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Mapping of temperature variables in Israel: a comparison of different interpolation methods

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ABSTRACT: Interpolating values of climate variables from measurement stations to large areas is important in a variety of disciplines. Each of the 38 climate observation stations in the Israel area represents an average area of 725 km^2. Therefore it is important to minimize the extent of interpolation errors by using a suitable interpolation method. In this study we compared the performance of 2 local interpolation methods, Spline and Inverse Distance Weighting (IDW), with the performance of multiple regression models. These interpolation methods were applied to 4 temperature variables: mean daily temperature of the coldest month (January), mean daily temperature of the warmest month (August), the lowest mean monthly minimum temperature (January) and the highest mean monthly maximum temperature (June). Spline and IDW models with a range of parameter settings were applied to elevation detrended temperature data. The multiple regression models were based on geographic longitude, latitude and elevation and included terms of first and second order. Two methods of variable selection (Stepwise, Forced Entry) were used to construct 2 regression models for each temperature variable. Accuracy was assessed by a one-left-out cross validation test. Mean daily temperature variables proved more predictable than mean monthly extreme temperature variables. Mean daily temperature variables were predicted more accurately by using a regression model, whereas mean monthly extreme temperature variables were somewhat better predicted by a local interpolation method. The Spline interpolator predicted more accurately than IDW for the 2 summer temperature variables, while IDW performed better for the winter temperature variables. Combining multiple regression and local interpolation methods improved prediction accuracy by about 5% for the extreme temperature variables but did not effect the prediction of mean daily temperatures. Errors in the estimation increased with the use of local interpolation methods in areas where neighboring data were not 'local enough' to show micro-climatic influences. Where the data supported strong short-range climatic factors (such as the cooling effect of the Mediterranean Sea on the shoreline in summer), local methods were more effective than regression models, which became complicated and tended to over extrapolate. These findings suggest that in some instances simple overall regression models can be as effective as sophisticated local interpolation methods, especially when dealing with mean climatic fields.

KEY WORDS: Climate variables · Interpolation methods · Israel

1. INTRODUCTION

Interpolated surfaces of climate variables are useful in many different areas of research. Amongst these are ecological modeling (Box et al. 1993, Gignac et al. 1991, Lindenmayer et al. 1991), land evaluation systems (Bibby et al. 1982), hydrology (Schreider et al. 1997), epidemiology (Lindsay et al. 1998), agriculture (Hill et al. 1996) and climate research (Klein & Dai 1998).

Surfaces of climate variables using point data have been interpolated for areas ranging from a few thousand square kilometers (Holdaway 1996) to the continental scale (Hulme et al. 1995, 1996, Willmott & Matsuura 1995) and even for the entire globe (Willmott & Robeson 1995). Many of these studies used local interpolation methods, estimating the value at a point from values recorded at neighboring points. This can be done using inverse distance weighting (Willmott &

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Matsuura 1995, Dodson & Marks 1997), splines (Hulme et al. 1995) and kriging (Holdaway 1996, Hudson & Wackernagel 1994, Hammond & Yarie 1996). It is also common to many of these studies that they use variables such as elevation, latitude and longitude as predictors of climatic variables. Some authors use methods where trends lie within the interpolator, for example the various versions of Universal Kriging (Hudson & Wackernagel 1994, Hammond & Yarie 1996), or Spline interpolators where a 2-dimensional trend is built in (Hulme et al. 1995), whilst others detrend the data and interpolate the residuals (Willmott & Matsuura 1995, Holdaway 1996). However, no recent studies were found which used only overall trends with no local interpolation.

Temperature maps of Israel (The New Atlas of Israel 1995) are only available at low scale and little is known of their accuracy and method of interpolation.

Our aim in this study was to compare the local interpolation approach and the overall multiple regression approach for establishing surfaces of different temperature variables. However, we dealt less with considerations of parameter fitting or variable selection within each approach and focused instead on differences in performance between the optimal parameter setting models from each approach. We limited our discussion to the reasons why one approach predicted more accurately than another did when interpolating the same variable.

2. METHODS

2.1. Data source. The data analyzed in this study are the best the authors could obtain from the Israeli Meteorological Service and were published by Bitan & Rubin (1991). This data set contains climate data from the 38 stations shown in Fig. 1. Out of this set we used all 38 monthly long-term averages (1964 to 1979) of mean daily temperatures in January (MDT1) and August (MDT8). Some stations averaged 24 hourly observation while others calculated mean daily temperature as (daily minimum + daily maximum)/2. The period 1964–1979 was chosen because of the availability of reliable continuous daily measurements (Bitan & Rubin 1991).

