Spatially weighted context data with the R package spacom:

Studying the indirect impact of war on well being of young adults in ex-Yugoslavia

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The team

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Spatially weighted context data approach

- A novel approach to contextual data analysis
- It complements multilevel analysis, by allowing to account for the spatial dimension of the studied phenomena
- Why should we account for the space in multilevel models (applied to geographically stratified data)?
- How should we account for it?

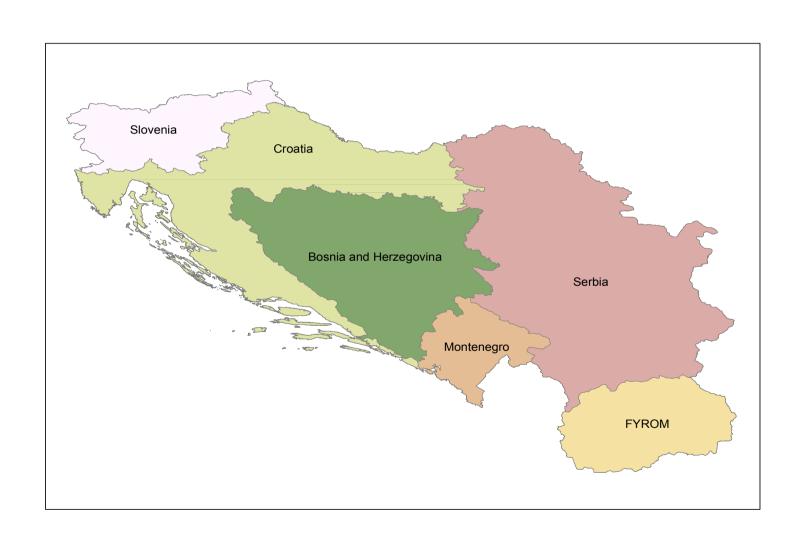
Outline

- TRACES project
- MLA: experiences of war and well-being
- Spatially weighted context data approach: 4 steps of analysis
- Spacom
- Extensions
- Conclusion

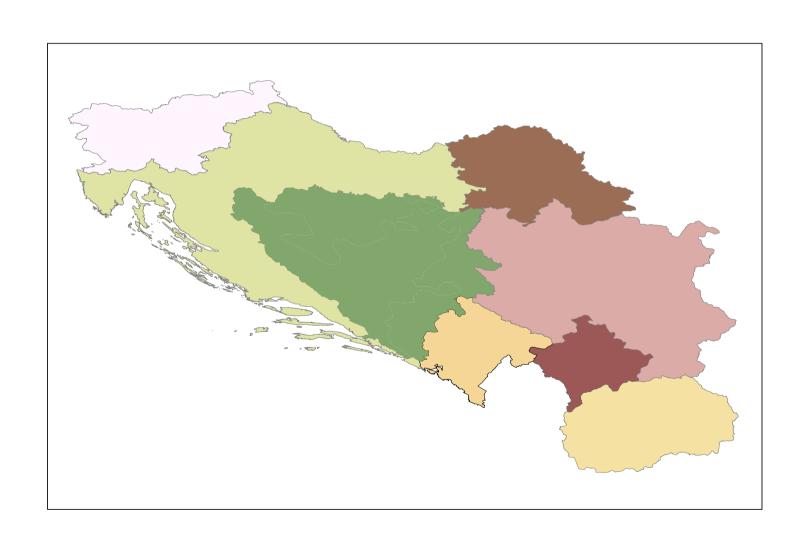
TRACES project

- **TRACES** (acronym for Transition to Adulthood and Collective Experiences Survey) a scientific project conducted in former Yugoslavia in 2006 with the ambition to collect information on the collective experiences of young adults' vulnerability in the beginning of the nineties.
- The general hypothesis is that collective experiences of vulnerability, be they due to armed conflicts or economic penury, shape social representations and attitudes related to societal issues like rights, justice or intergroup relationships.
- Regionally stratified sample design covering all area of former Yugoslavia

