A GIS approach to spatialize selected climatological parameters for wine-growing in Lower Silesia, Poland

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Abstract This paper investigates presents the results of a study of selected thermal parameters important for wine-growing: SAT (Sum of Active Temperatures), GDD (Growing Degree-Days), TY (annual mean temperature) and TJ (mean temperature of July) in their spatial context. In the first part, four selected interpolation algorithms: inverse distance weighting (IDW), ordinary kriging (OK), multiple linear regression method (MLR) and residual kriging (RK) are evaluated due to the quality and plausibility of spatial information, using cross-validation technique and visual inspection of maps. The MLR method is finally found to be the most accurate - in each case regression explains 94-95% of variation, so the inclusion of physically meaningful „environmental" relationships is found to improve prediction accuracies and quality of maps. A set o potential predictors, including coordinates and DEM-originated: elevation, convexity/concavity, foehn and solar radiation indices, show a great importance for air temperature parameters. In the second part of the paper, the obtained spatial information is designated for further processing in GIS that allows to delineate 3 regions of different suitability for wine-growing in Lower Silesia, SW Poland. These regions are dedicated mostly for moderately early, late and very late ripening grape's varieties and cover almost 85% of analyzed area.

Key words: *spatial interpolation, temperature, climate maps, grapevine, GIS, Lower Silesia*

Introduction

Up to the 20th century, Lower Silesia in south-west Poland was a traditional area of viticulture and wine-making. In spite of slow but continuous reduction of vineyards which has been observed since the 17th century, the first half of 20th century was in fact crucial for wine-growing in this region. In the beginning of the century, the total area of vineyards in Lower Silesia was still close to 1500 ha, whereas in 1929 there were only about 150 ha left. The last mass-producing vineyards were definitively closed in 1970s. Even though the main reason leading to decline of wine-growing trade was of economic and social nature, also unfavorable climatic conditions played an important role in that process.

Climate change, distinctly marked in the last 20-30 years, brought a vital improvement of climatic conditions especially as far as thermal conditions are concerned (Jones, 2005). One can observe growing trends of such important for vine parameters as sum of active temperatures, growing degree-days, mean annual and monthly temperatures, elongating growing seasons and others. On the other hand, nowadays new, frost- and disease-resistant vine varieties can be cultivated. Additionally, the accession of Poland to the European Union inspired changes in law and economic conditions and made wine-growing and grape-processing again possible and potentially profitable. Poland was classified into zone A of viticulture, where climatic conditions are not favorable (cool climate zone) but where there are no limitations on vineyards' areas and wine production. All these factors are conducive to gradual revival of wine-growing traditions in Lower Silesia. This tendency is observed in foundation of new and revival of old vineyards.

Success in wine-growing and wine-making is to a large extent determined by natural, environmental conditions of vineyard that can be expressed by a term *terroir* (Gladstones, 1992). The *terroir* is the coming together of climate, soil and landscape. It is the combination of an infinite number of factors: temperatures, rainfall distribution, hours of sunlight, soil acidity, presence of minerals, water retention, exposure to sunlight, slope and drainage as an example. All of these factors react with each other to form, in each part of the vineyard, what wine-growers call a *terroir*. The influence of climatic conditions can be observed both in local and regional scale. Thus the first step in searching for a good location for a future vineyard is to determine areas of favorable climate conditions in regional scale and then to recognize remaining factors (local climate, soils, geology etc.).

The main goal of the paper is to put forward the methodology of climatic data spatialization to receive results that can be used in further steps to find the best locations for new vineyards with the GIS procedures. This information is useful to determine where classic *Vitis vinifera* or its varieties of different thermal requirements can be cultivated successfully. Particularly essential is to obtain spatial distribution of a set of different air temperature parameters crucial for grapevine growing. These parameters are spatially dependent on the geographical location and, first of all, on the height and relief features. Thus, to take these factors into consideration it is necessary to apply proper spatialization algorithms. In this paper, the results of selected interpolation techniques, both of deterministic and stochastic groups or their combinations are compared, cross-validated and statistically described. The best one is chosen to work out the final maps of selected parameters and to delineate the most suitable areas for wine-growing in Lower Silesia.

Area of investigation

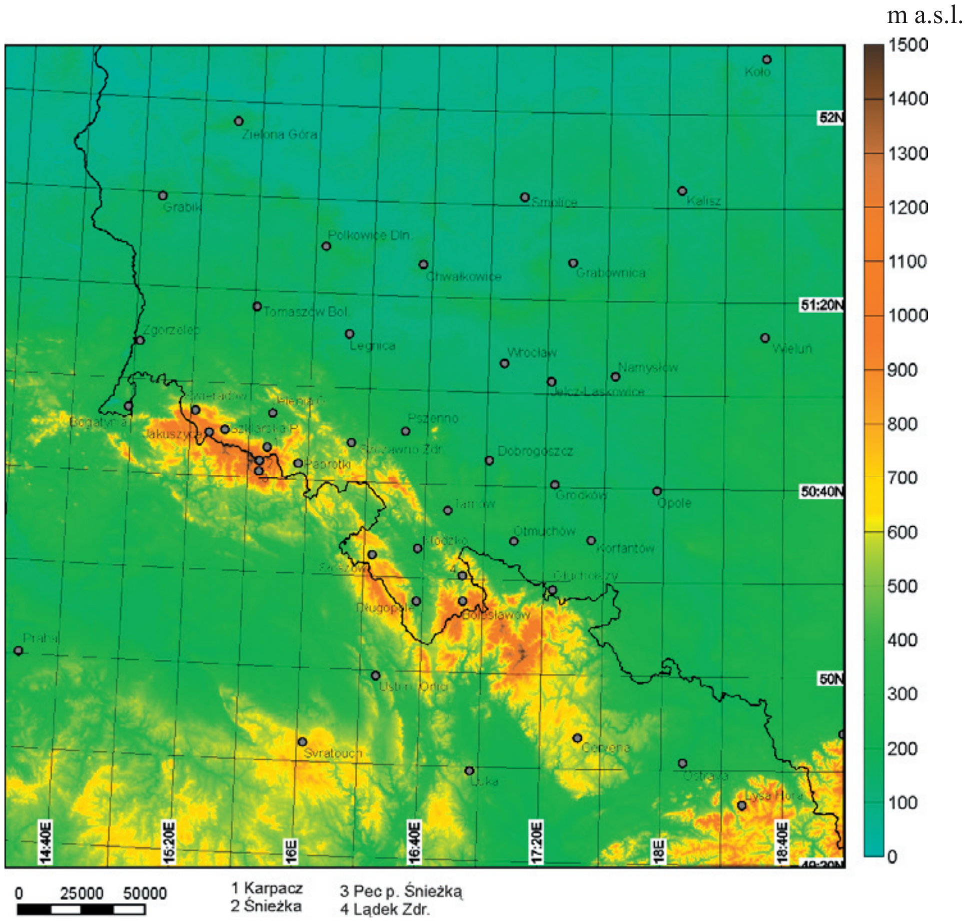

Fig. 1. The Lower Silesia region and the distribution of meteorological stations

Lower Silesia is a historical region in south-west Poland. In this study we analyzed Lower Silesia, together with its wide surroundings (15º30`-19º30`E and 50º30`-52º30`N). From an environmental point of view, the region is unique, with its heterogeneous topographical and climatic features. The topography ranges from flat areas like the Silesian Lowland, to hilly areas like terminal moraine banks

(Bank of Zielona Gora, Dalkowskie and Trzebnickie Hills) and mountainous zones of the Sudety Mts. There are also wide concave forms as the Valley of Jelenia Gora and the Valley of Klodzko. The elevation changes from 33 m a.s.l. to 1602 m a.s.l.

From a climatic viewpoint, Lower Silesia can be classified to the temperate climate zone with the westerly flow, influenced by a complex orographic structure of the Sudety Mts. Thermally, the region is very heterogeneous with the coldest mountain chains and intermountain depressions on one hand, and quite warm, foehn-influenced areas in the Silesian Lowland on the other hand. The landuse is predominantly agricultural on lowlands and mixed agricultural and forestry in hilly and mountainous areas.