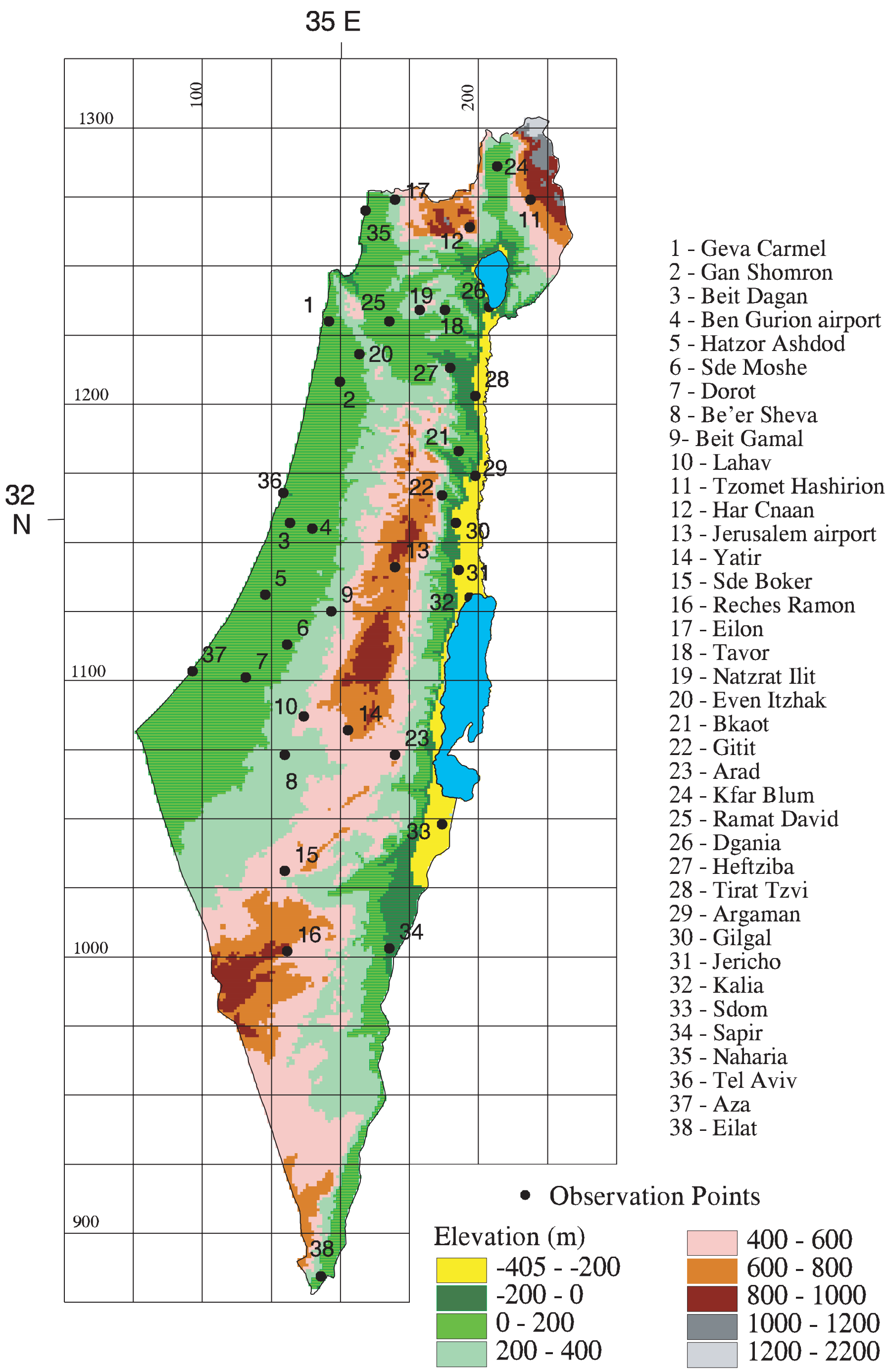


Fig. 1. The DEM (digital elevation map) and climatic observation stations in Israel and the Israel area

The monthly extremes of temperature data included 37 long-term average minimum temperatures for January (MMMin1) and 37 long-term average maximum temperatures for June (MMMax6). The mean monthly minimum of January is the mean of all the lowest temperatures measured in each January. The averaged monthly extreme temperatures were taken for the longest period available, 20 yr on average but at least 8 yr (Bitan & Rubin 1991). When calculating average precipitation surfaces, Willmott et al. (1996) found it preferable to take the greatest number of data points even though they were computed over unequal averaging periods. In keeping with this and in view of our lack of data we chose to use all available monthly extreme temperature data.

2.2. Data analyses. These 4 sets of temperature data were interpolated in 2 different ways, using both local interpolations and regression models.

2.2.1. Local interpolation methods: In mountainous and hilly areas, elevation is usually an effective predictor of temperature; we therefore decided to detrend our data for elevation before interpolating with local methods. We used a constant lapse rate in view of Dodson & Marks' (1997) findings that more explicit calculation of lapse rates did not improve interpolation model performance. These lapse rates were calculated by linear regression. The resulting regression equation was used to convert all temperature values to zero-elevation temperatures. The detrended data were then mapped as a point coverage using the Arc/Info (ESRI Inc. 1994) Geographic Information System. Two local estimation methods were applied to this detrended data using interpolation tools available in Arc/Info: splines and inverse distance weighting. The ordinary kriging interpolation method was not used due to the relative scarcity of our data, which made it impossible to calculate the coefficients of the semivariogram model with reasonable lag distances (<15 km).

2.2.1.1. Spline: This method minimizes the curvature of the estimated surface by minimizing the cumulative sum of squares of the second derivatives of the surface. In this study we used the 'Spline with Tension' method presented by Mitas & Mitasova (1988). In this method Mitas & Mitasova added to the minimization equation the cumulative sum of squares of the first derivatives of the surface, weighted by a controlled constant. This addition makes the surface less smooth. The Spline surface formula was constructed in our study from a constant trend, T, and a weighted function of the distance between the interpolated point x_0 and n close data points, r_{j0}.

$$S(x_0) = T(x_0) + \sum_{j=1}^{n} \lambda_j \cdot R(r_{j0}) \quad (1)$$

The N+1 unknowns T and λ_j are found by the N+1 equations:

$$S(x_j) = z_j \qquad j = 1, ..., \mathrm{N} \quad (2)$$

$$\sum_{j=1}^{n} \lambda_j = 0 \quad (3)$$

z_j is our detrended data at point j.

