and 3˚C to 5˚C in the rest of the country. However, the Southern part is not yet affected by the monsoon winds. In April, the temperature increases by 4˚C to 5˚C over most of Oman except the southern part where the temperature increases by a smaller magnitude which is about 2˚C. As summertime is approaching, the air temperature is getting warmer in May and the monthly mean air temperature increases with slightly smaller magnitude compared to the increase in April. However, the temperature in the southern coast is almost the lowest along the mountainous areas as well as the top summits along Al Hajar mountains. In June, the monsoon keeps the temperature at its lowest level along the areas where it affects the most especially the southeast coast of Oman as well as the southern coast and adjoining mountainous areas. The general increase in the monthly mean temperature is about 3˚C. In July, the monthly mean air temperature reaches the peak over Oman except the southeastern coast and the south where the monsoon keeps the temperature at its minimum between 21˚C and 31˚C. In August, the temperature is almost the same as the temperature in July with some differences which are mainly along the monsoon areas. In September, the opposite behaviour is observed. In other words, the temperature starts to decrease in Oman except the areas where the monsoon affect. In these areas, the temperature starts to increase by 1˚C to 2˚C. As the second transitional period approaches, the mean monthly air temperature decreases by 2˚C to 3˚C over Oman except the south and southeast coast where the temperature almost sustains itself. In November, the monthly air temperature is generally colder by 3˚C to 4˚C. In December, the situation is almost the same as January with slightly warmer temperature by almost 1˚C.

7. Discussion

Upon completion of the analysis, it is revealed that the provisional climate normal calculations did not meet the criteria of WMO. It is shown that there are 10 stations only with more than 30 years which means a very scattered data availability. Therefore, the project used the stations with 10 years of data and the start point is almost the same. It is shown that the station missing data varies between 0.78 and 35%. The criteria of WMO stated that the reanalysis and interpolated data can be used in calculating the anomalies [1]. The ERA-5 data showed almost more than 90% agreement with the stations which gave a higher confidence to use the reanalysis data to fulfil the gaps. The main challenge is to accept the stations with a significant percentage of missing data, but the critical locations over the highlands and the correlation with ERA-5 are high, which encourage the study to use them. The Homogeneity test showed good results even with the missing data. There are 70% of the stations with homogenised data and the others have a single checkpoint up to 4 checkpoints. The Homogeneity test faced a challenge when it is applied to Salalah station showing that there are 4 checkpoints which should be double-checked. The challenge is that the weather in Salalah in summertime is very susceptible to the cloudiness. The fluctuation in the cloud cover showed a profound effect on the daily behaviour of the temperature which can mislead the test to consider the variability as outliers. In addition to that, the missing data plays a critical role in the homogeneity test outcomes. It is shown that after applying the regression model, the checkpoints have been eliminated which means that the missing data in this station has a greater effect on the homogeneity of the data. The usage of regression model to fulfil the missing data improved the homogeneity level of the data to reach 79.4% of the stations which are considered as homogenized stations. On the other hand, the homogeneity test showed checkpoints after the post-processed data in Khasab_2 station. The pure observations have been considered as a homogenized data with the existence of the missing data. It is clear that the filled data has adjusted the outcomes as the checkpoints appear within the fulfilled periods. The trend in the data with time is changing as processed data is fed into the original data. Unfortunately, there are insufficient maintenance reports since 2010 for all stations to check whether there were maintenance visits causing the checkpoints. One of the most controversial factors affecting the ground observations is the urban heat island. This factor was investigated along the stations using the satellite data from MODIS. It is shown that the UHI is positive in areas where the urbanization invasion moves towards the station's sites. The most profound examples are Sohar station and Muscat where the source of heating is very close to the stations. The analysis of the skin surface temperature showed a significant fluctuation in the recent years for different reasons which can be due to climate variability or land use including agriculture and urbanization or instrumental related issues. It is known that the sensors have not been replaced since the satellite has been launched which means that it is more likely to be due to changes in the land surface properties by which the LST behaviours altered. For instance, the Sohar industrial project near the station is in trial phases since 2017 which is shown by LST behaviour from the satellite. On the other hand, there is a downtrend in the UHI effect in other stations, such as Rustaq which can be related to the effect of plantation and agricultural expansion. However, the downtrend could be due albedo difference between the two sides even if the difference is small, which is one of the reasons the study did not consider some stations because they are installed on a dark surface with low albedo. The other situation is where there is no trend in some stations, such as Dhank, Qarnalam, Ibri, Bidyiah and Marmul where the urbanisation has no significant effect or other human activities. The stations in desert areas have the advantage of urban-free spaces or at least far from oil activities to a limited extent. However, some desert stations have a downtrend in UHI effect which needs further investigation, such as Fahud.

Proceeding to the interpolation models, the results show that TPS2D, TPS3D and kriging models have struggled during summertime as shown in **Tables 6-8**. The issue with the summertime is that the climate diverse significantly between arid, semi-arid and wet climate. In other words, this season is affected by the Indian monsoon, especially in the south and the southeast coast of Oman, where the temperature changes dramatically as offshore towards the desert and this seasonal shift complicates the spatial prediction, which requires a relatively denser observations network to cover the complex topography [19]. Also, Al Hajar mountains chain has one station which is not adequate to reflect the mountain climatology. The challenge of diverse and sharp climate variation requires more weather stations to fulfil the gaps by which the interpolation models can predict the actual values. It is shown that the regions with atmospheric or oceanic contrast or topographic complexity can challenge the interpolation models [19] [20]. The wintertime and the rest of the year have smoother temperature variation on the daily scale due to homogenised transitional behaviours of the climate spatially. Except the GWR, the TPS3D shows the best performance and results comparing to IDW, ADW, N-N, TPS2D, TPS3D and Kriging in terms of RMSE with maximum error of 3˚C in July which is the lowest value comparing to the other methods which is shown by others [21] and the differences between the TPS2D and TPS3D is noticeable in some months, but the differences can be greater between the two comparing to the difference between TPS and Kriging methods [20]. The results show that the best interpolation method is GWR which could handle the significant contrast between the coastal areas and the inner land with a high correlation coefficient and low RMSE. In other words, the GWR can predict the spatial distribution of the temperature as shown by [10]. Finally, this project analysed the worldwide used interpolation models and calculated the Provisional Climate Normal of air temperature in Oman which helps different entities in the country to understand the air temperature variation in monthly scale.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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