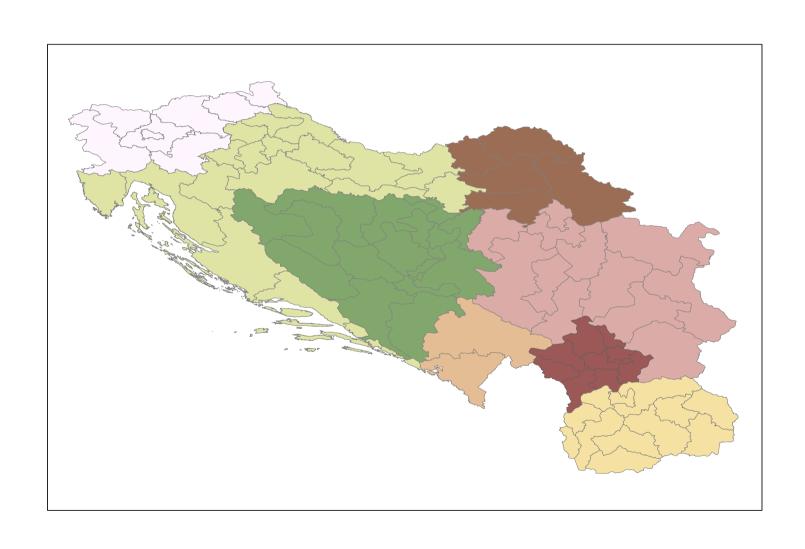
Former Yugoslavia in 2006



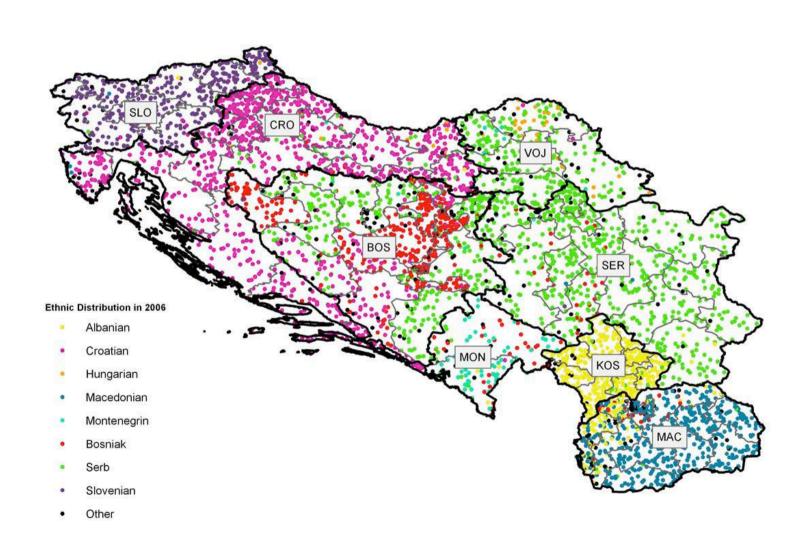
Political entities in 2006



80 TRACES areas



Geographically stratified sampling



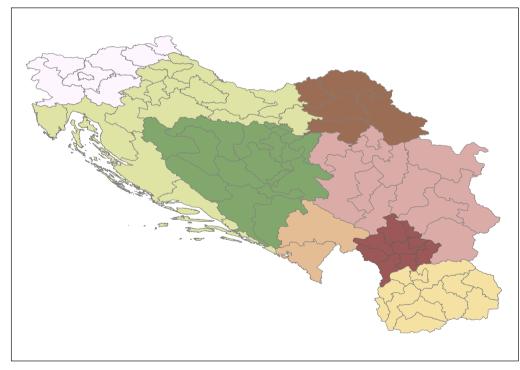
Sampling strategy

General adult population sample

- a random selection of 50 respondents belonging to the general adult population (born in 1981 or earlier) in each area
- -Construction of contextual indicators
- -N = 3975

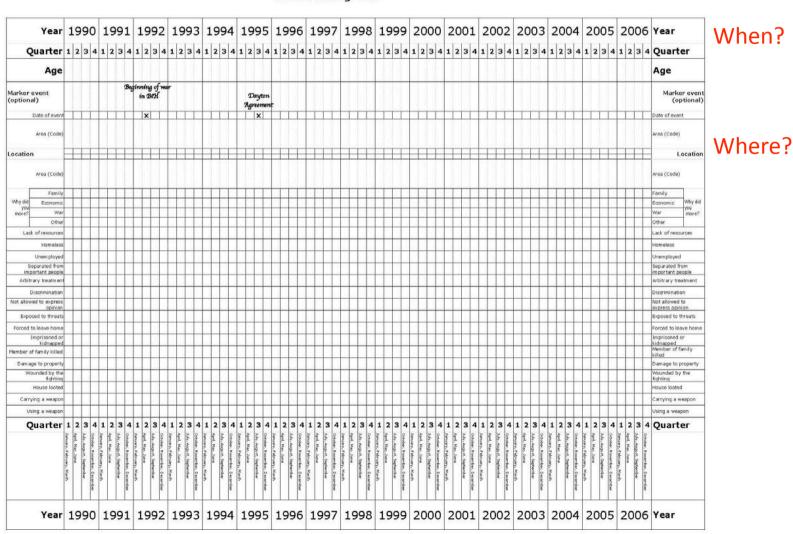
Cohort sample

- a random selection of 30 residents born between 1968 and 1974 within each area
- -N = 2254