For this Spline with Tension method the generating function is:

$$R(r_j) = -\frac{1}{2\pi\varphi^2}\left[\ln\left(\frac{r_j\varphi}{2}\right) + 0.577215 + K_0(r_j\varphi)\right] \quad (4)$$

φ is the controlled weight of the tension addition (higher φ increases tension). K_0 is the modified Bessel function of the zeroth order (Mitas & Mitasova 1988).

Since we wished to test a wide range of parameter settings, the Spline method was applied using 3, 5 and 8 neighboring stations, and for each number of neighbors with tension weights φ of 1 and 5.

2.2.1.2. Inverse Distance Weighting (IDW): This interpolation method estimates a point using the nearest sample points, which are weighted by a power proportional to the inverse of their distance from the estimated point. The higher the power the stronger the influence of the closer sample points. To be consistent with the Spline method the IDW method was also tested using 3, 5 and 8 neighboring stations. In order to cover a wide range of parameter settings each number of neighbors was tested with powers of 0.5, 1 and 2.

All interpolated surfaces were constructed with a resolution of 1 km. First the zero-elevation temperature was interpolated for each grid cell, these estimates were then converted into actual elevation estimates, using the lapse rate found earlier, and an elevation surface (DEM) of 1 km grid size.

This DEM (Fig. 1) was derived originally from 1:50 000 topographic maps at a resolution of 25 m (Hall & Cleave 1989). The DEM was re-sampled to a resolution of 1 km by taking the mean value of the 1600 original elevation pixels for each new grid cell.

2.2.2. Multiple regression models: The predictors used in the regression models were x coordinate (latitude), y coordinate (longitude), x^2, y^2, xy and elevation. The units of x and y were km in accordance with the Israel Grid (see Figs. 1 to 5) and elevation was expressed in m above sea level. Two standard techniques of variable selection were used in the multiple regression models, Stepwise selection and Forced Entry (Norusis/SPSS Inc. 1993).

2.2.2.1. Stepwise selection: In this procedure the first independent variable considered for entering the regression equation is the variable with the highest absolute correlation with the dependent variable. This enters the equation if the probability of the null hypothesis of slope = 0 is ≤ 0.05 (the probability of F).

The next variable is selected in accordance with the highest partial correlation. If it passes the same entrance criteria, it also enters the equation.

The *F* probability of each variable in the equation is then checked. Where $F \geq 0.1$ the variable is removed from the equation. Finally, after determining which variables need to be removed, the next variable is checked for entry. The process continues until no variables enter or are removed from the equation.

2.2.2.2. Forced Entry: All independent variables are forced into the equation in 1 step. Independent variables that are not significant ($p > 0.05$) are dropped out and the regression is performed again.

The difference between these 2 methods lies in the partial correlation coefficient and the *F* probability of the variable that is tested in the Stepwise method. Because this adjusts for the other variables in the equation (Norusis/SPSS Inc. 1993), some variables that have significant *F* probabilities when all independent variables are forced into the equation in 1 step cannot enter the equation in the Stepwise method.

Once the regression equation had been determined for a given temperature variable, it was applied to the 1 km grid surfaces of the predictors to construct the interpolated temperature surface.

2.2.3. Evaluation of the estimated surfaces: The performance of each of the 17 interpolation procedures described above (6 variants of Spline interpolation, 9 variants of IDW interpolation and 2 variants of the regression approach) was evaluated for each temperature variable using a cross validation approach. One station was taken out of the database in each iteration, then a new surface of estimations was constructed (for the regression methods a new model was calculated in each iteration). The estimates for the missing data points were saved. The largest error, mean error and mean absolute error of estimation were then calculated. Scatter plots (not shown) were drawn up for predicted values against observed and their coefficients of determination (R^2) were calculated.

2.2.4. Combined regression-local interpolation approach: In addition to the analyses described above, we tested the performance of other interpolations based on a combination of regression and local approaches. This was done by interpolating the data locally after detrending all topographic and geographic variables according to the regression model. By combining the most effective (best validation test results) local interpolation method and the most effective regression model, this combined method was applied once for each temperature variable.

3. RESULTS

3.1. Lapse rates and regression models

Elevation predicted mean temperatures better in winter than in summer (Table 1a). It also predicted daily mean temperatures better than monthly extreme temperatures. The addition of the geographic predictors (Table 1b) explains the variation in summer temperature variables better than in winter temperature variables. This makes it more difficult to predict MMMin1 by regression than the other 3 temperature

Table 1. Summary of regressions. (a) The linear lapse rates used for detrending before applying Spline and IDW interpolations. (b) The regression models derived from using all observation stations. Temperature variables: MDT1 = mean daily temperature in January; MDT8 = mean daily temperature in August; MMMin1 = mean monthly minimum temperature in January; MMMax6 = mean monthly maximum temperature in June. R^2 in (b) is adjusted

Temperature variable	Constant (°C)	Elevation (m)	x (km)	y (km)	xy (km^2)	x^2 (km^2)	y^2 (km^2)	R^2	p
(a) Lapse rates									
MDT1	12.7	−0.0053						0.84	<0.00001
MDT8	27.7	−0.0059						0.57	<0.00001
MMMin1	3.3	−0.0033						0.38	0.00005
MMMax6	39.0	−0.0051						0.26	0.00133
(b) Regression models									
Stepwise									
MDT1	19.4	−0.0054		−0.0058				0.90	<0.00001
MDT8	39.3	−0.0054	0.0513	−0.0174				0.92	<0.00001
MMMin1	10.8	−0.0034		−0.0065				0.45	<0.00001
MMMax6	69.7	−0.0044		−0.0380	6.7×10^{-5}			0.75	<0.00001
Forced Entry									
MDT1	28.4	−0.0052	0.1625	−0.0475	−0.00015		3.0×10^{-5}	0.93	<0.00001
MDT8	22.8	−0.0035			2.4×10^{-5}			0.37	0.00010
MMMin1	26.9		0.6130		−0.00091	0.0014	6.1×10^{-5}	0.48	0.00004
MMMax6	58.5	−0.0074	−0.7060	−0.0930	−0.00130	0.0022	1.5×10^{-4}	0.88	<0.00001

variables. It is notable that both variables (elevation and *y)* which were entered into the Stepwise equation for MMMin1 were absent from the Forced Entry equation. The *F* probability of these variables was higher than 0.05 when all 6 predictors were forced into the equation at once but they were the only predictors that passed the Stepwise selection.

