Climatological modeling of monthly air temperature and precipitation in Egypt through GIS techniques

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ABSTRACT: This paper shows the results of modeling and mapping monthly maximum and minimum temperature, and total precipitation in Egypt with the purpose of obtaining accurate climate maps. A multivariate linear regression model enhanced by spline interpolation was undertaken. Climate variables were obtained from 40 quality controlled and homogenized series for the period 1957 to 2006. The predictors, including geographical variables (e.g. latitude, longitude, altitude and distance to water bodies) and the Moderate Resolution Imaging Spectroradiometer (MODIS) remote sensing indices, were integrated as raster layers in a Geographical Information System (GIS) environment. Inclusion of meaningful remote sensing indices (e.g. the Normalized Difference Vegetation Index and the Normalized Difference Temperature Index) generally improved accuracy of the predictions. The model integrating geographical and remote sensing indices explained an average of 76.5 and 51.7 % of the spatial variability of maximum and minimum temperatures, respectively. For precipitation, the model explained an average of 60.2 % of the spatial variability during the whole year and 70.7 % during the wet season (September to April). The accuracy of the models was assessed through cross-validation between predicted and observed values using a set of statistics including the coefficient of determination (R^2), Mean Absolute Error (MAE) and Willmott's D . The cross-validation results were satisfactory for maximum temperature (average MAE = 1.03°C) and total precipitation (average MAE = 2.73 mm). A poorer fit of the model was obtained for minimum temperature (average MAE = 1.72°C). For each climatic variable, digital maps were finally obtained at a spatial resolution of 1 km. Considering the favourable results obtained using only a small number of observatories, such digital maps have significant potential for the study of climate change and climate impact assessment.

KEY WORDS: Multivariate regression · Temperature · Precipitation · Digital elevation model · GIS · Remote sensing · Egypt

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1. INTRODUCTION

Spatially and temporally continuous climatic data are important for hydrological and ecological modeling, natural resources monitoring, agricultural management and environmental assessment (Daly et al. 1994, Holdaway 1996, Perry & Hollis 2005). However, climatic data are commonly measured at discrete points presenting a challenge to these applications, particularly in mountainous regions and deserts (Daly et al. 1994, Brown & Comrie 2002, Frei et al. 2003). Several models have been developed to improve spa-

tial continuity of climatic variables at local and regional scales, especially temperature and precipitation. The potential increase in computational capacity and ongoing development of Geographical Information Systems (GIS) have benefited model development (Goovaerts 2000, Li et al. 2006). Generally, a number of methods with different algorithms, theoretical backgrounds and underlying mathematical processes have been proposed for spatial interpolation. Nevertheless, determination of the most appropriate method for each region is still problematic (Moral 2009). These methods vary from simple interpolation methods, such as the

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Thiessen polygons and Inverse Distance Weighting (IDW), to more complicated techniques, such as geostatistical procedures (e.g. kriging) (Phillips et al. 1992, Lennon & Turner 1995, Vicente-Serrano et al. 2003). Also, these approaches differ in their applicability according to terrain complexity and spatial density of stations (Allen & DeGaetano 2001). A list of some studies involving spatial interpolation of climate variables is included in Table 1.

In general, local and geostatistical interpolation methods give more account to the spatial structure of points of interest rather than the physical influences of the surrounding environment on climate distribution (e.g. water bodies and vegetation) (Phillips et al. 1992, Ninyerola et al. 2000). Additionally, spatial interpolation has certain limitations when stations are unevenly distributed over space (Nalder & Wein 1998). Inadequate density of points retained for interpolation may affect the nature of the interpolated surfaces (i.e. localized surfaces). On the other hand, multivariate regression models can employ the secondary information that is highly dense over space to explain variability of climatic variables that are measured at irregular points (Goovaerts 2000, Brown & Comrie 2002). This algorithm is global since it uses the data of all sampling

points (Moral 2009). It is also deterministic because it predicts variables at unsampled points based on well-known influencing processes. It may also be extended to incorporate extra information available from other sources of spatial data. Given that many studies employed multivariate regression for spatial interpolation of climatic variables, particularly temperature and precipitation (e.g. Holdaway 1996, Agnew & Palutikof 2000, Ninyerola et al. 2000, 2007a,b, Brown & Comrie 2002, Vicente-Serrano et al. 2007, Portales et al. 2009), the regression-based techniques seem to be superior to the classical interpolation models (Brown & Comrie 2002). Multivariate regression models employ measurements from a network of stations to fit the best equation as a function of a range of topographical and environmental predictors.

Geographic and topographic predictors, such as elevation and distance to water bodies, are commonly used in regression-based techniques (e.g. Goovaerts 2000, Vicente-Serrano et al. 2003, Diodato 2005). Furthermore, satellite observations are able to provide invaluable information related to the spatial distribution of different climate parameters. This information can be employed as predictors in regression models, reflecting local climatic differences (Florito et al. 2004).