Life events calendars

CALENDAR B Bosnia-Herzegovina

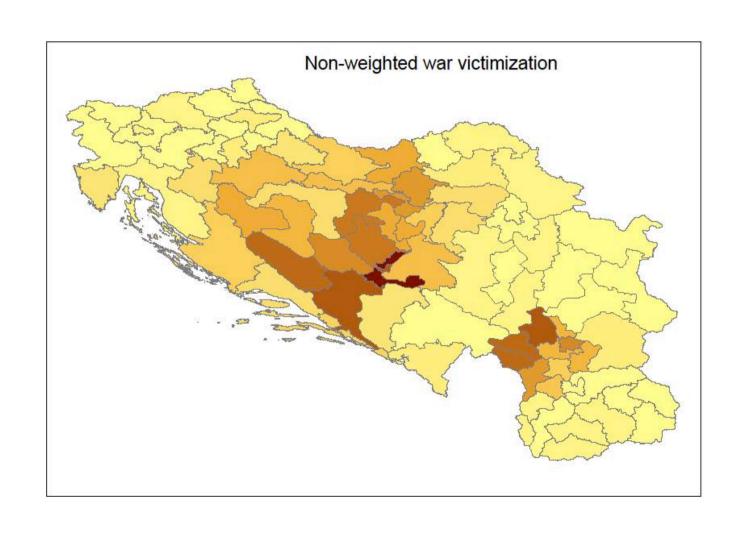


Risk of war victmization

- Life events calendars
- 6 events: forced to leave home, imprisoned, family member killed, damaged property, wounded, house looted

$$Risk_{i} = \frac{n_{i}^{events}}{indiv \times time_{i}}$$

Non-weighted risk of war victimization



Life satisfaction and war victimization – Standard multilevel analysis

- How does war trauma impact on individual well-being?
- MLA allows disentagling individual (composition) and contextual effects
- How individual and collective exposure to war impacts individuals' well-being?

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_1 + ... + \beta_{nj}X_n + e_{ij}$$

$$Y_{ij} = \beta_{0j} + \beta_{1j} X_1 + ... + \beta_{nj} X_n + e_{ij}$$

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_1 + ... + \beta_{nj}X_n + e_{ij}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}Z_j + u_{0j}$$

$$LIFE_SAT_{ij} = \underline{\beta_{0j}} + \beta_{1j}WAR_VICTIM + \beta_{2j}COMB$$

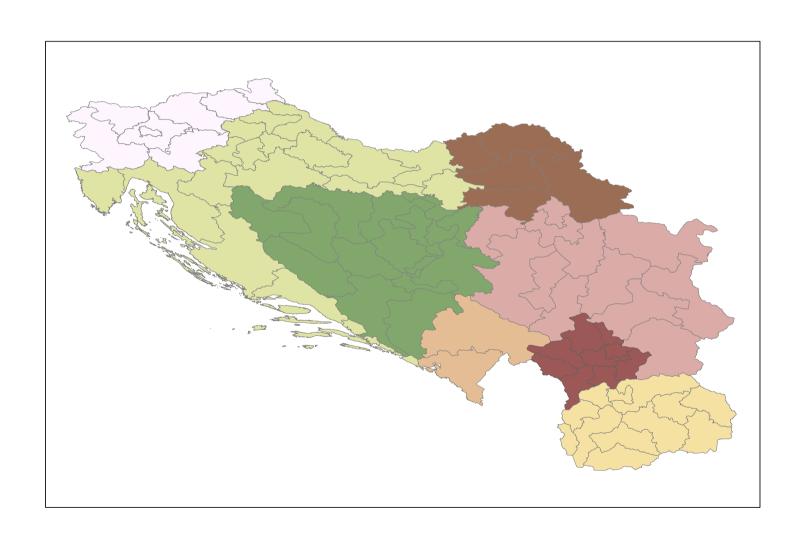
$$+\beta_{3j}GENDER + \beta_{3j}AGE + \beta_{4j}EDUC + \underline{e_{ij}}$$