3.2. Evaluation of model performance

3.2.1. January mean daily temperature (MDT1)

For MDT1, the Forced Entry regression produced the lowest mean absolute error and the highest R^2 (Table 2). The IDW and the Stepwise regression performed next best, but the Spline estimator performed poorly for this variable. The maximum errors were around 1.5°C in all methods. The choice of Spline parameters had little effect on mean absolute errors and R^2. The IDW mean absolute errors were more sensitive to changes in the parameters, large numbers of neighbors and small powers consistently performing better. Fig. 2 compares the best (lowest mean absolute error) local interpolation method with the best regression model for MDT1. In the IDW map (Fig. 2a) the temperature values are highly accurate at the observation points (they are not, however, exact due to the detrending process), this is not the case in the smoother regression map (Fig. 2b). For example the maximum error of the Forced Entry regression model in Beit Gamal (x = 150, y = 1125) is noticeable when compared to the IDW map. Generally, the regression map shows cooler temperatures than the IDW map, even though for both methods no meaningful bias resulted in the validation tests (Table 2).

3.2.2. August mean daily temperature (MDT8)

For MDT8 the Forced Entry regression resulted in only 2 significant variables and a poor R^2 compared with the Stepwise regression (Table 1). In this case, where the best method of variable selection was so clear, there was little point continuing the interpolation and cross validation analysis with Forced Entry regression model. The Stepwise regression resulted in a smaller mean absolute error than both the Spline and the IDW estimation methods (Table 3). In contrast to MDT1, the Spline estimator for MDT8 performed better than did the IDW estimator, but the difference was smaller than in the case of MDT1. Increasing the power of the IDW slightly improved mean absolute errors. Increasing the number of neighbors had a similar effect, though less pronounced. The large errors in Sdom (Table 3, maximum error) act as an example of a typical local interpolation misestimation; this will be discussed later.

Table 2. Cross validation test results for mean daily temperature of January (MDT1) estimates. The parameters in the Spline interpolations are (φ, number of neighbor samples used in interpolation), and in the IDW interpolation (power, number of neighbor samples used in interpolation). The interpolation model that gave the lowest mean absolute error in each method is given in **bold**

Method of interpolation and parameters	Mean error (°C)	Mean absolute error (°C)	Maximum error, respective station (°C)	Observed/ predicted R^2
Spline (1, 3)	0.002	0.668	1.6 Ramat David	0.83
Spline (1, 5)	0.002	0.678	1.6 Ramat David	0.83
Spline (1, 8)	0.007	0.669	1.5 Ramat David	0.84
Spline (5, 3)	**0.0004**	**0.654**	**1.6 Ramat David**	**0.84**
Spline (5, 5)	0.0004	0.668	1.6 Ramat David	0.83
Spline (5, 8)	–0.005	0.663	1.5 Ramat David	0.84
IDW (0.5, 3)	–0.009	0.543	–1.4 Beit Gamal	0.87
IDW (0.5, 5)	0.01	0.518	–1.4 Beit Gamal	0.89
IDW (0.5, 8)	**–0.006**	**0.474**	**1.4 Sde Boker**	**0.90**
IDW (1, 3)	–0.002	0.540	–1.4 Beit Gamal	0.88
IDW (1, 5)	–0.002	0.516	–1.4 Beit Gamal	0.89
IDW (1, 8)	–0.01	0.486	1.4 Sde Boker	0.90
IDW (2, 3)	–0.05	0.554	1.4 Sde Boker	0.88
IDW (2, 5)	–0.02	0.539	1.4 Sde Boker	0.88
IDW (2, 8)	–0.03	0.516	1.4 Sde Boker	0.89
Stepwise regression	**0.005**	**0.510**	**1.6 Sde Boker**	**0.89**
Forced Entry regression	**0.002**	**0.468**	**–1.4 Beit Gamal**	**0.91**

Table 3. Cross validation test results for mean daily temperature of August (MDT8) estimates. The parameters in the Spline interpolations are (φ, number of neighbor samples used in interpolation), and in the IDW interpolation (power, number of neighbor samples used in interpolation). The interpolation model that gave the lowest mean absolute error in each method is given in **bold**