Table 1. Overview of some of the gridded datasets that employed spatial modeling of climate variables. IDW: Inverse Distance Weighting

Region	Climate variable(s)	Independent variables	Interpolation method	Source
Ireland	Temperature, precipitation and solar radiation	Elevation	Multiple regression	Goodale et al. (1998)
UK	Temperature, rainfall, sunshine, cloud and wind speed	Easting, northing, terrain height, percentage of open waters, mean altitude within 5 km	Multiple regression and IDW	Perry & Hollis (2005)
Arizona and New Mexico (USA)	Temperature and precipitation	Elevation, slope, aspect, latitude, longitude	Stepwise regression, kriging and IDW	Brown & Comrie (2002)
Cataluña (NE Spain)	Temperature and precipitation	Latitude, altitude, continentality, solar radiation, cloudiness factor	Multiple regression	Ninyerola et al. (2000)
Great Britain	Temperature	Altitude, distance from sea, slope, topographical roughness	Multiple regression, thin plate spline, mixed spline-regression	Lennon & Turner (1995)
Portugal	Precipitation	Elevation	Simple kriging, kriging with external drift, colocated kriging	Goovaerts (2000)
Iberian Peninsula	Precipitation	Altitude, latitude, continentality, terrain complexity, solar radiation	Multiple regression, spline and IDW	Ninyerola et al. (2007a)
Western Canada	Temperature and precipitation	Latitude, longitude and elevation	Kriging, mixed multiple regression-IDW	Nalder & Wein (1998)
Israel	Temperature	Latitude, longitude and elevation	Spline, IDW, multiple regression	Kurtzman & Kadmon (1999)
The Mediterranean basin	Temperature and precipitation	Latitude, longitude, elevation, distance from the sea, slope and aspect	Multiple regression	Agnew & Palutikof (2000)
Andorra	Temperature and precipitation	Altitude, latitude, continentality, weighted solar radiation and terrain curvature	Multiple regression with spline and IDW	Esteban et al. (2009)

Vegetation dynamics can be a valuable indicator to track climate change and variability, particularly in transitional regions such as the Mediterranean. Spatial and temporal variability of the Normalized Difference Vegetation Index (NDVI), for example, has been increasingly used to explore impacts of climate variability on ecosystems. Maselli et al. (1998) used the NDVI to model climate parameters in Italy. Also, Mallick et al. (2008) and Cristóbal et al. (2009) utilized land surface temperature derived from satellite imagery to improve spatial interpolation of surface air temperature. Remote sensing information can be highly valuable when the network of observatories is sparse, which is common in large regions of the world.

Egypt is still a poor coverage region in the existing gridded climate databases. For instance, Hijmans et al. (2005) developed a global climatology at a 1×1 km resolution. However, this climatology still has limitations in terms of the spatial density of the contributing network of stations, the quality and homogeneity of the series and the number of predictors included. Accordingly, the present study could provide an improvement to previous datasets since it employs the densest network of quality controlled, homogenous and long-term (1957 to 2006) historical climate data in Egypt. More particularly, our study incorporates various geographical, topographical and remotely sensed variables known to have effects on climate variability. In data-sparse regions like Egypt, this developed climatology could enhance climatic, hydrologic and environmental modeling applications that require fine spatial resolution.

The main objective of this work was to create continuous surfaces of monthly temperature and precipitation in Egypt at a finer spatial resolution (1 km). For this purpose, the ability to model temperature and precipitation climatologies for the whole of Egypt was tested by means of regression-based techniques using geographic and remote sensing-derived parameters as auxiliary variables. In this context, 24 digital maps were produced for maximum and minimum temperature (1 map for each month), whilst 9 maps were yielded for total precipitation excluding the dry summer months (June to August). All the resulting maps were created based on the (1957 to 2006) monthly averages for temperature and precipitation.

2. DATA AND METHODS

2.1. Study area

Egypt is located in the northeast of Africa extending approximately between 22° and $31^\circ 36' \text{N}$ and 25° and 35°E with an area of approximately $1 \times 10^6 \text{ km}^2$. It is bounded by the Mediterranean Sea to the north and

the Red Sea to the east. Egypt is generally homogeneous with low relief (Fig. 1). The altitude varies gently from 133 m below the mean sea level (Qattara Depression) to nearly 2500 m (Southern Sinai), with an average of 306 m. Southern Sinai and the Red Sea hills are the most elevated areas, representing a topographic barrier for maritime influences from the Red Sea. The climate of Egypt is generally characterized by moderate and rainy winters, hot and dry summers and a relatively high number of sunny hours (10 h per d). Generally, precipitation shows more local variation where dry conditions prevail, as is the case for the major part of the country for most of the year. The rainy season extends only from September to April. The total monthly precipitation varies from 15.9 mm in September to nearly 543.6 mm in January, concentrated largely along the Mediterranean coast, while a pattern of zero precipitation predominates in the majority of southern Egypt. The average maximum and minimum temperatures are 33.3 and 21.1°C , respectively. January (July) is the coldest (warmest) month with an average temperature of 19.3°C (33.9°C) (Fig. 2). Summer maximum temperatures commonly exceed 30°C , whilst winter minimum temperatures rarely fall below 5°C .

2.2. Data

2.2.1. Climatic data

The analysis was based on quality controlled and homogenized datasets of maximum temperature, minimum temperature and total precipitation measured at 40 observatories. The original data was maintained by the Egyptian Meteorological Authority. Since quality

Fig. 1. Topography of Egypt and spatial distribution of the 40 meteorological observatories