Climatological data and parameters

The climatological data from 46 stations - 38 meteorological stations in Lower Silesia and its surroundings and additional 8 stations in the Czech Republic were used to derive spatial representation on selected climatological indices (Fig. 1). All data originated in the decade 1996-2005. Climatological parameters (described below) for 27 stations were prepared by the IMGW (Institute of Meteorology and Water Management) – the Polish national meteorological agency. Data for the rest of the stations were obtained from the GSOD (Global Summary of the Day) database (ftp.ncdc.noaa.gov/pub/data/gsod). Missing data were complemented using regression techniques and the data from the closest stations.

Based on the daily climatological data, five parameters commonly used by wine-growers were derived. These included annual mean air temperature (T_Y), mean temperature of July (T_J), SAT, GDD and LTI. The parameters for each year were calculated separately and then averaged for the 10-year period.

SAT (Sum of Average (Active) Temperatures) is the sum of mean daily temperatures equal or higher than 10ºC from the period: 1st Apr – 31st Oct (Jones and Davis, 2000). It is calculated as:

$$SAT = \sum_{1.04}^{31.10} \frac{T_{\max} + T_{\min}}{2} \qquad \text{for} \qquad \frac{T_{\max} + T_{\min}}{2} \geq 10°C$$

GDD (Growing Degree-Days) follows the equation:

$$GDD = \sum_{1.04}^{31.10} \frac{T_{\max} + T_{\min}}{2} - 10°C$$

and is used to predict the vine's ability to mature as high quality crop in the northern hemisphere (Amerine and Winkler, 1944). Therefore, suitability models must measure heat unit accumulation to ensure sufficient crop maturity.

LTI is an index based on the latitude and mean temperature of the warmest month (T_{WM}) as a proxy indicator of the amount of solar energy that areas are likely to receive during the growing season (Jackson and Cherry, 1988):

$$LTI = T_{WM} * (60 - latitude)$$

The annual mean temperature and mean temperature of July are put in the analysis for the better description, as it is said that it is favorable for grapes if the year mean temperature is ≥8°C and the mean temperature of the warmest month is ≥17°C (Bosak, 2004).

Data and methods

Spatial interpolation which creates a continuous field of variable is often the important first step in converting irregular point data for use in GIS. Given a set of climatological data we are confronted with a variety of spatial interpolation techniques to estimate variables at unsampled locations. The choice of spatialization method is very important for climatological purposes because of usually limited and sparse network of measurement sites, especially in the areas of complex terrains (Tveito and Schöner, 2002; Ustrnul and Czekierda, 2003). There are many algorithms with different underlying mathematical basis that can be used for spatial interpolation. Interpolation methods are divided into stochastic and deterministic techniques (or their combination). The stochastic (geostatistical) interpolators are based on the probability theory and the spatial autocorrelation of geographical data (Cressie, 1991). On the other hand, the deterministic methods can be more physically-based providing the opportunity to explain and predict a variable at an unsampled location due to known processes causing the spatial variation of data (Ustrnul and Czekierda, 2003). Additionally, the interpolation techniques can be subdivided into local and global interpolators. The latter use all available data to make prediction for the entire area, whereas the local interpolators operate within a small zone using the data from the direct neighborhood of the point being estimated. The spatialization methods can also be exact or inexact interpolators depending on whether they preserve the measured value at the location of the measurement or not. The inexact methods tend to remove the local variation in order to minimize predictive errors across the whole interpolation domain. In this study, four interpolation algorithms are applied:

a. inverse distance weighting (IDW; local, exact, deterministic)
b. ordinary kriging (OK; local, exact, stochastic)
c. multiple linear regression (MLR; global, inexact, deterministic)
d. residual kriging (RK; global, exact, deterministic-stochastic).

IDW is a deterministic technique using a linear combination of values at sampled points to determine variable at unsampled points. This method has been successfully used to interpolate climatic data (Legates and Wilmott, 1990).

Kriging is a stochastic estimation procedure using linear combination of weights (similar to IDW) depending on the spatial correlation expressed by semivariogram (Matheron, 1963). Linear coefficients are computed under the constrain of minimal prediction error variance.

The multiple linear regression method (MLR) is one of a few multi-dimensional interpolation schemes which are in use in modern climatology (Agnew and Palutikof, 2000; Ninyerola et al., 2000; Tveito and Schöner, 2002; Ustrnul and Czekierda, 2003). The MLR was previously used for the spatial interpolation of climate data, providing better results than simple interpolation schemes, especially in complex terrains (Kryza et al., 2007). The mathematical background of the MLR is given by the formula (Tveito and Schöner, 2002):

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i$$

where Y is a modeled climatological variable (the dependent variable) and Xi are independent variables (predictors). If the regression coefficients (β) are known and the predictors (X) are spatially continuous, the dependent variable Y can be calculated for any given location. Statistically important predictors were identified with the stepwise method and included into the regression models. Using the MLR method, one should remember that addition of regressor which does not contribute significantly to the model may cause the unwanted effect of increasing multicollinearity which can affect negatively the quality of prediction outside the convex hull of data points. In this paper, the spatially continuous independent variables were derived from the digital elevation model (SRTM level 2 converted to 100 m resolution) to quantitatively describe the morphological relations in the target area (Jarvis and Stuart, 2001). The set of potential predictors can be merged into six groups, based on the formula applied to their calculations.

1. Average elevation index (AEI). The height above the sea level was averaged using low-pass filter within the given radius for each raster element. The selected radius sizes were: 0.5, 1, 2.5 and 4 km. This variable is used to remove small terrain features which do not change the airflow significantly. AEI usually gives better results than real elevation, especially if DEM is of high spatial resolution.

2. Concavity/convexity index (CCI), calculated as a difference between the raster height and the average elevation index. The positive/negative value of the predictor suggests that the given raster is higher/lower then its surroundings, and can be treated as being convex/concave. This predictors were used to describe the effect of the cold valley bottoms.

3. Foehn index (FI), calculated in three steps (Fig. 2):

a. for each raster element the maximum raster height was found separately in the 90-degree sectors, spread along the W, SW and S direction (i.e. foehn preferred directions) for the given distance,
b. for each raster element, the results from a) were averaged,
c. the difference between the averaged maximum from b) and the actual raster was calculated.

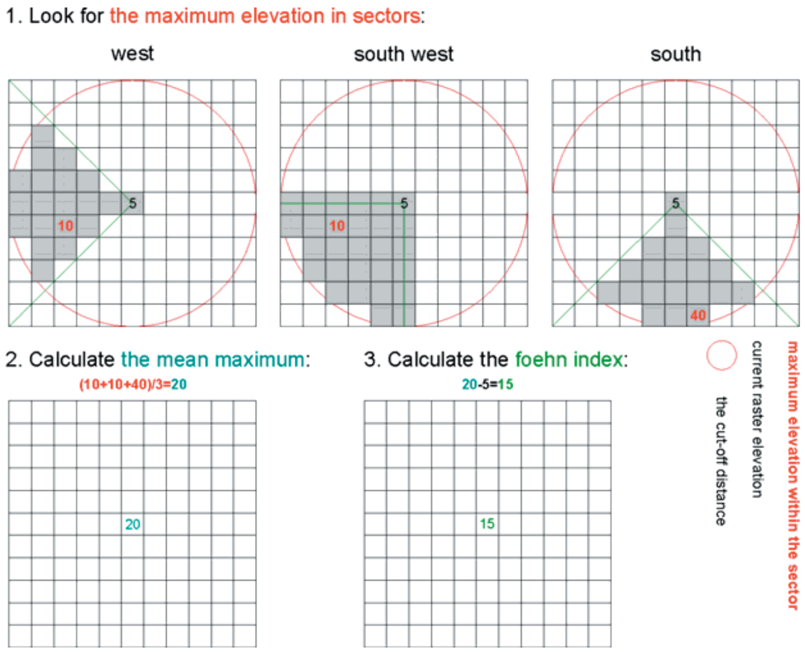

Fig. 2. The foehn index (FI) calculation scheme

Because the difference between the maximum height (located at the top of the mountain barrier) and the raster is large, the foehn effect is expected to be clearly pronounced. Therefore, the predictor is expected to have the positive regression coefficient and the areas with the higher value of the foehn index are supposed to be warmer on the final maps. Three cut-off distances were used: 10, 25 and 50 km.