Method of interpolation and parameters	Mean error (°C)	Mean absolute error (°C)	Maximum error, respective station (°C)	Observed/ predicted R^2
Spline (1,3)	0.04	0.699	−2.2 Sdom	0.89
Spline (1,5)	0.03	0.725	−2.5 Sdom	0.88
Spline (1,8)	0.04	0.725	−2.4 Sdom	0.88
Spline (5,3)	**0.04**	**0.689**	**−2.2 Sdom**	**0.89**
Spline (5,5)	0.03	0.707	−2.4 Sdom	0.88
Spline (5,8)	0.04	0.709	−2.4 Sdom	0.88
IDW (0.5,3)	−0.14	0.781	−2.3 Sdom	0.87
IDW (0.5,5)	−0.15	0.836	−2.9 Sdom	0.85
IDW (0.5,8)	−0.09	0.797	−3.0 Sdom	0.85
IDW (1,3)	−0.13	0.776	−2.4 Sdom	0.87
IDW (1,5)	−0.12	0.809	−2.8 Sdom	0.86
IDW (1,8)	−0.09	0.762	−3.0 Sdom	0.87
IDW (2,3)	−0.10	0.767	−2.5 Sdom	0.86
IDW (2,5)	−0.08	0.769	−2.8 Sdom	0.86
IDW (2,8)	**−0.07**	**0.733**	**−2.9 Sdom**	**0.87**
Stepwise regression	**0.07**	**0.657**	**1.7 Jerusalem airport**	**0.91**

The well-defined area of the warmer inner plains of Israel is very clear in the regression surface of estimations (Fig. 3b; 1100 < y < 1210, 120 < x < 155). However, the zone reduces to only a small region around the Beit Gamal station in the best local interpolation surface of estimations (Fig. 3a; y = 1125, x = 150).

3.2.3. January mean monthly minimum temperature (MMMin1)

Table 4 shows poor estimations of MMMin1. With all methods the mean absolute error was higher than 1.1°C. The IDW (0.5,8) and the Stepwise regression estimators performed similarly and are the best of the 17 presented in Table 4. For MMMin1, the Spline interpolation is not sensitive to changes in the parameter φ or the number of neighbors, while the IDW performs better as the power decreases and the number of neighbors increases. The relatively small slope and coefficient of determination in the lapse rate for MMMin1 (Table 1a) led us to try the IDW method without detrending, but in all categories of the validation test results (not presented) were inferior, suggesting that detrending still improves the estimation.

The Stepwise selection result for MMMin1 (Table 1b) produces a simple south-north oriented map in Fig. 4b. In Fig. 4a, which is just as accurate, the small regions around observation points, such as the one around the Aza station (x = 100, y = 1100), are peculiarities of the local interpolation method that cannot be explained climatologically.

3.2.4. June mean monthly maximum temperature (MMMax6)

Evaluation of the MMMax6 interpolated surfaces (Table 5) indicates a bias in estimates of the local interpolations (mean error >0.1) as compared with the regression estimates. For MMMax6, the Spline estimators resulted in noticeably lower mean absolute errors than the IDW and the regression models. The Forced Entry regression method is the next accurate, whilst the IDW and Stepwise regression methods are less reliable. In all estimates, the maximum error is in Tel Aviv.

The advantage of the Spline method for this variable can be observed in Fig. 5. The Spline interpolator captures the strong gradient that occurs between the shoreline and 10 km inland, due to the short-distance cooling effect of the Mediterranean Sea. The Forced Entry regression for MMMax6 is too complex (Table 1b) as can be seen by the rough surface of Fig. 5b. The relatively high coefficients of x^2 and xy cause overextrapolation south west of Aza and in the east Golan Heights (y = 1275, x > 225). The Spline

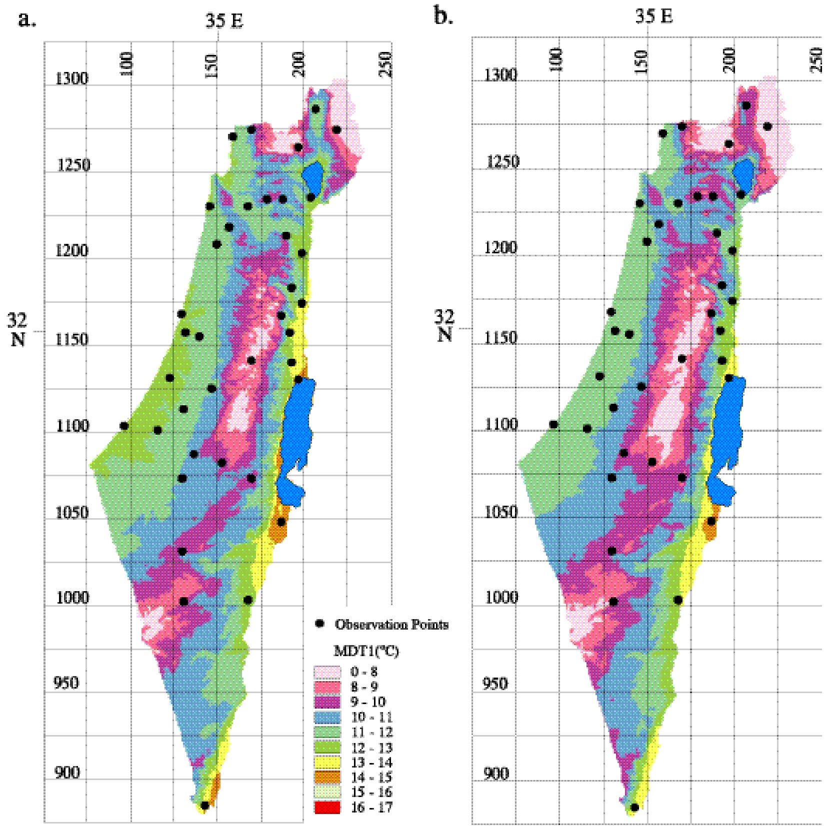


Fig. 2. Mean daily temperature of January (MDT1) interpolated with: (a) the detrended IDW (0.5,8) method (mean absolute error: 0.47°C); (b) the Forced Entry regression model (mean absolute error: 0.47°C)

surface is smoother, even though it passes through the detrended observation points.