Fig. 2. Intraannual variability of long-term average (1957 to 2006) of maximum and minimum temperature and sums of precipitation based on the average records from the 40 available meteorological stations (central line: median; top and bottom of boxes: 75th and 25th percentile, respectively; upper and lower whiskes: 90th and 10th percentile, respectively; dots: outliers)

control is fundamental to ensure the quality of climate data, the data was subjected to several quality control tests. Firstly, it was checked for internal and external consistency with the aim of detecting erroneous data resulting from archiving, transcription, digitization processes or other potential sources of error (e.g. non-existent dates, $T_{\min} \geq T_{\max}$, and precipitation below 0). External consistency was adopted to eliminate the worst data by identifying potential outliers that differed greatly from the neighbors located within a distance of 100 km. The same approach has been adopted by many researchers (e.g. Eischeid et al. 1995, Hubbard 2001). The aim was to trim outliers that were undoubtedly erroneous. The rank of each value compared with the average rank of all other values in the series, expressed as quantiles, was computed for each testable series. Next, the quantiles corresponding to each target station were checked against those of nearby stations. A similar approach was recently used by Štěpánek et al. (2009) for daily data. Application of different statistical methods can improve the degree of certainty for identification of discontinuities in a series (Wijngaard et al. 2003, Menne & Williams 2005). Accordingly, 3 well established tests were applied to check homogeneity of the series at a 5% significance level: the Standard Normal Homogeneity Test (SHNT) for a single break (Alexandersson 1986), the Easterling and Peterson test (Easterling & Peterson 1995) and the Vincent method (Vincent & Gullett 1999). The SHNT single break test determines the most significant break in a time series and has the advantage of detecting breaks close to the beginning and the end of the series (Wijngaard et al. 2003). On the other hand, the Easterling and Peterson 2-phase regression-based technique has the advantage of detecting multiple potential cut points in the series, specifically when they are very close in time (Easterling & Peterson 1995). In addition, Vincent & Gullett (1999) introduced a new technique to

identify multiple breaks in the Canadian temperature series, particularly undocumented change points. Based on the combined results of the tests, a correction (adjustment) factor was applied to the candidate series resulting in a new dataset compiled of homogenized monthly maximum and minimum temperatures and total precipitation. All the procedures were automatically performed using the PROCLIM software developed by Štěpánek (2007).

The WMO identified 30 yr as the minimum series length required for climatic predictions (WMO 1989). Although the use of series covering the same temporal interval is desirable in climate studies to accurately explain inter-annual variability as well as spatial variability, the analysis was restricted to those stations with at least 30 yr of non-missing data between 1957 and 2006 to improve spatial coverage of stations. The monthly averages of precipitation, and maximum and minimum temperature were calculated for the 1957 to 2006 baseline period. As shown in Fig. 1, the distribution of the meteorological observatories is unevenly distributed across Egypt with an average density of 1 station for approximately 25 000 km². The network of observatories is densest in highly populated regions, e.g. the Delta, with irregular distribution in the sparsely populated areas, e.g. the eastern and western deserts, and Sinai Mountains.

2.2.2. Geographical predictors

Selection of appropriate input variables is crucial for obtaining accurate results with any spatial modeling (Diodato 2005). We selected a range of topographical predictors which were likely to have the potential to explain spatial variability of the climatic patterns. Numerous studies obtained better results when including topographical parameters as predictors (e.g. Lennon &

Turner 1995, Agnew & Palutikof 2000, Ninyerola et al. 2000, Portales et al. 2009). In this context, the Digital Elevation Model (DEM) is a valuable, cheap and robust source of auxiliary information about topographical parameters, particularly when topographic maps are not fully available or not easily accessible. The DEM has been a source of information for spatial interpolation in many studies (e.g. Ninyerola et al. 2000, Vicente-Serrano et al. 2003). A section of the GTOPO30 DEM with a resolution of approximately 1 km was obtained for Egypt from the US Geological Survey (GTOPO30 1996). The predictors were retrieved using the standard raster operations in a GIS environment. A low-pass filter was applied to all independent variables using the MiraMon software (Pons 2004) to obtain smooth surfaces and remove any noisy data. The local/regional relief expressed as the difference in altitude between each observatory and the lowest point within a radius of 5, 10, 25 and 50 km was considered to assess its effects on local and regional climates. In this context, although some studies have employed absolute elevation as a key factor influencing climate (e.g. Goodale et al. 1998, Brown & Comrie 2002, Esteban et al. 2009), our concern was oriented toward using a measure of the relative topography in terms of differences in altitude at different radii. This is mainly justified by the fact that the absolute elevation may not be significant—given that distribution of stations is vertically sparse—as the majority of stations (about 90 %) are located in low-lying areas (below 100 m). Therefore, the topography-induced effects may be captured through relative topography measures. The same approach has been adopted by several authors (e.g. Agnew & Palutikof 2000, Vicente-Serrano et al. 2003). Continentality was measured as a function of the distances from the sea to each raster. The geographical predictors including latitude, longitude, elevation and distance to main water bodies (i.e. the Mediterranean Sea, the Red Sea and the Nile) were also obtained at 1 km spatial resolution. Although aspect and slope are often important topographical variables, they were not considered in this study as a consequence of the flatness of the surface in the majority of Egypt, in addition to a lack of observatories in mountainous areas.

2.2.3. Remote sensing indices

Remote sensing data have great potential to improve spatial modeling of temperature and precipitation, since they are captured on the basis of a fixed temporal interval with high spatial resolution (Jackson et al. 2004). Therefore, they can provide a high degree of detail about local characteristics which are likely to influence climate. The remotely sensed data was ac-

quired from the Moderate Resolution Imaging Spectroradiometer (MODIS) on board NASA's Terra and Aqua satellites for the period from November 2001 to December 2005. The information is available for 32 d reflectance composites corresponding to spectral bands 1 to 7, with spatial resolution varying from 250 m to 1 km. These bands cover the spectral regions from the visible to the middle infrared channels. Further details about the MODIS data are available in Justice et al. (1998). Each grid cell in the MODIS images has a resolution of 500 m and, therefore, they were resampled to a resolution of 1 km to match with other topographical predictors.