4. Slope-related predictors. Slope steepness (SL), as well as the profile (PC) and tangential (TC) curvature were calculated from the digital elevation model. The standard GIS procedures were applied here.

5. Solar radiation. The monthly averaged potential global solar radiation (GSR) for the area was calculated with the r.sun model (Hofierka and Šuri, 2002). Based on the monthly data, the average flux was calculated for the growing season (April-October) and for two warmest months: July-August.

6. Coordinates – X (easting) and Y (northing).

The CCI and FI, as well as the slope-related variables were further filtered by the low-pass filter to produce a smooth surface. The filter size was set to 2.5, 5.0 and 10.0 km. All independent variables were standardized to the 0-1 interval.

The MLR method usually provides good estimation but may not be sufficient because the variation of temperature parameters is not necessarily linear and it does not take into account regional variations. In the MLR approach, there is a part of variation which is not explained by the regression model. This part is called residuals (ε). Basing on that point of view estimation formula of MLR can be specified as follows:

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon$$

So, to complete the process of spatialization, one should map residuals. The combination of MLR and krigged residual maps seems to be essential to obtain both regional and local variations and is known as a residual kriging (RK). In this approach residuals were spatialized using the ordinary kriging method.

Finally, a spatial interpolation of 4 parameters: SAT, GDD, T_Y and T_J was performed using the four methods described above: IDW, OK, MLR and RK.

The cross-validation method, as the universal one, was applied to estimate the interpolation quality of each technique (Isaaks and Srivastava, 1989; Faraway, 2002). The idea consists of removing temporarily one datum at a time from the data set and to interpolate this value from remaining data using the alternative algorithms. The root mean square error (RMSE), mean absolute error (MAE), extreme (MAX and MIN) errors and distribution of residuals (KUR – kurtosis, SKE – skewness) were used as the basic statistics (Tab.1, Fig.3). This analysis was complemented by visual inspection of achieved spatial patterns of thermal indices, based on the climatological knowledge (Figs. 4-7).

GIS GRASS and R statistical software (with the gstat library) were used for statistical analysis, as well as for the interpolation and visualization.

Results

The IDW algorithm with the power index equal to 2, gave consistent, albeit poor performance (Tab. 1, Fig. 3). Where data are sparse IDW's results are implausible with the "bull's-eyes" effect being clearly visible (Fig.4-7).

Similarly to the IDW, the ordinary kriging does not use the ancillary „environmental" information, but the advantage of kriging is that the geostatistical process provides the user with the detailed information on spatial variability of regionalized variable (parameter) via variograms surfaces. The crucial moment to the predictive quality of this method is the proper modeling of theoretical variogram on the basis of empirical one (Cressie, 1991). In this approach, the spherical model of semivariogram, together with the nugget effect (if needed), was manually fitted to the empirical one. Even though the results of the cross-validation of OK are as poor as in the IDW (Tab. 1, Fig. 3), this method was more visually plausible and gave more precise information where data are anisotropic (e.g. mountains – lowlands boundary). In most cases, the OK has lower MAE than IDW which confirms earlier findings of Ishida and Kawashima (1993).

Tab. 1. Cross-validation results for the selected spatialization techniques and parameters

Cross-validation statistics	**IDW**	**OK**	**MLR**	**RK**
SAT				
RMSE	422,89	450,64	148,23	160,32
MAE	311,62	291,16	110,50	124,20
MIN	-1360,33	-1380,36	-451,29	-457,21
MAX	967,75	1097,35	304,85	387,54
KUR	7,56	5,85	4,51	3,56
SKE	-1,78	-0,77	-0,90	-0,37
GDD				
RMSE	194,79	204,58	66,04	67,23
MAE	150,93	143,92	55,50	56,94
MIN	-598,22	-671,44	-160,13	-137,37
MAX	404,64	452,77	99,17	118,59
KUR	6,28	5,21	2,27	2,17
SKE	-1,58	-0,88	-0,38	-0,31
T_Y				
RMSE	1,56	1,69	0,43	0,52
MAE	1,13	1,09	0,32	0,38
MIN	-4,98	-5,40	-1,28	-1,63
MAX	3,64	4,08	0,86	1,39
KUR	7,42	6,00	3,80	4,68
SKE	-1,69	-0,87	-0,55	-0,19
T_J				
RMSE	1,80	1,95	0,58	0,70
MAE	1,29	1,20	0,38	0,45
MIN	-6,41	-6,32	-2,64	-3,08
MAX	3,90	4,77	1,21	2,07
KUR	4,56	6,86	10,41	10,47
SKE	-0,96	-0,92	-1,90	-1,17

A comparison of the cross-validation results and visual inspection of maps gives a basis for the evaluation of spatialization techniques and makes the final choice of the method possible. Analyzing the statistics of cross-validation, it should be stressed that in all cases the poorest results were obtained with the IDW and OK methods. The smallest errors (RMSE, MAE, MAX, MIN) were observed for the MLR method (Tab. 1, Figs. 3-7). Therefore, it is evident that the inclusion of physically meaningful „environmental“ relationships improves the prediction accuracy, even by up to 35% (Wilmott and Matasura, 1995). The regressors and results of regression analysis are shown in Tab. 2. For each temperature parameter, the most significantly independent variable is the elevation averaged by 2,5 km radius low-pass filter (AEI) and northing coordinate (Y). The foehn index is also a good predictor in almost all cases, excluding T_J. The profile curvature (PC) for SAT and GDD, and CCI for SAT complemented the regression equations. The statistically important predictors were selected with the stepwise method and included into the regression models. The relations between the dependent variables and the predictors were supposed to be linear. In each case, the regression explained 94-95% of the variation. The highest R^2 was obtained for the annual mean air temperature.

Tab. 2. Regression analysis for selected parameters (description of predictors in text)

Predictors	Min Residual	Max Residual	Adjusted R^2	dF	F
SAT					
Y, AEI, CCI, PC, FI	-259,48	273,27	0,94	40	152,8
GDD					
Y, AEI, PC, FI	-152,36	92,56	0,94	41	164,2
T_Y					
X, Y, AEI, FI	-0,97	0,79	0,95	41	206,7
T_J					
Y, AEI	-1,80	1,06	0,94	43	346,4