3.2.5. Combination of a regression model and a local interpolator

The use of a local interpolation method after detrending all topographic and geographic variables according to the regression equation was tested once for each variable. The 2 methods combined in each temperature variable were the regression model and the local interpolation method which gave the lowest mean absolute error.

When we compare the validation test results of the combined methods shown in Table 6 with the results of the separated methods in Tables 2 to 5, we can see that for MDT1 and MDT8 the combined method did not improve predictions over the best method in Tables 2 & 3. For MMMin1 and MMMax6 the combined methods reduced the mean absolute error by 0.05°C and also reduced the maximum error.

4. DISCUSSION

We compared the local interpolation approach and the multiple regression approach for each of the 4 variables.

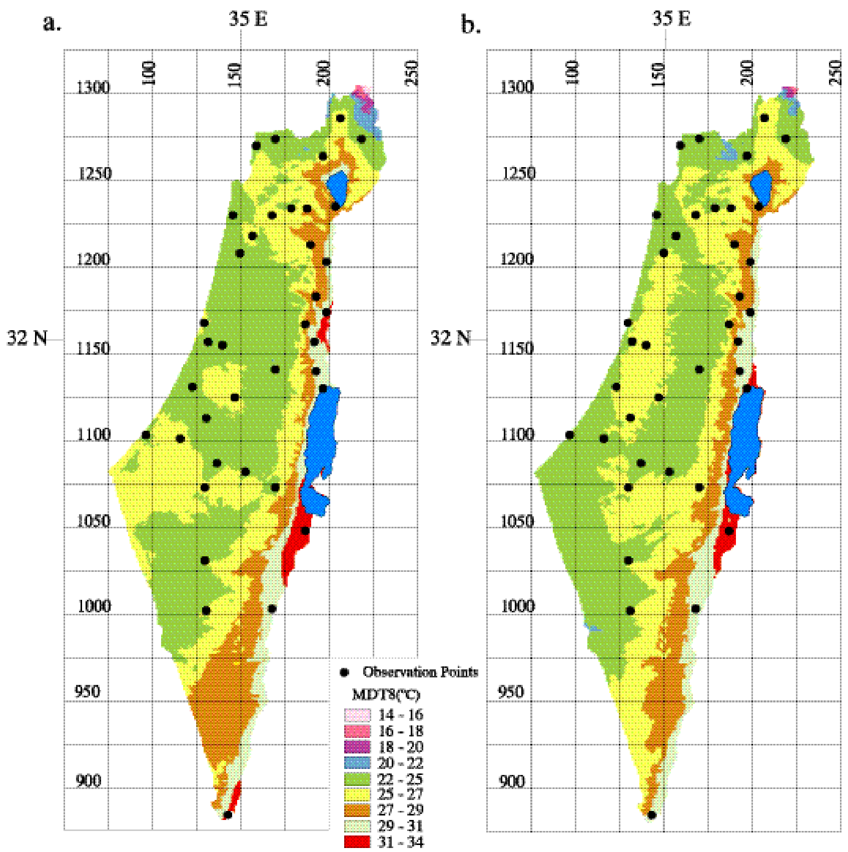


Fig. 3. Mean daily temperature of August (MDT8), interpolated with: (a) the detrended Spline (5,3) method (mean absolute error: 0.69°C); (b) the Stepwise regression model (mean absolute error: 0.66°C)

Table 4. Cross validation test results for mean monthly minimum temperature of January (MMMin1) estimates. The parameters in the Spline interpolations are (φ, number of neighbor samples used in interpolation), and in the IDW interpolation (power, number of neighbor samples used in interpolation). The interpolation model that gave the lowest mean absolute error in each method is given in **bold**

Method of interpolation and parameters	Mean error (°C)	Mean absolute error (°C)	Maximum error, respective station (°C)	Observed/ predicted R^2
Spline (1,3)	0.14	1.66	3.9 Ramat David	0.09
Spline (1,5)	0.17	1.67	3.8 Ramat David	0.07
Spline (1,8)	0.18	1.70	3.8 Ramat David	0.07
Spline (5,3)	**0.15**	**1.63**	**3.8 Ramat David**	**0.08**
Spline (5,5)	0.16	1.66	3.8 Ramat David	0.08
Spline (5,8)	0.19	1.68	3.8 Ramat David	0.07
IDW (0.5,3)	0.10	1.33	3.0 Ramat David	0.20
IDW (0.5,5)	0.06	1.24	–3.3 Beit Gamal	0.24
IDW (0.5,8)	**0.02**	**1.17**	**2.7 Sde Boker**	**0.30**
IDW (1,3)	0.08	1.36	3.1 Ramat David	0.19
IDW (1,5)	0.06	1.28	–3.3 Beit Gamal	0.22
IDW (1,8)	0.03	1.21	–2.7 Beit Gamal	0.27
IDW (2,3)	0.08	1.40	3.2 Ramat David	0.17
IDW (2,5)	0.08	1.35	–3.2 Beit Gamal	0.18
IDW (2,8)	0.06	1.29	2.9 Ramat David	0.20
Stepwise regression	**0.02**	**1.18**	**–2.9 Sde Boker**	**0.40**
Forced Entry regression	**0.14**	**1.38**	**5.4 Geva Carmel**	**0.30**

None of the individual interpolation approaches proved to be robust with all 4 variables. In some cases, simple regression methods can interpolate with the same order of accuracy as local interpolation methods. Given the simplicity of the regression models and the comprehensive maps they produced, they should be preferred in cases where the accuracy of the 2 approaches is of the same order. The local interpolation approach, on the other hand, was more suitable in cases where there is a short-range climatic factor supported by the data (such as the short distance cooling effect of a water body).