The spectral information obtained from the MODIS data was summarized by means of a set of widely used indices that reflect characteristics and conditions of the land surface. These indices included the average reflectance, the NDVI, the Normalized Difference Water Index (NDWI) and the Normalized Difference Temperature Index (NDTI).

The NDVI was developed by Rouse et al. (1973) to estimate leaf activity, and is computed as follows:

$$\text{NDVI} = \frac{(\rho_2 - \rho_1)}{(\rho_2 + \rho_1)} \quad (1)$$

where ρ_2 refers to the reflectance in a near infrared channel (841 to 876 nm) and ρ_1 denotes the reflectance in a visible channel (620 to 670 nm). This index has increasingly been used, not only to assess drought conditions in many environments (e.g. Peters et al. 2002, Vicente Serrano 2007), but also to model precipitation (e.g. Nicholson & Farrar 1994, Creech & McNab 2002). Other studies have documented the significant relationship among the temporal variability of NDVI, temperature and precipitation (e.g. Smith & Choudhury 1990, Wang et al. 2003).

The NDWI was proposed by Hardisky et al. (1983) to measure vegetation water content. The NDWI is derived similarly to the NDVI. However, the inclusion of the SWIR (short-wave infrared) channel in the NDWI maximizes not only the ability to enhance the presence of soil features or terrestrial vegetation, but also the presence of water features by using the green wavelengths (Mcfeeters 1996, Jackson et al. 2004). Zero and negative values of this index denote soil and terrestrial vegetation, whereas positive values refer to water features. This index is very sensitive to drought conditions and changes in vegetation water content. It is computed according to Gao (1996):

$$\text{NDWI} = \frac{(\rho_6 - \rho_7)}{(\rho_6 + \rho_7)} \quad (2)$$

where ρ_6 and ρ_7 are the reflectance of MODIS channels 6 (1628 to 1652 nm) and 7 (2105 to 2155 nm), respectively.

The NDTI was proposed by Jackson et al. (1983) mainly as a measure of moisture availability. However, this index has also been successfully applied to map surface air temperature in the northern plains of China (Tian 1993) and to interpolate changes in moisture availability in Australia (McVicar & Jupp 2002). The NDTI is derived from the MODIS data as:

$$\text{NDTI} = \frac{(\rho_2 - \rho_5)}{(\rho_2 + \rho_5)} \quad (3)$$

Where ρ_2 is the reflectance from the 500 m near-infrared channel (841 to 876 nm) and ρ_5 is the reflectance from the shortwave-infrared channel (1230 to 1250 nm).

Finally, the average reflectance was calculated following the equation:

$$\text{ref} = \left(\frac{\rho_1 + \rho_2 + \rho_3}{3} \right) \quad (4)$$

Where ρ_3 is the reflectance from the 500 m near-infrared channel (459 to 479 nm).

To account for the possible influences of vegetation and land surface characteristics at different spatial scales on climate variability, a low-pass filtering of the remote sensing indices was carried out at various radiuses. Table 2 shows the geographical and remote sensing indices used to model temperature and precipitation in Egypt.

Given the exploratory analysis of the topographical variables, the Komolgorov-Smirnov test of normality at $p = 0.05$ was carried out to assess normality of the

model predictors. This is a prerequisite to meet the conditions of multiple regression models which are mainly based on an assumption of normality of all input variables (i.e. mean and median are similar, skewness is close to zero). Whenever the conditions of normality were not met for any variable, a variety of the traditional transformation algorithms (e.g. natural logarithmic, difference, square root, sin and cos) were tested to correct nonconstant variance and improve normality of data.

2.2.4. The regression model

Given the limited number of stations and its simplicity, the linear multivariate regression model was selected for our study. However, we also made a preliminary attempt to test the nonlinearity of relationships between climatic variables and independent variables using Generalized Additive Models (GAMs) (Wood & Agustin 2002). Nevertheless, it was found that the results did not vary greatly, also increasing the difficulty of assessing the contribution of predictors to the final models through GAMS. In general, the model incorporated a set of predictors which were assumed to have effects on the spatial and temporal variability of climatic variables. The MiraMon software was used to run the stepwise multivariate regression models between the average maximum and minimum temperature and precipitation, and independent variables retrieved from the GIS. All statistics were conducted at

the 0.05 level of significance. Using the calculated long-term monthly averages of climate data, the regression predictions were computed as follows:

$$Y_i = \beta_0 + \beta_1\chi_1 + \beta_2\chi_2 + \beta_n\chi_n \quad (5)$$

where Y_i is the dependent variable for case i , β_0 is the intercept, $\beta_1, \beta_2, \dots, \beta_n$ are the regression coefficients determined by ordinary least-squares methods and χ_{n-1} are the independent variables for case i . In this respect, only statistically significant predictors were included in the regression model following the results of the stepwise method. This step is crucial to reduce effects of multicollinearity resulting from introducing non-significant variables or local variation in the model (Perry & Hollis 2005). The multivariate regression model was firstly used to account for geographical predictors. Afterwards, the model was applied combining geographical variables and remote sensing indices. This

Table 2. List of geographical and topographical variables and remote sensing indices

Independent variable	Description	Unit
Geographical & topographical variables		
Y	Latitude	m
X	Longitude	m
Z 5, 10, 25, 50	Maximum difference in elevation within a radius of 5, 10, 25, 50 km	m
DM	Shortest distance to the Mediterranean Sea	m
DR	Shortest distance to the Red Sea	m
DN	Shortest distance to the Nile	m
Remote sensing indices		
REF 5, 10, 25, 50	Average reflectance within a radius of 5, 10, 25, 50 km	unit
NDVI 5, 10, 25, 50	Normalized Difference Vegetation Index within a radius of 5, 10, 25, 50 km	unit
NDTI 5, 10, 25, 50	Normalized Difference Temperature Index within a radius of 5, 10, 25, 50 km	unit
NDWI 5, 10, 25, 50	Normalized Difference Water Index within a radius of 5, 10, 25, 50 km	unit

procedure aimed to draw a comparison between the model's performance using the geographical and topographical variables alone and following introduction of the remote sensing indices, in order to assess enhancement of its accuracy.