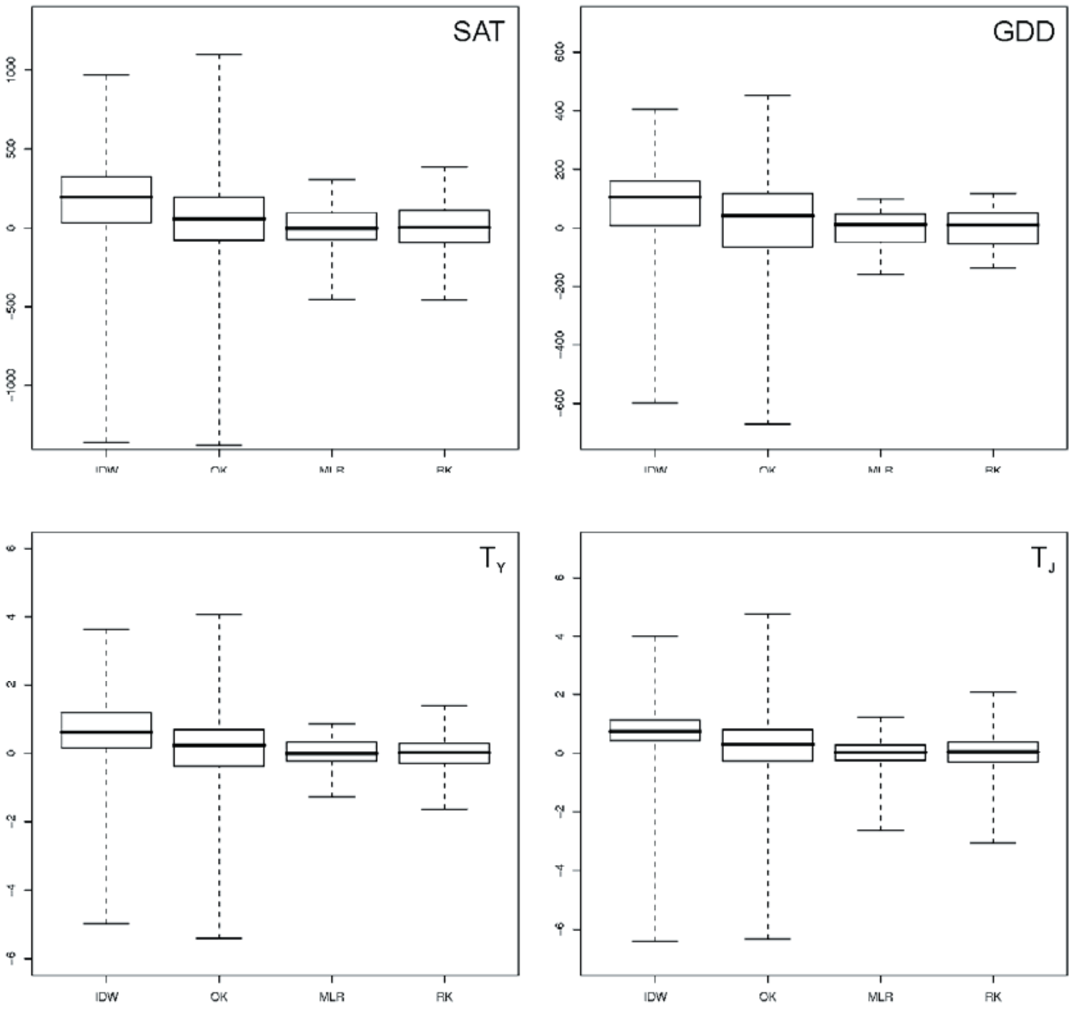

Fig. 3. Distribution of the cross-validation errors for selected methods and parameters (median, 1^{st} and 3^{rd} quartile, minimum and maximum)

It should be mentioned that the RK did not improve the results of spatial interpolation (Tab. 1), compared with the MLR, which was rather unexpected due to earlier attempts of temperature field modeling (Kryza et al., 2007; Szymanowski and Kryza, 2006). Among possible causes of that might be the very high level of variation explained by MLR that caused no spatial autocorrelation of residuals, so the MLR was hard to improve by the RK method.

The analysis of the cross-validation errors (quantities and spatial distribution) and the visual inspection of maps (Figs. 4-7) confirmed the previous statistical analysis and showed that most proper and plausible results were obtained using the MLR method. This technique was finally chosen to prepare maps for the preliminary climatic analysis of wine-growing potential in Lower Silesia.

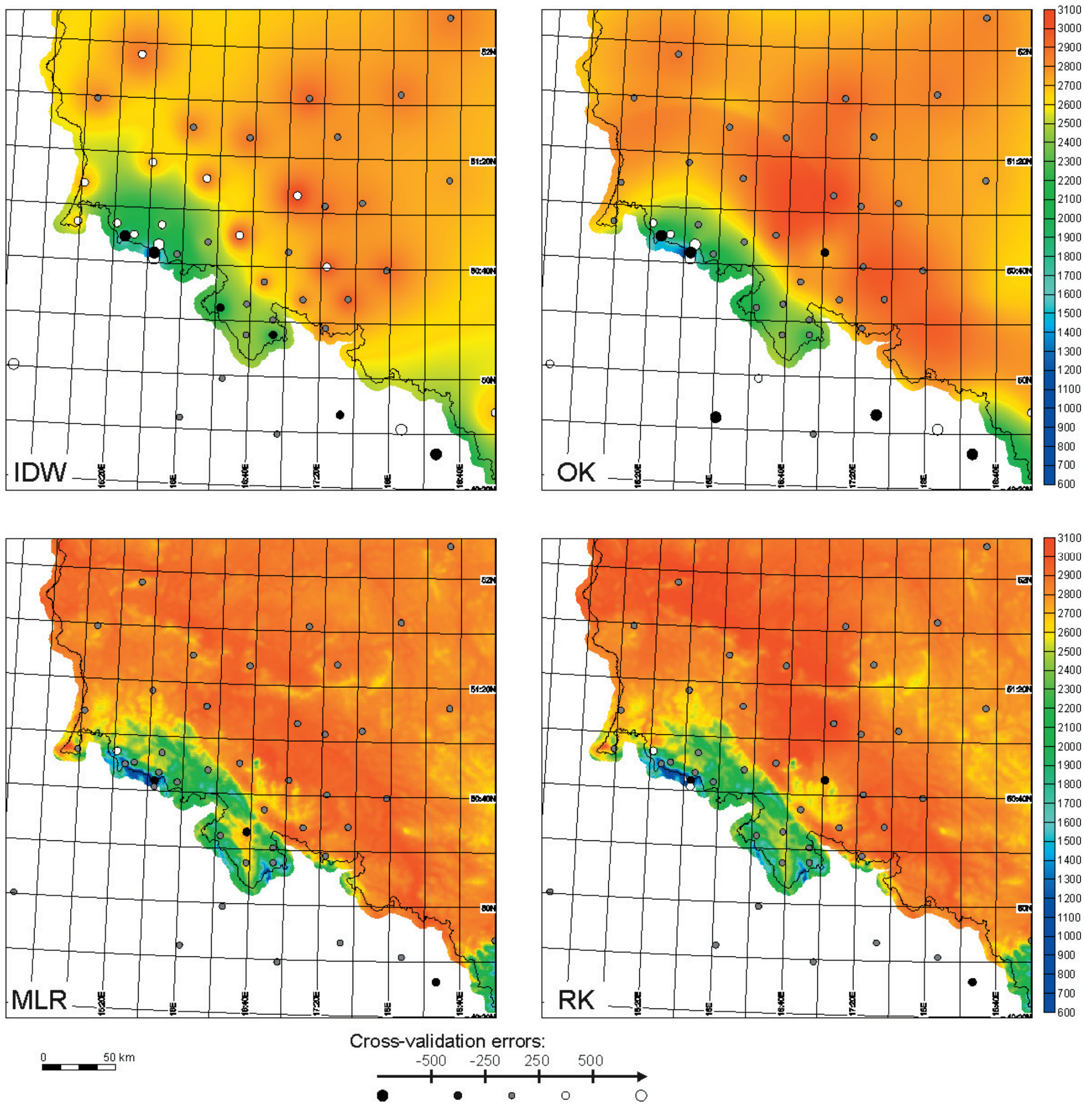

Fig. 4. Annual mean sum of active temperatures (SAT) estimated by inverse distance weighting - IDW, ordinary kriging - OK, multiple linear regression - MLR and residual kriging - RK