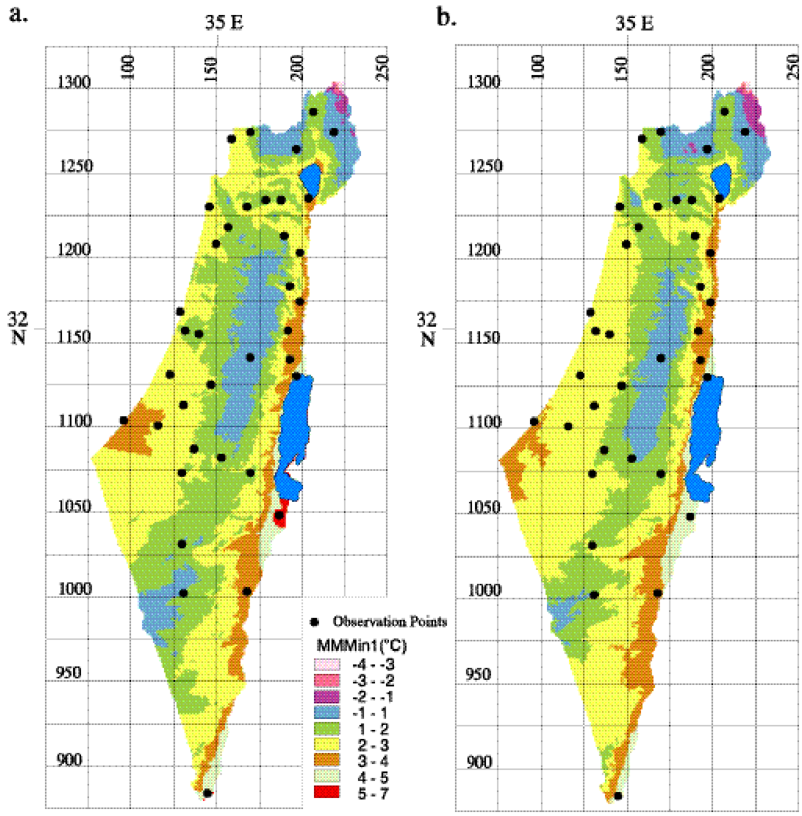
The mean error (bias) found in the validation tests did not exceed 0.1°C in the Stepwise regression model with all 4 variables. This value was exceeded with MMMin1 when interpolated by Spline and with MMMax6 when interpolated by both local estimators. So, the study shows no significant overall bias to the surface of estimations using the best fitting regression model.

The mean absolute error was smaller for the regression estimates than for local-based estimates of 1 variable, with 2 variables the difference was very small. The smallest mean absolute error was achieved by the Spline interpolation with 1 variable. The errors we obtained were within the range 0.4 to 0.7°C for mean daily temperatures, so are about the same magnitude as the errors Holdaway (1996) obtained by kriging interpolations for a 35 station data set in Minnesota. Willmott & Matsuura (1995) reported errors of around 0.4°C for annual average temperature in the US. The mean absolute errors we obtained for mean monthly extreme temperatures, 0.9 to 1.1°C, are higher than the 0.5 to 0.8°C which Hulme et al. (1995) achieved for mean estimation errors for daily minimum and maximum temperatures in 'greater Europe'.

The maximum error column in Table 3 can shed some light on the advantages and disadvantages of the different methods. In MDT8 the Spline and the IDW estimators failed to estimate the high temperatures in Sdom because of the influence of the neighboring stations (Arad, Yatir, Sapir) which were much cooler. The regression was out by only 0.9°C in Sdom because the overall geographical trend explains this data better than the closest stations, which are just not close enough. The Spline and the IDW estimators were out by less in their estimates for August temperatures in Jerusalem, which are cooler than would be expected from the north-south warming trend resulting from the regression (Table 1b).

The 2 summer variables MDT8 and MMMax6 are explained by the geographical predictors better than the winter variables chiefly because the northward cooling is more consistent in summer than in winter.

Fig. 4. Mean monthly minimum temperature of January (MMMin1) interpolated with: (a) the detrended IDW (0.5,8) method (mean absolute error: 1.17°C); (b) the Stepwise regression model (mean absolute error is: 1.18°C)



This could explain why the Spline interpolator, which includes some kind of a trend term (Eq. 1), performed better than IDW for the summer variables but not for the winter ones.

It was harder to estimate extreme temperatures than mean temperatures mainly because cold air drainage and summer inversions make elevation a less reliable predictor of extreme temperature variables (Table 1a). MMMin1 was the most difficult to predict because, in addition to elevation, the latitude is also not as effective a predictor as it is in summer. Local effects such as cold air drainage in valleys cause shorter correlation distances of winter minimum temperatures than those of the other temperature variables; this can explain the failure of the local interpolation methods for MMMin1. The clear advantage of Spline over IDW and the regression models in MMMax6, can be explained by the trend term as previously mentioned, and by the strong short-distance cooling effect of the Mediterranean that the regression models could not cope with. This effect caused all methods to fail in their estimation of the MMMax6 in Tel Aviv. Holdaway (1996) added a term to the detrending equation that took into account a similar influence of Lake Superior on the mean temperature fields in northern Minnesota. Such a term was not added here as it would

