APPLICATION OF GEOSTATISTICAL MODELLING TO STUDY THE RELATIONSHIPS BETWEEN THE SURFACE URBAN HEAT ISLAND EFFECT AND LAND-COVER USING LANDSAT TIME SERIES DATA

Paulina Bartkowiak, Katarzyna Osińska-Skotak

INTRODUCTION

The dynamics of urbanisation processes is one of the most common phenomenon causing both climate and ecological problems worldwide. Intensification of urban built-up areas and rapid population growth result in higher land surface temperature (LST) and maximize the surface urban heat island (SUHI) effects for heterogeneous structure of big agglomerations. The resulting increase in the LST affects thermal comfort of the inhabitants of an agglomeration.

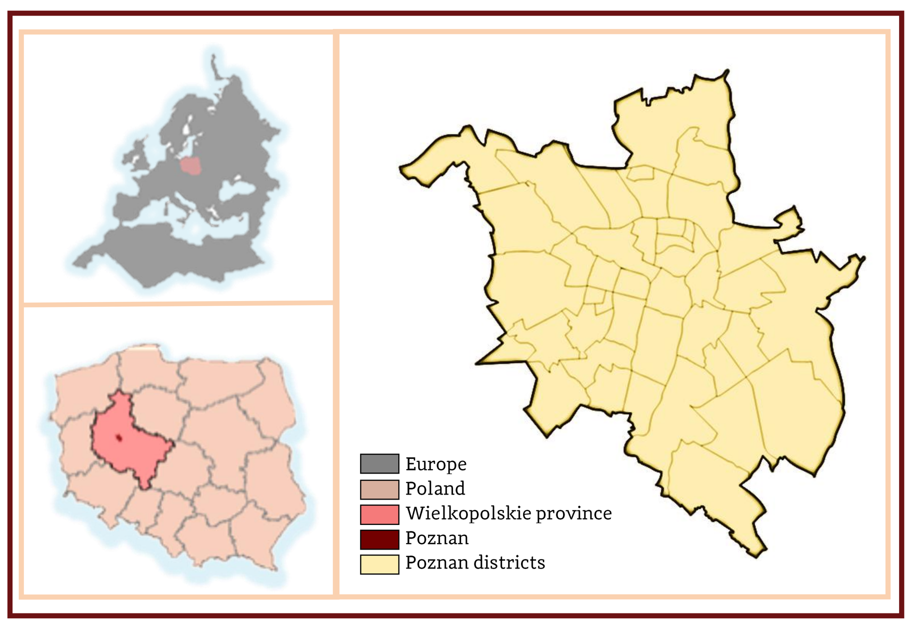
The development of remote techniques for observing the Earth's surface through the use of satellite imagery has significantly contributed to facilitating the interpretation and qualitative analyses of objects and phenomena occuring in the natural environment. Also, satellite remote sensing has enabled scientists to explore urban areas and monitor changes resulting from human activity. Due to continuous information, such as satellite imagery it is possible to assess climatology phenomena and determine which factors have a noticeable influence on the intensity of surface urban heat island.

OBJECTIVES OF THE STUDY

The subject of the research was to analyse the spatio-temporal thermal properties of land surface with the use of geostatistical modelling for cadastral districts of the Poznań city based on the Landsat satellite images. The main objectives of the research include the following:

- Identify the zones of SUHI occurrence, and in consequence to examine the dependence between SUHI and urban land-cover indices.
- Examine whether land-cover types and their derivatives determined SUHI values ($MSUHI^{i}_{intensity}$) and if changes in land cover effected thermal conditions of surface between 2001 and 2011 ($\Delta MSUHI^{i}_{intensity}$) for each district within the city.
- Explore the strength of the correlation between predictors (e.g. impervious surface areas - ISA, porosity index, road density) and thermal properties of the surface with the use of Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR).
- Analyse the effectiveness of the used geostatistical modelling for heterogeneous structure of cities.

STUDY AREA AND DATA



Satellite imagery
1. Landsat ETM+ (24.05.2001)
2. Landsat TM (29.06.2011)

Vector layers
1. Urban Atlas
2. Districts' boundaries
3. Roads

Meteorological data
1. Water temperatures for Warta river
2. Land surface temperatures