The unexplained variance resulting from nonlinearity between the dependent variable and predictors is commonly expressed as 'residuals' and calculated as the difference between observed and predicted values (Ninyerola et al. 2000). To correct residuals in the model, the spline interpolation technique was used to reduce the estimation uncertainty by interpolating the surfaces of the residuals using map algebra. This technique has been applied in other studies to interpolate climate variables (e.g. Lennon & Turner 1995, Hutchinson 1998, Ninyerola et al. 2007a). Other interpolators such as the IDW may be problematic if the distribution of sampling points is inadequate over space (Luo et al. 2008). For example, when using the IDW, more weight will generally be given to areas where data are particularly dense (e.g. the Delta). This may produce unrealistically steep gradients at irregularly spaced data points. Also, kriging requires a sufficient density of points to fit a reliable variogram (Nalder & Wein 1998). Conversely, the spline method is simple and easy to run in terms of computation time and storage. Moreover, it can improve map accuracy by obtaining exact interpolators at the meteorological sites (i.e. the interpolated surface passes through the actual observations producing rougher surfaces with fine-scale spatial variability) (Ninyerola et al. 2007a). In this sense, the spline technique is recommended compared to other techniques (e.g. IDW and kriging). Finally, the linear regression component and residuals were combined using map algebra to generate the final maps. This procedure was performed independently for each month of the year.

Given the low spatial density of observatories in some areas, the interpolation of residuals did not solve all of the existing problems. Therefore, some statistical artifacts were introduced and a decision was made to correct them. In particular, less stable behavior of precipitation during the winter months was found southward in areas well-known as 'extremely dry' regions throughout the year. A square-root transformation of precipitation was applied as recommended by Hutchinson (1998). However, this did not solve the problem. Therefore, a manual correction was applied where values were converted to zero to match the actual climatic conditions and avoid unrealistic findings. This was the case in 2 geographical areas: south of Aswan (23.9°N, 32.9°E) and the south-west corner of Egypt. The likely explanation of this in the first region is the influences of the reflectance caused by the High Dam artificial lake south of Aswan (approx-

mately 5578 km²). Meanwhile, the second case can be considered a 'typical' edge effects example, where a lack of observatories is markedly evident at this marginal geographical domain.

2.3. Model validation

The cross-validation method was carried out to estimate the goodness-of-fit of the model. The aim was to assess the performance of the model using geographical variables and the model incorporating the MODIS indices. Also, a comparison between the 2 models before and after correcting residuals was made. In the absence of a sufficient number of observatories (40 observatories for the whole country), the 'jack-knifing' method was adopted, based on withholding, in turn, one station out of the network, estimating regression coefficients from the remaining observatories and calculating the difference between the predicted and observed value for each withheld observatory (Phillips et al. 1992). This method has frequently been used in climatology (e.g. Daly et al. 1994, Holdaway 1996, Hofstra et al. 2008), particularly when dealing with low numbers of cases for validation purposes. Although the Root Mean Square Error (RMSE) is commonly used as a measure of model accuracy, it has limitations because it is sensitively influenced by extreme values (Nalder & Wein 1998), as is the case in precipitation. Accordingly, 2 accuracy estimators resistant to outliers were used to assess the agreement of the predictions: the Mean Absolute Error (MAE) and Willmott's *D* index of agreement (Willmott 1982). Basically, these statistics estimate the errors by calculating the difference between the predicted and the observed values. The accuracy estimators are given as:

$$\text{MAE} = N^{-1} \sum_{i=1}^N |P_i - O_i| \quad (6)$$

$$D = 1 - \frac{\sum_{i=1}^N (P_i - O_i)^2}{\sum_{i=1}^N (|P'_i| + |O'_i|)^2} \quad (7)$$

where *N* is the number of observations, *O* is the observed value, *P* is the predicted value, *i* is the counter for individual observed and predicted values, $P'_i = P_i - \bar{O}$ and $O'_i = O_i - \bar{O}$.

The MAE is a measure of how far the predicted value is from the actual value, as it is simply calculated as the average of absolute residual values of each linear model. Willmott's *D* is a reliable estimator of the model performance because it gives a relative measure of the model performance (0 to 1) compared with other absolute measures (e.g. MAE, MBE, RMSE); it indi-

rectly facilitates comparison between the performance of the model for different climate variables (e.g. temperature and precipitation). Overall, the model is considered perfect when the value of MAE is close to zero and the value of Willmott's D is close to 1. Finally, the model that exhibited the largest R^2 and the lowest residuals was used to generate the final maps. It is worth mentioning that the model applied to generate the digital maps for each climate variable was not fixed in time, and followed the validation results for each month independently.