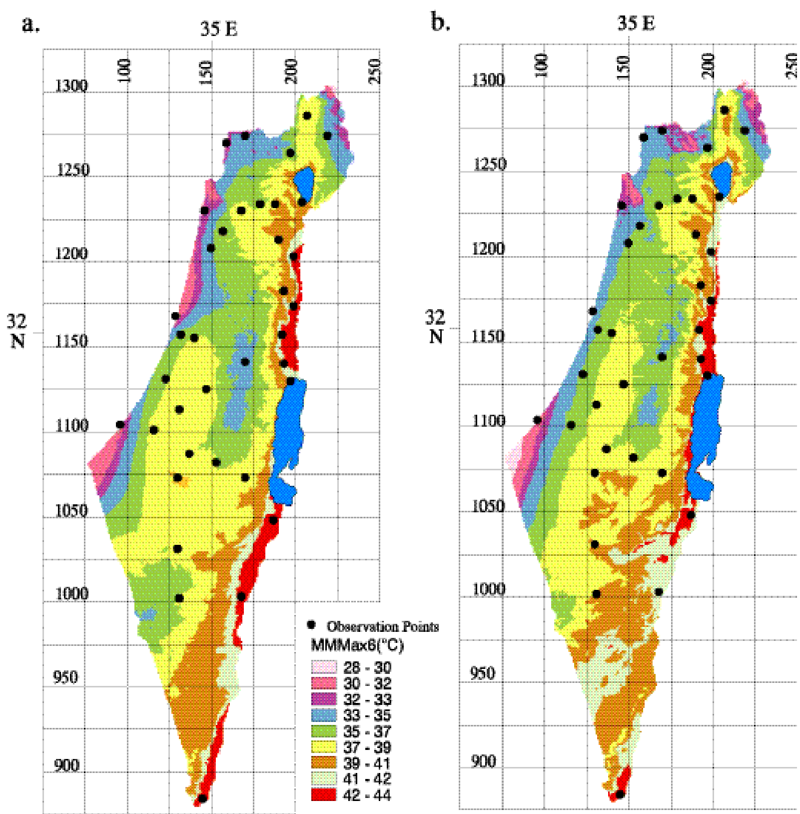


Fig. 5. Mean monthly maximum temperature of June (MMMax6) interpolated with: (a) the detrended Spline (1,8) method (mean absolute error: 0.88°C); (b) the Forced Entry regression model (mean absolute error: 0.98°C)

Table 5. Cross validation test results of mean monthly maximum temperature of June (MMMax6) estimates. The parameters in the Spline interpolations are (φ, number of neighbor samples used in interpolation), and in the IDW interpolation (power, number of neighbor samples used in interpolation). The interpolation model that gave the lowest mean absolute error in each method is given in **bold**

Method of interpolation and parameters	Mean error (°C)	Mean absolute error (°C)	Maximum error, respective station (°C)	Observed/ predicted R^2
Spline (1,3)	−0.14	0.89	3.4 Tel Aviv	0.87
Spline (1,5)	−0.15	0.89	3.3 Tel Aviv	0.87
Spline (1,8)	**−0.17**	**0.88**	**3.1 Tel Aviv**	**0.88**
Spline (5,3)	−0.13	0.90	3.6 Tel Aviv	0.87
Spline (5,5)	−0.14	0.89	3.5 Tel Aviv	0.87
Spline (5,8)	−0.17	0.88	3.2 Tel Aviv	0.87
IDW (0.5,3)	−0.29	1.42	5.3 Tel Aviv	0.66
IDW (0.5,5)	−0.29	1.34	5.5 Tel Aviv	0.71
IDW (0.5,8)	−0.14	1.41	6.0 Tel Aviv	0.66
IDW (1,3)	−0.26	1.38	5.2 Tel Aviv	0.68
IDW (1,5)	−0.25	1.31	5.4 Tel Aviv	0.72
IDW (1,8)	−0.14	1.34	5.7 Tel Aviv	0.69
IDW (2,3)	−0.22	1.36	5.6 Tel Aviv	0.70
IDW (2,5)	−0.19	1.28	5.1 Tel Aviv	0.73
IDW (2,8)	**−0.12**	**1.26**	**5.3 Tel Aviv**	**0.72**
Stepwise regression	**0.06**	**1.51**	**−4.3 Tel Aviv**	**0.71**
Forced Entry regression	**0.01**	**0.98**	**−3.3 Tel Aviv**	**0.86**

have hindered comparison between the different interpolation methods. It should, however, be tested when trying to find an optimal interpolator. The combined method showed somewhat better results than either of the methods separately when predicting extreme temperature variables. This could be because local climate factors are stronger and the local interpolators add more information to the overall geographic trends. It should, however, be stated that we did not fully optimize the combined method in this study as the parameter setting for the local component was taken from the optimal setting using only the local interpolation. We expect that the residuals of the full geographic regression would give shorter correlation distances than the elevation residuals, and therefore would lead to a different optimal parameter setting. A full analysis of the local interpolation parameters may improve the performance of the combined method. On the other hand, tuning the parameters within the local interpolation method did not show dramatic changes in the performances of any interpolator in this study (Tables 2 to 5) so we would not expect a great improvement.

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Table 6. Cross validation test results for the combined interpolation method estimates. The parameters in the Spline interpolations are (φ, number of neighbor samples used in interpolation), and in the IDW interpolation (power, number of neighbor samples used in interpolation). FE = Forced Entry; SW = Stepwise

Variable	The 2 methods combined	Mean error (°C)	Mean absolute error (°C)	Maximum error (°C), respective station	Observed/ predicted R^2
MDT1	IDW (0.5,8) + FE regression	0.06	0.472	1.4, Beit Gamal	0.90
MDT8	Spline (5,3) + SW regression	0.05	0.657	−2.1, Sdom	0.90
MMMin1	IDW (0.5,8) + SW regression	0.08	1.12	−2.3, Elon	0.37
MMMax6	Spline (1,8) + FE regression	0.07	0.837	3.0, Dgania	0.88

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