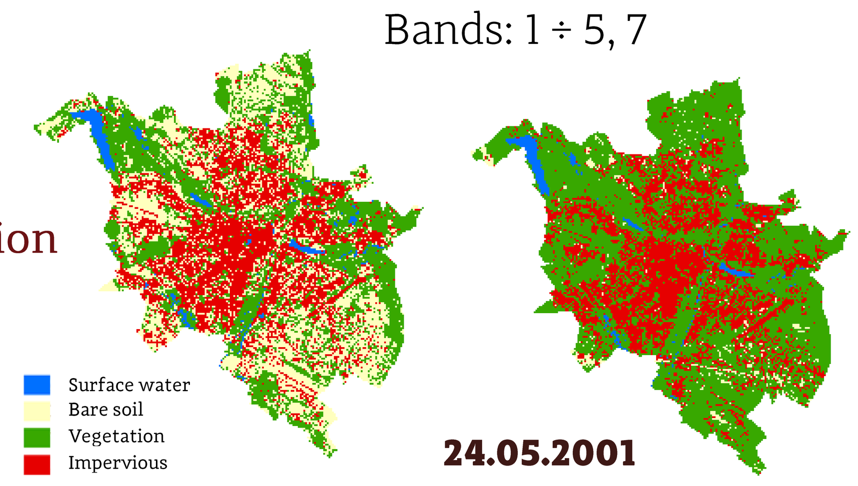
The research area was Poznań, the capital of the Wielkopolskie province in Poland. The conducted analyses were performed within the boundaries for each of the 40 cadastral districts of the city.

METHODOLOGY

MULTISPECTRAL PROCESSING

Bands: 1 ÷ 5, 7

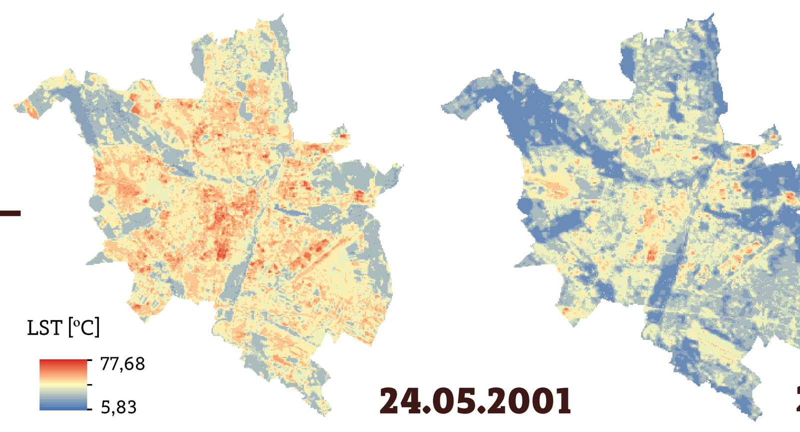
ANN classification results



SINGLE CHANNEL PROCESSING

Thermal band: 6

the LST distributions



Cross- sectional analysis (2011)

Dependent variable: $MSUHI^{i}_{intensity}$ ($\overline{SUHI}^{\,i}_{intensity}$)

Explanatory variables:
- ISA (2011)
- porosity index (2011)
- road density

For each district:
$SUHI^{i}_{intensity} = LST^{i} - LST^{i}_{mean\ non\text{-}urban}$

MULTIVARIATE MODELING

OLS — GWR

Longitudinal analysis (2001-2011)

Dependent variable: $\Delta MSUHI^{i}_{intensity}$ ($\overline{\Delta SUHI}^{\,i}_{intensity}$)

Explanatory variables:
- ΔISA (2001-2011)
- Δporosity index (2001-2011)
- road density
- porosity index (2001)
- ISA (2001)

For each district:
$\Delta SUHI^{i}_{intensity} = \Delta LST^{i} - \Delta LST^{i}_{mean\ non\text{-}urban}$

RESULTS

CROSS-SECTIONAL ANALYSIS

Selected predictors: Porosty index (2011) | Road density

	Road density	ISA(2011)	Porosity index(2011)
Road density	1		
ISA(2011)	0,84	1	
Porosity index(2011)	-0,53	-0,66	1

Values of the Pearson correlation for cross-sectional analysis

OLS results

I STEP – 2 explanatory variables:

	Explanatory variables: Intercept	Road density	Porosity index
Coefficient	1,586078	197,119611	-0,00064
Probability	0,002248	0,006355	0,004881
Robust Probability	0,005999	0,007322	0,004309
VIF	-	1,383927	1,383927
Number of observations	40		
AIC_c	132,832		
R^2	0,497		
$R^2_{adjusted}$	0,470		
I – Moran index	0,256		

→ Negative correlation
→ No dependence between predictors
→ Positive spatial autocorrelation

GWR results

II STEP – 2 explanatory variables:

Number of observations	40
Number of neighbourhoods	31
AIC_c	129,496
R^2	0,678
$R^2_{adjusted}$	0,586
I – Moran index	0,051