3. RESULTS AND DISCUSSION

3.1. The regression model results

3.1.1. Mean maximum temperature

The R^2 value was derived from fitting the model to all the data. As shown in Fig. 3, the model including geographical and topographical attributes explained between 56% (January and December) and 81% (April) of the variation of maximum temperature. The variation of maximum temperature was highly dependent on latitude and distance to the sea. Although latitude was a significant determinant of the variation of maximum temperature throughout the year, distance to water bodies only contributed to the model in spring and summer (Table 3). This implies that continentality

was more linked to maximum temperature in warm seasons (i.e. spring and summer) than in cold seasons (i.e. winter and fall). Apparently, topography parameters did not contribute significantly to the spatial variation of maximum temperature. Holdaway (1996) suggested that influences of elevation on temperature prediction appear only in highly elevated areas where thermal and dynamical conditions corresponding to topographical influences are more pronounced. In our case, the potential lapse rate effect may not exist given that most of the observatories are located in low elevations (<100 m) (Fig. 1). More observatories in highly elevated regions are still required to confirm this assumption.

Considering the remote sensing indices, the variation explained by the model lay in the range of 56% (January and December) and 89% (May and July). It was noted that the NDVI and the average reflectance within a distance of 50 km only contributed to the model in the late spring and summer months (Table 3). This may be governed by vegetation activity at this period of the year where there are differences in the thermal properties of the soil and other land covers leading to variability in maximum air temperature. Presumably the NDVI also gives some information on the time-varying albedo of the land surface. Apart from the very quick-growing grass dominating in some portions of the eastern and western deserts as a reaction to the irregular winter precipitation in some years, bare surfaces and sandy soils enhance reflectance

from the vast deserts during the long dry season. Overall, the effects of NDWI on temperature variability cannot be established. This can perhaps be attributed to the fact that the positive influences of green coverage on the NDWI are limited by the negative impacts of soil reflectance (Gao 1996). Similarly, the NDTI is not correlated with maximum temperature during the summer months as a consequence of a lack of moisture. In brief, the improvement in the fit of the prediction associated with incorporating remote sensing indices was more prominent in spring and summer than in winter and fall as a consequence of the relatively high biomass amounts produced by plant communities during this period of the year. For both models, latitude was the only contributor to maximum variation in the winter months. Likewise, the influence of distance to the Nile was less marked when mapping maximum temperature throughout the year, confirming a weak

Fig. 3. Percentage of variance explained by the model using the geographical predictors versus the model incorporating the remote sensing indices. The solid line refers to the average of all months using the geographical predictors and remote sensing indices, whereas the dashed line is the same but for geographical predictors only

Table 3. List of predictors included in each model. The names of variables correspond to those in Table 2

Using geographical variables		Using geographical variables and remote sensing indices
Minimum temperature		
Jan	DM, Z50	DM, NDWI25
Feb	Z50	REF50, NDTI25
Mar	Z50	Z50, NDTI, REF, NDTI5
Apr	Z50	Z50, REF, NDTI
May	Z50, Y	Z50, REF, Y
Jun	Z50, X	Z50, X
Jul	Z50	Z50
Aug	Z50, DM	NDVI50, Z50, REF25
Sep	DM, Z50	DM, Z50
Oct	DM, Z50	DM, Z50
Nov	DM	DM, NDWI50, REF25
Dec	DM, Z50	NDWI25, REF25, REF10
Maximum temperature		
Jan	Y	Y
Feb	Y	Y
Mar	Y DM	Y, REF50, NDTI5, X
Apr	Y, DM, DR	Y, NDVI50, NDTI50, REF
May	Y, DM, DR	Y, NDVI50, REF50, X, DR
Jun	Y, DM, DR	Y, NDVI50, REF50, REF, X
Jul	Y, DM, DR	Y, REF50, NDVI50, X, REF
Aug	Y, DM, DR	Y, REF50, REF, NDVI50, X
Sep	Y, DM, X	Y, DM, X
Oct	DM, X	Y, NDTI50
Nov	Y	Y
Dec	Y	Y
Total precipitation		
Jan	Z25	REF50, DR, NDTI
Feb	DM, DR, DN	REF50, DR, NDTI10, Z50
Mar	Z25, DM, DR	Z25, REF50, NDTI, DR
Apr	Y	REF25, NDTI, Z5
May	Y	NDTI50
Sep	DM, DR, Z5	DM, DR, Z5
Oct	DM, DR	X, REF50, NDVI10, REF5
Nov	Z25, DM, DR	NDVI50, REF50, X, DN
Dec	DM, DR, DN	REF50, DR, NDTI5, Z50

local warming/cooling effect of the Nile. The monthly resolution of the data or insufficient number of observatories close to the Nile probably failed to resolve the local impacts. Comparing the 2 models shows that introduction of remote sensing indices improved the ability to predict maximum temperature, particularly in spring and summer. During these seasons, the model considering remote sensing indices explained between 85.9 (August) and 89.5 % (May and July) of the spatial variability of maximum temperature.

3.1.2. Mean minimum temperature

As illustrated in Fig. 3, the model using only the geographical predictors explained between 26.4 % (March) and 57.4 % (June) of the variance in minimum temperature. The maximum difference in altitude within a radius of 50 km and the distance to the main water bodies (i.e. the Mediterranean Sea and the Red Sea) were the most important factor explaining the spatial distribution of minimum temperature (Table 3). Following this finding, the influence of orography appeared only at a relatively coarse spatial scale (a radius of 50 km) during the majority of the year, suggesting that the more local relief does not affect airflow at night. While an important factor for modeling maximum temperature, latitude was not significant for modeling minimum temperature in most months. Unlike the maximum temperature, continentality seemed to have more influence on minimum temperature in cold seasons (fall and winter) than in warm seasons (spring and summer). Similarly to maximum temperature, distance to the Nile did not influence to the spatial variability of minimum temperature.