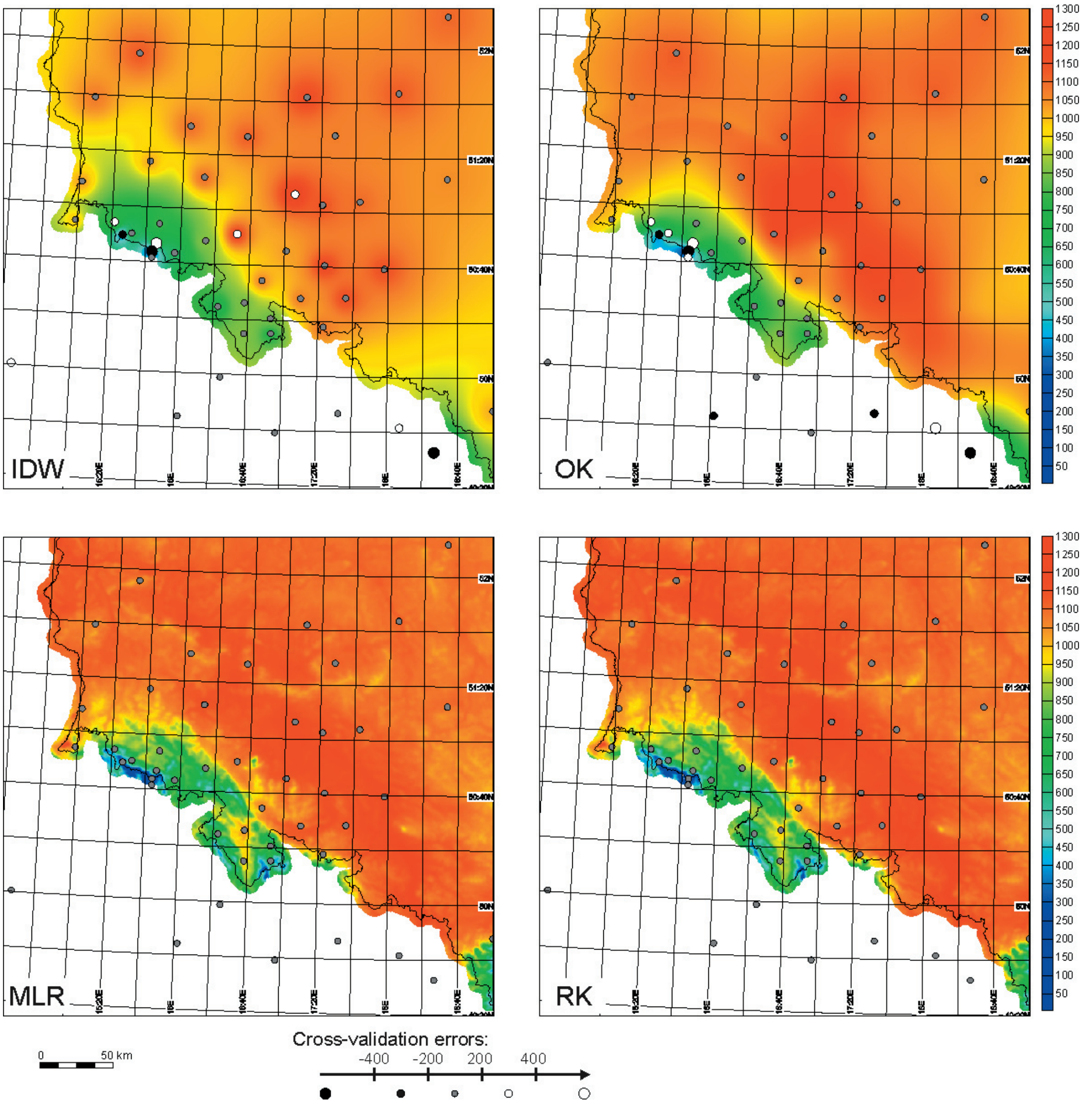

Fig. 5. Annual mean growing degree-days (GDD) estimated by inverse distance weighting - IDW, ordinary kriging - OK, multiple linear regression - MLR and residual kriging - RK

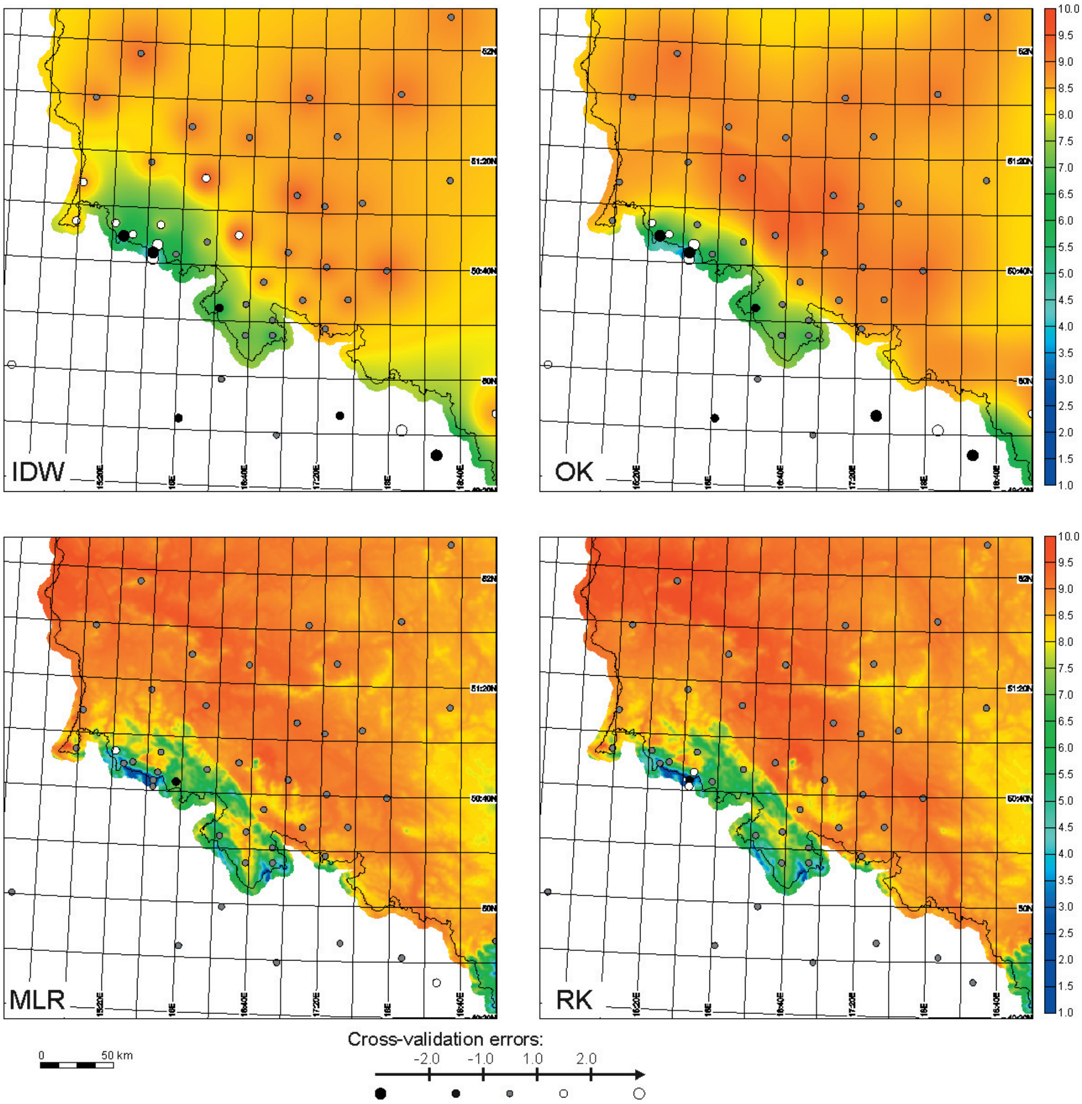

Fig. 6. Annual mean air temperature (T_Y) estimated by inverse distance weighting - IDW, ordinary kriging - OK, multiple linear regression - MLR and residual kriging - RK