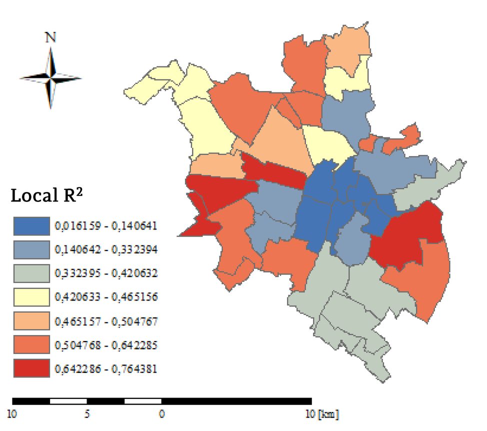
→ Decrease in the AIC_c value
→ Better result -> spatial non-stationarity
→ Random distribution of residuals

GWR results

III STEP – porosity index (2011):

Number of observations	40
Number of neighbourhoods	12
AIC_c	124,948
R^2	0,843
$R^2_{adjusted}$	0,730
I – Moran index	-0,192

→ Decrease in the AIC_c value
→ Increase in the $R^2_{adjusted}$
→ No spatial autocorrelation



LONGITUDINAL ANALYSIS

Selected predictors: ΔISA | Road density

Values of the Pearson correlation for cross-sectional analysis

	ΔISA	Δporosity index	Road density	ISA(2001)	Porosity index(2001)
ΔISA	1				
Δporosity index	-0,23	1			
Road density	0,22	-0,39	1		
ISA(2001)	0,14	-0,49	0,83	1	
Porosity index(2001)	0,03	0,81	-0,58	-0,74	1

OLS results

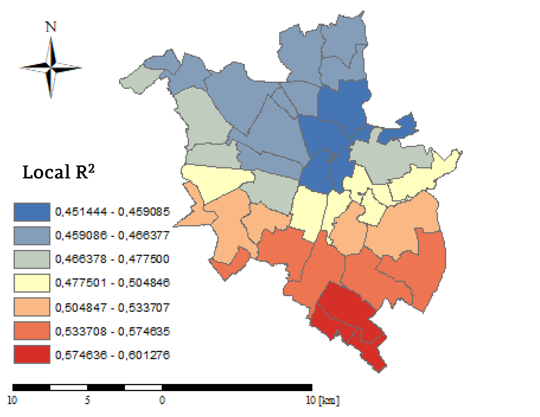
I STEP – 2 explanatory variables:

	Explanatory variables: Intercept	Road density	ΔISA
Coefficient	0,003726	-93,156973	0,066758
Probability	0,974111	0,000006	0,000031
Robust Probability	0,966666	0,000011	0,000003
VIF	-	1,052926	1,052926
Number of observations	40		
AICc	35,870		
R^2	0,526		
$R^2_{adjusted}$	0,501		
I – Moran Index	-0,210		

GWR results

II STEP – 2 explanatory variables:

Number of observations	40
Number of neighbourhoods	30
AIC_c	38,124
R^2	0,573
$R^2_{adjusted}$	0,500
I – Moran index	0,248



CONLUSION

- CROSS-SECTIONAL with 2 predictors: compared to the results for OLS method ($R^2_{adjusted}$=0,47; AIC_C=132,83), the goodness of fit of the GWR model ($R^2_{adjusted}$ = 0,59, AIC_C = 129,50) turned out to be more effective, which is evidence of the spatial non-stationarity in the relationships between land cover and SUHI effect.
- LONGITUDINAL: the goodness of fit for the longitudinal OLS model (R^2 = 0,501) was similar to the GWR results (R^2 = 0,500). As a result of the conducted analyses from 2001 to 2011 we did not noted significant changes related to increase in the impervious areas (ΔISA). This spatial pattern of the city translated into relatively unchanged $\Delta MSUHI^{i}_{intensity}$ distributions over time.
- LOGITUNDINAL: The result indicated that unlike other cities for which the longitudinal GWR modelling gave better results, for Poznan the GWR did not improve the modelling effectiveness. This means that associations between dependent and explanatory variables are stationary and as a result $\Delta MSUHI^{i}_{intensity}$ is not spatially variable.
- CROSS-SECTIONAL & LONGITUDINAL: Geographically Weighted Regression for cross-sectional analysis explains SUHI associations for every district in Poznań. Based on the GWR results we can observe that local coefficients of determination were differentiated within the city. In contrast to the cross-sectional analyses, the longitudinal GWR model resulted in better R² values for the most polygons of the study area.
- The conducted analyses using OLS and GWR methods have shown that there is a need to take into account the proportion of ISA to natural areas in urban planning concept. The LST distribution within the city could be helpful in reduction of negative human activity influencing intensity of SUHI effect. Geostatistical modelling of thermal properties of the land surface could be effective method to predict which factors have negative impact on living conditions in big agglomerations.

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geopoz

Contact information
Paulina Bartkowiak
paulina.bartkowiak@pw.edu.pl
Warsaw University of Technology
Faculty of Geodesy and Cartography
Department of Photogrammetry, Remote Sensing and GIS