Adding the remote sensing predictors slightly improved the model prediction. As for maximum temperature, the model improvement occurred principally in the spring months (Fig. 3). The model also did better in the winter months. Among the remote sensing predictors, the NDWI contributed significantly to the spatial variability of minimum temperature in winter. Probably, minimum temperature is likely to be influenced by more local conditions (e.g. urban heat islands) rather than 'global' conditions relative to maximum temperature. Minimum temperature likely occurs close to sunrise hours where more stability prevails in the atmosphere boundary layer (Oke 1987, Menne et al. 2009). Accordingly, modeling minimum temperature is expected to be more influenced by local conditions near the land surface, such as topography, vegetation cover and wind velocity. These local processes are quite complicated and difficult to resolve using a 1 km DEM. This could explain why it was more difficult to model minimum temperature compared to maximum temperature in Egypt.

3.1.3. Precipitation

As indicated in Fig. 3, the geographical predictors explained between 21.8 (April) and 65 % (October) of the spatial variability of total precipitation. Elevation filtered within a radius of 25 km and the distances to water bodies were found to be the primary contributors affecting precipitation variation (Table 3). In late spring, latitude was the only predictor included in the

model. On the other hand, the presence of remote sensing predictors improved the model and explained between 25.1 (May) and 78.3% (October) of the measured variation in total precipitation. Interestingly, among the independent predictors, distance to the Red Sea was the predictor that best explained the variability of total precipitation during the rainy season (September to April). This implies that the convectonal precipitation processes originating in the mountainous areas close to the Red Sea contribute more to the model compared with the synoptic precipitation associated with the Mediterranean Sea. Among the remote sensing indices, the NDTI and the average reflectance were the main contributors to the model in the rainy season. This could be a direct response to the increased total amount of vegetation during the rainy season, which also comes in conjunction with the greening of the irrigated cropland. At that time, available plant moisture is transferred to the atmosphere through evapotranspiration. As shown in Fig. 3, accounting for remote sensing indices clearly improved the precipitation prediction in spring and winter. However, this did not significantly improve the prediction during the dry season (May to September). This is

mainly due to the lack of meaningful monthly totals of precipitation in the summer months (June to August) and in May and September (7.2% of the annual precipitation). The remote sensing indices seem to be more sensitive to spatial and temporal variations in precipitation.

3.2. Model validation results

3.2.1. Mean maximum temperature

The residuals obtained from cross validation of maximum temperature are shown in Fig. 4. In general, smaller residuals were obtained using the model including the remote sensing indices compared with the model using only geographical and topographical predictors. Values of D close to 1 indicated that the remote sensing indices gave more accurate estimates. Nevertheless, these residuals were not uniform throughout the year. Seasonal differences were evident since prediction residuals were larger in hot seasons (i.e. spring and summer: $MAE < 1.4^{\circ}\text{C}$) and smaller in cold seasons (i.e. winter and fall: $MAE < 1^{\circ}\text{C}$) (Fig. 4). This finding is

Fig. 4. Cross-validation results for the maximum temperature model before and after correcting residuals (averaged Mean Absolute Error [MAE, bars], and Willmott's D [solid line] for all stations) for model using remote sensing indices and/or geographical predictors

mainly associated with the observation that the spatial variability of maximum temperature in Egypt is more pronounced in the hottest months, when more differences are found between stations, compared with the coldest months, when less variability predominates. For instance, the differences between the maximum temperature at the hottest and coldest stations are 5.9 and 11.6°C for January and July, respectively (Fig. 2). Another interesting observation was that spring was the season with the largest residuals. This suggests more spatial variability of maximum temperature in spring, which could have drastic impacts on agriculture in Egypt since it approximately corresponds to the end of the winter growing season (October to April).

The residuals estimated for maximum temperature have a spatial component. Fig. 5 shows that large amounts of residuals were found in areas with sparse stations (e.g. eastern and western deserts), particularly for the model using geographical predictors. Additionally, the residuals were found more in highly elevated areas along the Red Sea. These mountainous areas are also data-poor regions. In contrast, visual inspection of the maps we produced confirmed that a very good fit was obtained in the Delta. This region is homogenous in terms of terrain complexity and also dominated by a

relatively dense network of stations. It is worth noting that adding the interpolated residuals to the model generally improves the accuracy when using either the geographical predictors or the remote sensing indices (Fig. 4).

3.2.2. Mean minimum temperature

For minimum temperature, the higher residuals corresponded to winter and spring when the residuals of the model incorporating the remote sensing indices were corrected (approximately 2°C) (Fig. 6). In this sense, the average MAE throughout the year was 1.7°C, which is high in comparison to other regional studies. For example, Kurtzman & Kadmon (1999) obtained a MAE of 1.18°C for the January minimum temperature in Israel using a stepwise regression model and employing a relatively dense network of stations. In our study, the optimum fit of the January minimum temperature was obtained when using the remote sensing indices without adding residuals (MAE = 1.6°C) (Fig. 6). It is important to note that the average network density of Israel is over 1000 times greater than that of Egypt, so it is hardly surprising that the

MAE is much lower. Therefore, these differences can be understood in terms of the low number and sparse density of observatories, in addition to the local behavior of minimum temperature, which makes it quite difficult to predict. As illustrated in Fig. 7, the poorest estimates were found in the topographically diverse regions along the Red Sea, as well as areas with sparse networks of stations in the eastern and western deserts. The estimates are generally better in areas of even terrain (e.g. the Delta) where spatial density of observatories is greater. The errors obtained after correcting residuals were greater, suggesting that the corrected maps were, in general, less accurate than the uncorrected maps (Fig. 6). This may demonstrate that the residuals have a complicated spatial pattern. In this sense, more sampling points may better reflect the more local behavior of minimum temperature. Additional explanatory variables (e.g. atmospheric circulation patterns, soil moisture, land use and urbanization) could probably capture the high spatial variability of minimum temperature.