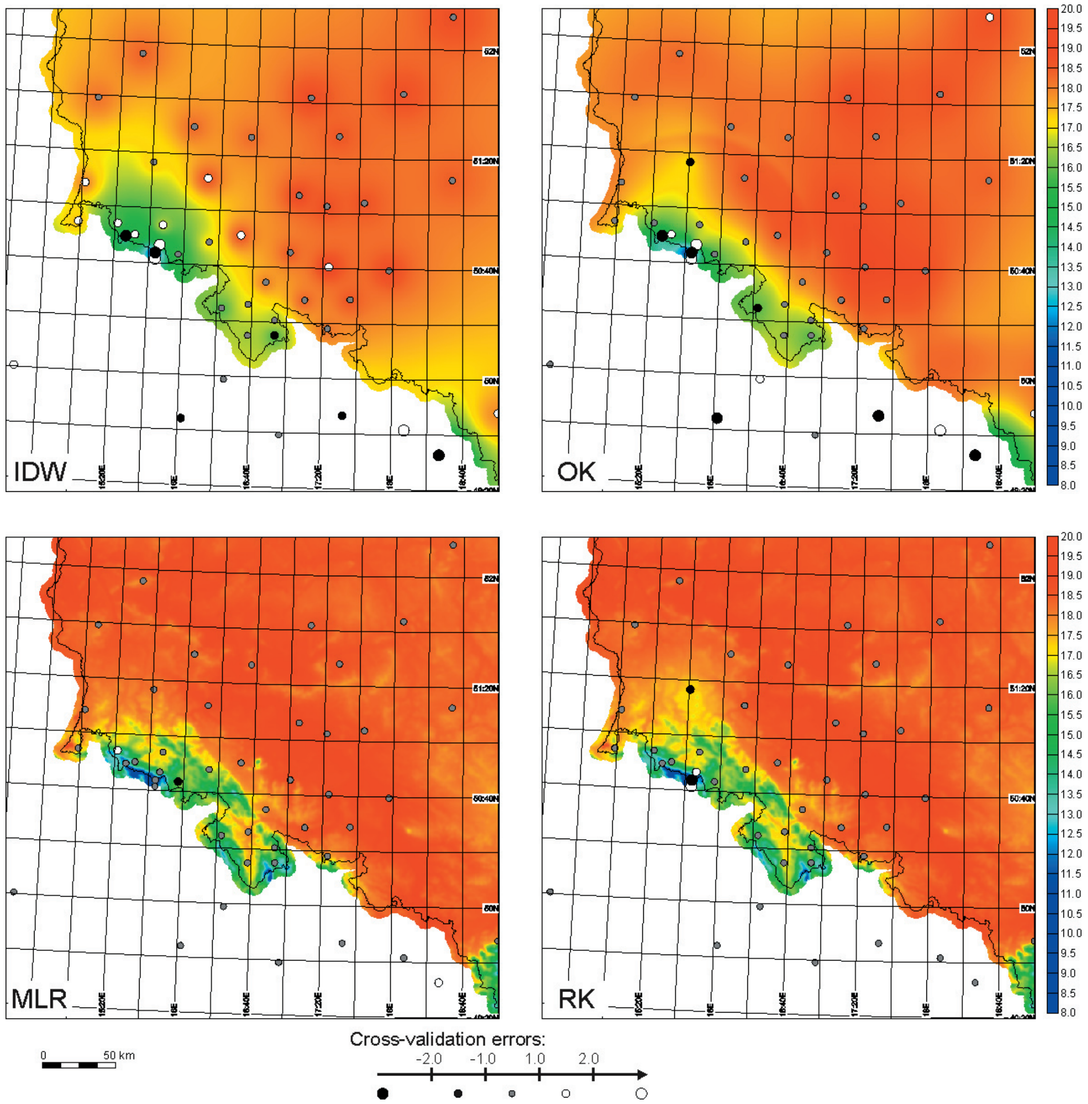

Fig. 7. Mean air temperature of July (T_J) estimated by inverse distance weighting - IDW (upper left), ordinary kriging - OK (upper right), multiple linear regression - MLR (bottom left) and residual kriging - RK

Applications

Following the prior assumptions, the maps of SAT, GDD, T_Y and T_J were further processed in GIS to delineate the areas most favorable for wine-growing in Lower Silesia from the thermal point of view. First of all, the map of Latitude-Temperature Index was prepared based on the latitude and spatial distribution of T_J (Fig. 8). The LTI is quite often used for the determination of areas suitable for the viticulture and to compare the viticultural regions located on different latitudes (Jackson and Cherry, 1988; Gustafsson and Martensson, 2005). Based on this index, four climatic zones were distinguished for grapes cultivation (Tab. 3). In our case, the LTI map shows that the entire area of Lower Silesia can be classified into zone A with the LTI less than 190. But it should be noted that this map is based on the mean temperature of July which is usually not the warmest month of the year (according to the definition of LTI). On average, the warmest month in Lower Silesia is August. Unfortunately, the authors did not have access to these data for the whole set of stations analyzed, so the LTI should be treated as slightly underestimated. This seems to be confirmed by reports on successful cultivation of Pinot Noir and Riesling varieties in the northern part of the region, the district of Zielona Gora (Fig. 1), which suggests that the LTI is high enough in this area (Kuleba, 2005).

Tab. 3. Suggested groups of *Vitis vinifera* varieties according to Latitude-Temperature Index (LTI) and ripening ability in different climates (adapted from Gustafsson and Martensson, 2005)

Group	LTI	Varities
A	< 190	Bacchus, Chardonnay, Pinot Blanc, Pinot Gris, Perle, Riesling and others
B	190-270	Pinot Noir and Riesling
C	270-380	Cabernet Sauvignon, Cabernet Franc, Malbec, Merlot, Sauvignon Blanc and Semillon
D	>380	Carignan, Cinsaut, Grenache, Shiraz, Zinfandel

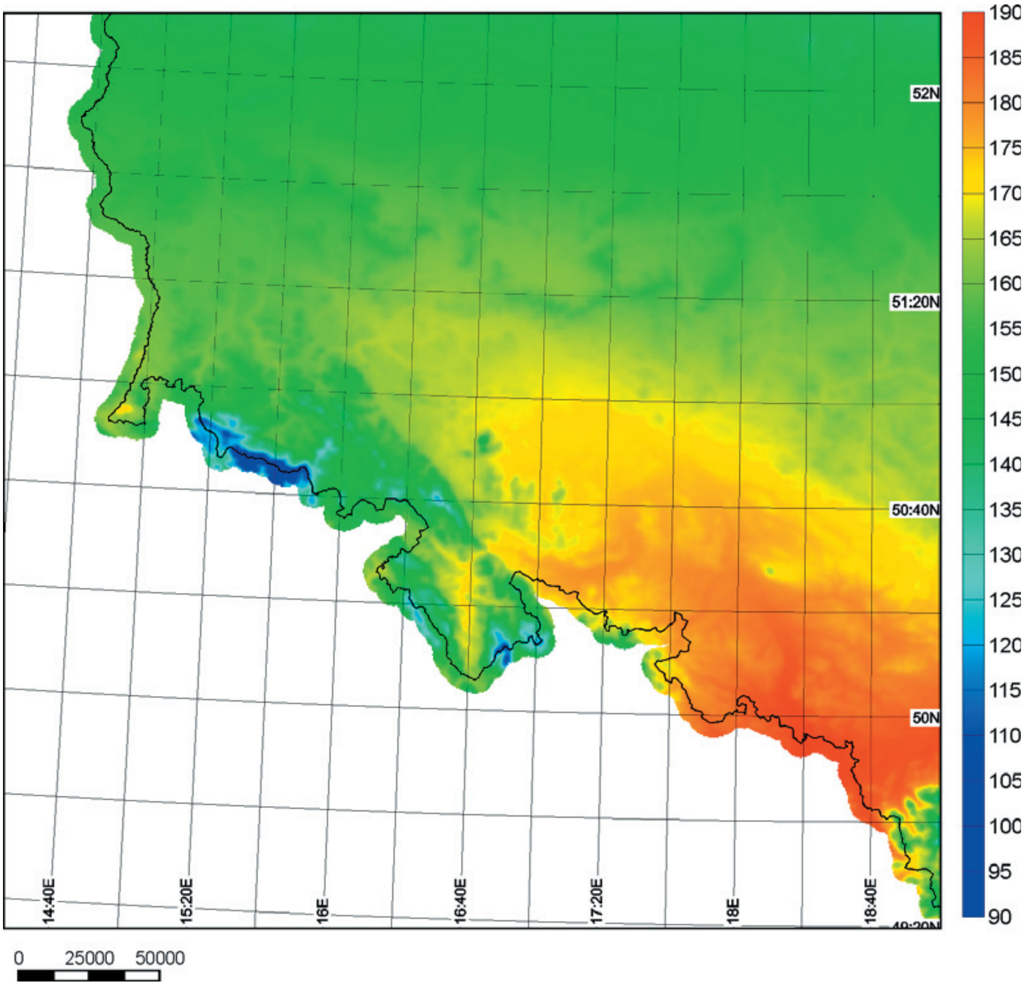

Fig. 8. Spatial distribution of Latitude-Temperature Index (LTI) calculated using mean temperature of July (T_J)

The sum of the active temperatures (SAT) is considered to be one of the most important thermal parameters in agroclimatology in general, and in viticulture as well. It is estimated that the SAT in a vineyard should be equal or higher than 2500ºC. In fact, each variety has got its own minimum average SAT value required during the vegetation period (Tab. 4).