Fig. 5. Spatial distribution of residuals of maximum temperature in January and July for models using remote sensing indices and/or geographical predictors

Fig. 6. Cross-validation results as in Fig. 4, but for the minimum temperature model

3.2.3. Precipitation

The highest residuals of total precipitation were found close to the Mediterranean Sea and the Red Sea during the rainy seasons, particularly in winter and early spring (Fig. 8). This is not surprising when considering that the average amount of precipitation and the variability of precipitation are higher close to the Mediterranean and the Red Sea. For instance, the maximum error obtained for the precipitation prediction was 22.3 mm at the Kossier station in the Red Sea (26° 08' N, 34° 18' E). In contrast, the residuals decreased in internal parts of the country, particularly in the arid summer and late spring

Fig. 7. Spatial distribution of residuals of minimum temperature in January and July for models using remote sensing indices and/or geographical predictors

Fig. 8. Spatial distribution of residuals of total precipitation in January

seasons. When the remote sensing indices were considered, the MAE of total precipitation varied from approximately 1.5 mm in spring and late fall to 8 mm in winter with an average of 2.73 mm (Fig. 9). This is mainly attributed to the high differences of precipitation among stations in winter months (e.g. 54.5 mm in January) (Fig. 2). According to Fig. 9,

adding remote sensing indices as predictors and interpolation of model residuals improved the precipitation prediction in the winter months (November to January) with slight improvement in other months of the rainy season. It is also notable that the model overestimated precipitation in the mountainous areas due to the low density of observatories.

Fig. 9. Cross-validation results as in Fig. 4, but for the total precipitation model

Fig. 10. Spatial distribution of the annual total precipitation and the annual averages of maximum and minimum temperature based on a model that uses geographical variables and remote sensing indices after correction

3.2.4. Summary

The models with the best goodness of fit were retained to construct the 33 final maps on a monthly scale for maximum and minimum temperature, and total precipitation for the whole of Egypt. Fig. 10 is included as an example of the annual average of the monthly maximum and minimum temperature maps and the total annual precipitation produced by combining the geographical variables and the remote sensing indices. A climate grid of monthly maximum and minimum temperature, and total precipitation at a 1×1 km resolution was created for Egypt. The maps could provide an important component in many environmental, hydrological, agricultural and ecological applications, taking into account their 1 km spatial resolution. Given that the national economy in Egypt depends mainly on agriculture, accurate mapping of climate variables at a finer spatial scale could be advantageous to this sector. Although the performance of the multivariate regression model is constrained by the limited number of measurement sites available in Egypt, the maps obtained have a reasonable quality, as shown by the objective assessment of the cross-validation results, mainly for maximum temperature and total precipitation. However, we believe that uncertainties are still introduced in regions of sparse data, particularly hilly and mountainous regions. Improving the density of network stations at high elevations could optimize the performance of the multivariate regression model.

4. CONCLUSION

GIS is a valuable tool for modeling temperature and precipitation in Egypt. Through this technique, it was possible to integrate geographical and topographical variables and remote sensing indices which were believed to be the most influential in the spatial variability of the climate in Egypt. A linear multivariate regression model combined with the spline interpolation technique was used to construct high resolution (1 km) maps of monthly maximum and minimum temperature and total precipitation for Egypt. Various topographic and remote sensing predictors, such as longitude, latitude, elevation, distance to water bodies, the NDVI and the NDWI, were taken into account to map climate variables. It is concluded that the model based on introduction of auxiliary remote sensing indices is superior to the model only considering geographical attributes. The model incorporating remotely sensed data markedly improved the accuracy of prediction and quality of maps, particularly for total precipitation and maximum temperature. This model yielded smaller errors for all climatic variables assuming that remote

sensing attributes are excellent proxies to explain the spatial variation of the climate in Egypt. The model accounting for remote sensing indices explained between 56 and 89.5 % of the variance in maximum temperature. For precipitation, inclusion of remote sensing indices also maximized the performance of the model, particularly during the winter months. With respect to the minimum temperature, the model using remote sensing indices performed quite poorly explaining between 35 and 63.3 % of the measured variation. It was also confirmed that correction of the residuals did improve the precision of the model for predicting precipitation and maximum temperature. It is also evident that the model performed poorly in predicting all climatic variables in the mountainous areas, particularly in southern Sinai and south of the western desert.

The chosen models were easily run in a GIS environment to build a total of 33 digital and detailed raster maps of high resolution (1 km), including 12 maps for monthly maximum temperature, 12 maps for monthly minimum temperature and 9 maps for monthly total precipitation. These maps are among the first to be produced for Egypt and could be important for hydrological, ecological and agricultural applications at various spatial scales. In a country which has been the subject of very limited climate research, such climatology could provide a useful baseline for studies related to detecting, monitoring and predicting climate change and climate impact assessment. However, the addition of further independent variables (e.g. solar radiation, distance to the fronts of regional atmospheric circulations, soil moisture, soil type, land use and urbanization) would be useful for improving the results. In addition, improving the density of network stations could reduce the model uncertainty. All the digital maps will be made freely available to the research community through personal communication.

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