Tab. 4. Average Sum of Active Temperatures (SAT) [°C] and ripening ability of groups of varieties (Myśliwiec, 2003)

Varieties	SAT
very early ripening	2000-2200
early ripening	2200-2500
moderately early ripening	2500-2700
late ripening	2700-2900
very late ripening	>2900

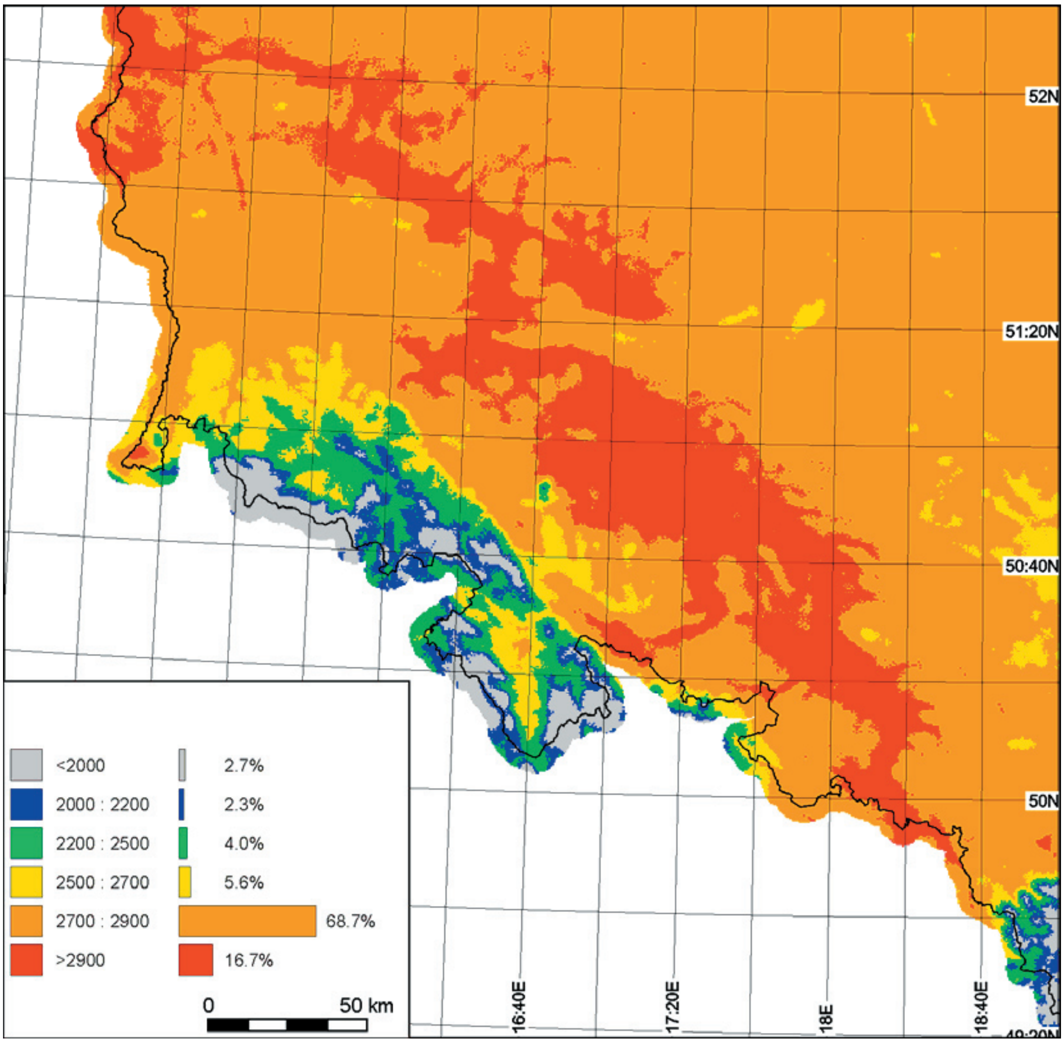

Fig. 9. Spatial distribution of Sum of Active Temperatures (SAT) classified according to Tab. 6

The analysis of SAT's spatial distribution shows that almost the entire area of Lower Silesia, excluding mountainous region of the Sudety Mts, is suitable for vine cultivation. The area of SAT higher than 2500°C covers more than 90% of the domain. Almost 17% of that, mainly on lowlands, is the area extremely suitable for wine-growing with SAT exceeding 2900°C (Fig. 9).

As mentioned above, the Growing Degree-Days (GDD) summation of daily temperature in the growing season (10ºC base) is used to predict the vine's ability to mature a high quality crop in the northern hemisphere (Amerine and Winkler, 1944). Therefore, suitability models must heat unit accumulation to ensure sufficient crop ripening. Amerine and Winkler (1944) divided the viticultural areas into five regions based on the GDD value (Tab. 5).

Tab. 5. Grape growing regions based on Growing Degree Days (Amerine and Winkler, 1944)

Region	**GDD [ºF] [ºC]**	**Suggested varieties**	**Type**	**Similar region to:**
I	≤ 2500 ≤1371	Early ripening varieties to achieve high quality	Very Cool	the coolest European districts such as Champagne in France and the Rhine in Germany
II	2501-3000 1372-1648	Early and mid-season table wine varieties	Cool	Bordeaux in France
III	3001-3500 1649-1927	High yield of standard to good quality wines	Warm	the Rhone in France or Tuscany in Italy
IV	3501-4000 1928-2204	High yield, but wine quality is only acceptable	Hot	the San Joaquin Valley
V	≥ 4000 ≥ 2204	High production of late season wine and table varieties for bulk production	Very Hot	only table grapes are usually grown commercially in this region

Using this classification, the entire Lower Silesia should be classified into the very cool grape growing regions. In fact, for the cool climate growing regions like German Rhine area, the GDD equal to 944 was found as the lowest accumulates degree-day acceptable for commercial wine grapes (Tab. 6).

Tab. 6. Growing Degree-Days' suitability classes for cool climate growing regions (http://www.geog.ubc.ca/courses/klink/g470/class02/apirzade/growingdegrees.htm)

Class	**GDD**	**Suitability**
1	> 1389	Most suitable
2	1165-1389	Good suitability
3	945-1164	Fair suitability
4	< 945	Questionable suitability

Following the above classification almost 90% of Lower Silesia can be considered as suitable for wine-growing but only less than 1% of the area is characterized by good suitability (Fig. 10).

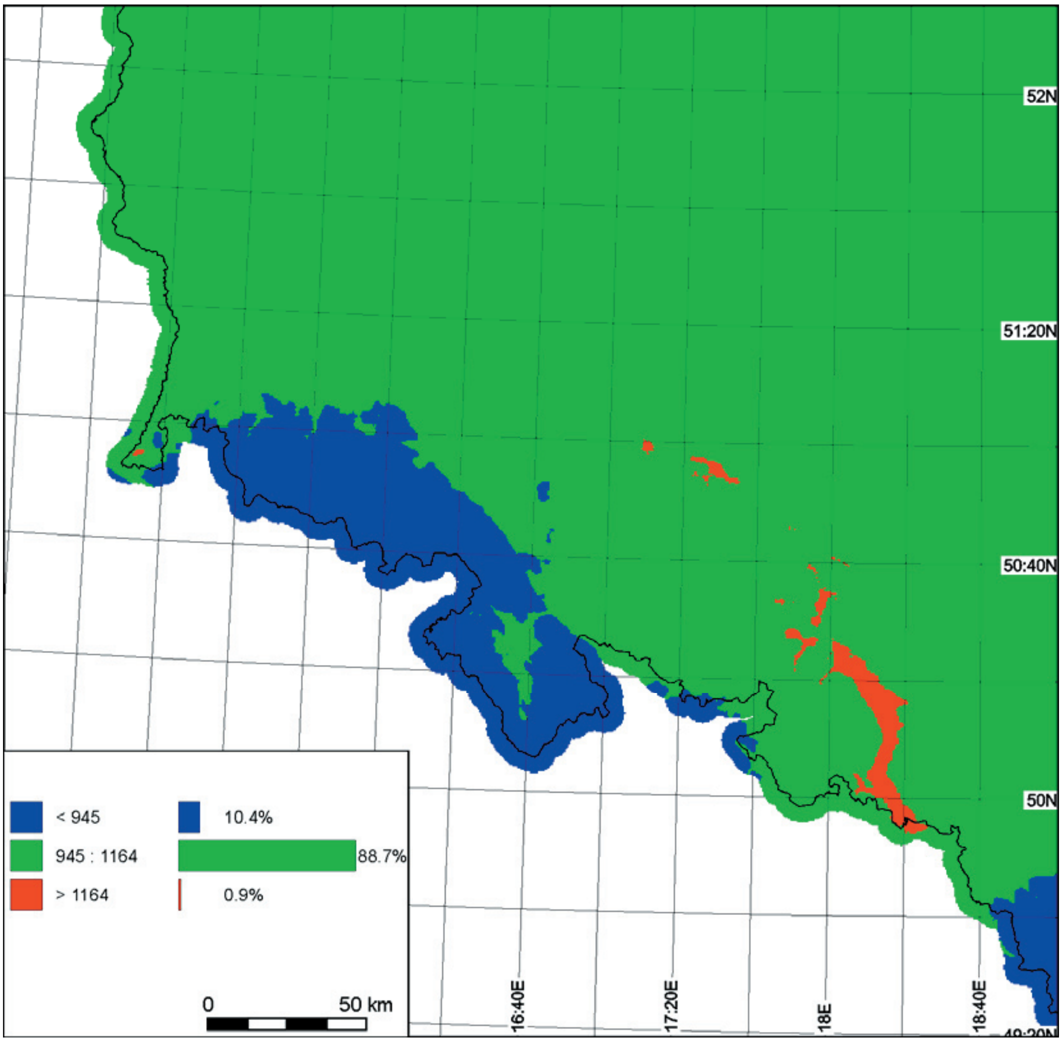

Fig. 10. Growing Degree-Days (GDD) classes according to Tab. 6

The SAT's (Fig. 9) and GDD's (Fig. 10) regionalization allows delineation of the areas suitable for wine-growing from the thermal point of view in regional scale (Tab. 7, Fig. 11). Additionally, regions 2, 3 and 4 meet the criterion of $T_Y \geq 8°C$ and $T_{WM} \geq 17°C$.

Tab. 7. Wine-growing region classification due to SAT and GDD criterion

Region	SAT and	GDD	Profile
1	< 2500	< 945	Not suitable and questionable suitability for very early and early ripening
2	2500-2900	945-1164	Fair suitability for moderately early and late ripening
3	> 2900	945-1164	Fair suitability for very late ripening
4	>2900	> 1164	Good suitability for very late ripening

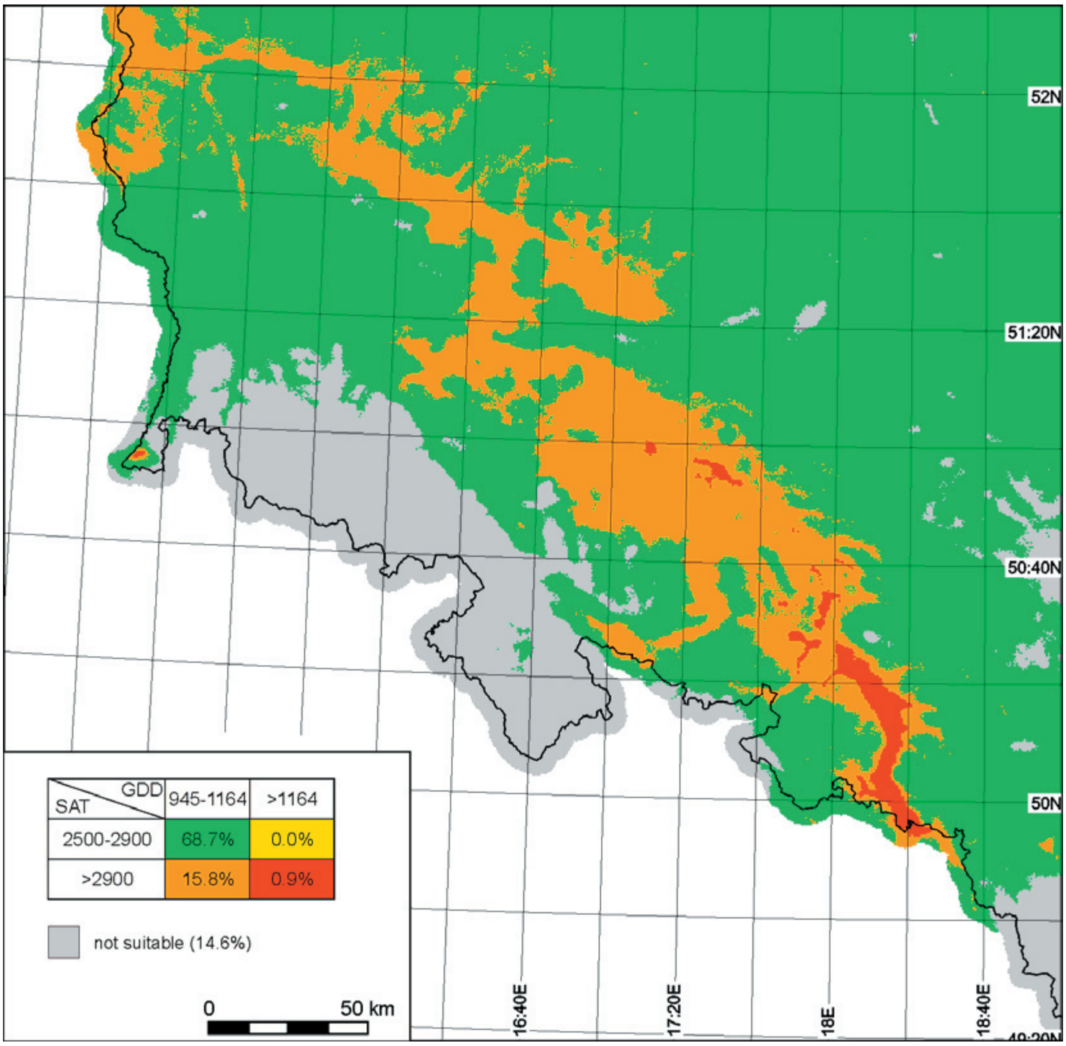

Fig. 11. Wine-growing region classification due to SAT and GDD criterion

This draft delineation shows that almost 85% of the area analyzed can be considered as suitable for grapes characterized by moderately early, late and very late ripening. More demanding, late-maturing grapes can be cultivated on less than 1% of area, mostly in the south-eastern part of the region (Fig. 11).

Summary and conclusion

Our conclusions are two-folded due to their methodic and application nature.

The first part of our study is devoted to problems of spatial interpolation of selected thermal parameters important for wine-growing in the Lower Silesia region. Four of these parameters: mean 10-year (1996-2005) SAT (Sum of Active Temperatures), GDD (Growing Degree-Days), T_Y (annual mean temperature) and T_J (mean temperature of July), were spatialized using selected estimation algorithms: inverse distance weighting (IDW), ordinary kriging (OK), multiple linear regression method (MLR) and residual kriging (RK). In each case the poorest results and least plausible maps were obtained using the IDW and OK methods. It was evident that inclusion of physically meaningful „environmental" variables was found to improve the prediction accuracies and quality of the maps. The MLR method was finally found to be the most accurate - in each case the regression model explained 94-95% of variation. From the set of potential predictors, some were of great significance for thermal parameters, especially: averaged elevation, northing coordinate and foehn index. Surprisingly, residual kriging did not improve the results of spatial interpolation made by the MLR, which was expected due to earlier attempts of temperature field modeling. Among possible causes might the be very high level of variation explained by the MLR that caused no spatial autocorrelation of residuals, so the MLR was hard to improve by the RK method.

The maps of SAT, GDD, T_Y and T_J were used in further processing in GIS to delineate the areas most favorable for wine-growing in Lower Silesia. Thermal spatial information allowed distinguishing 3 regions of fair and good suitability for moderately early, late and very late ripening grape varieties. This draft delineation shows that almost 85% of study area can be considered as suitable for viticulture.

Evidently, this approach is just the first step to find what wine-growers call a *terroir*, which is the combination of an infinite number of factors: temperature, rainfall distribution, hours of sunlight, soil acidity, presence of minerals, water retention, exposure to sunlight, slope and drainage, etc. The influence of climatic conditions is observed not only on regional scale but, what is of special importance for vine, on local one too. Thus, the next step would require more detailed analysis, including other specific factors (local climate, soils, geology etc.) and could be successfully done using spatial information and different GIS techniques.

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