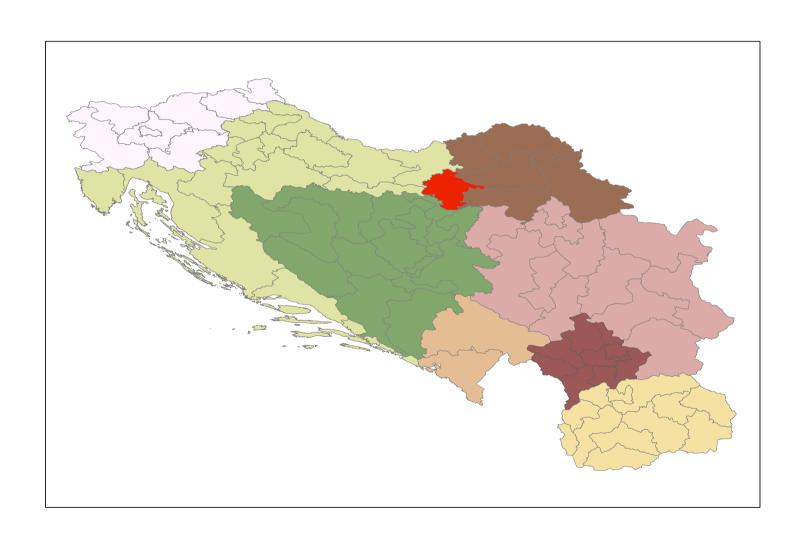
$$\beta_{0j} = \gamma_{00} + \gamma_{01}RISK_WAR + \underline{u_{0j}}$$

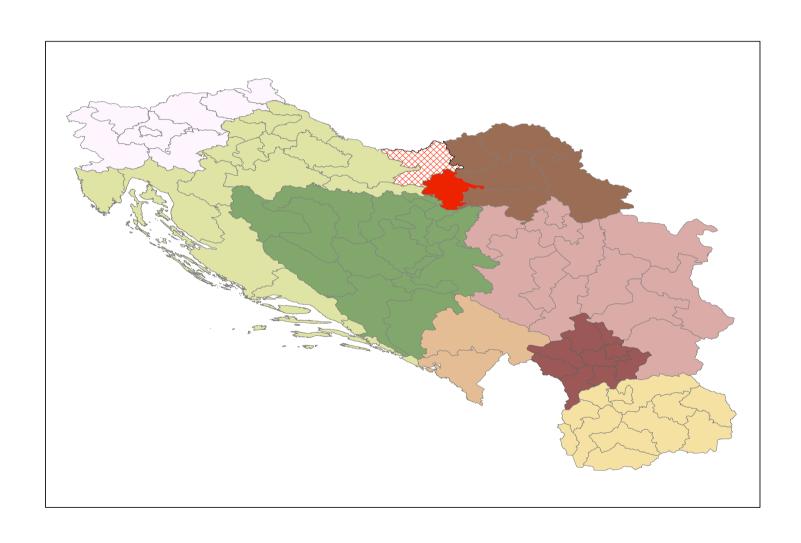
Results of MLA across 80 areas

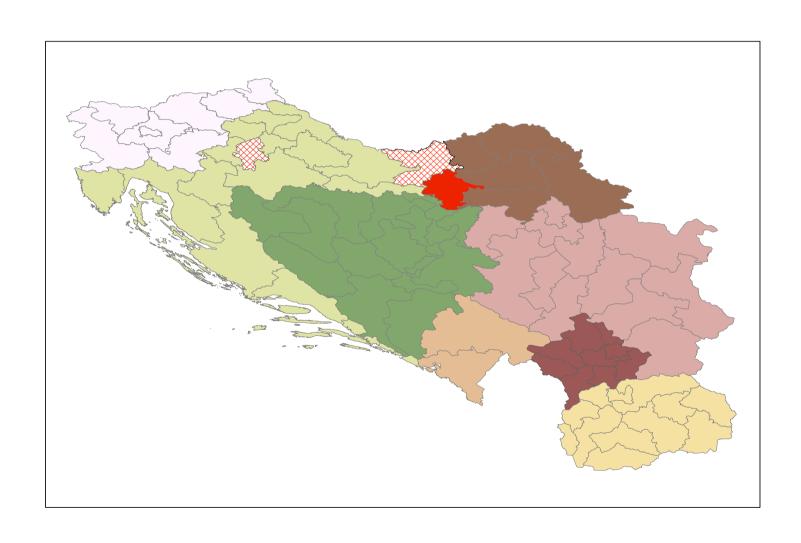
	В	SE
Victim of war	-0.17*	0.08
Combatant	-0.05	0.08
Men	-0.10	0.06
Age in 1990	-0.01	0.01
High school	0.11	0.08
Higher education	0.44**	0.09
Risk of war victimization	-1.71	9.17

Non-significant effect of the Risk of war victimization









Modifiable areal unit problem

- Openshaw (1984)
- Scale effect the strength and direction of ecological correlations depend on the level of aggregation
- Zoning effect ecological correlations depend on the precise drawing of contextual boundaries

Illustration: Zoning effects in neighbourhood influences on health

	Ecological correlation: % long-term illness and			
	% whites	% kids	% home owners	
Official wards	-0.20	0.02	0.19	
Distribution across 50 pseudo-wards				
MIN	0.00	-0.56	0.22	
MAX	0.08	-0.19	0.86	
M	-0.03	-0.39	0.43	
SD	0.06	0.06	0.09	

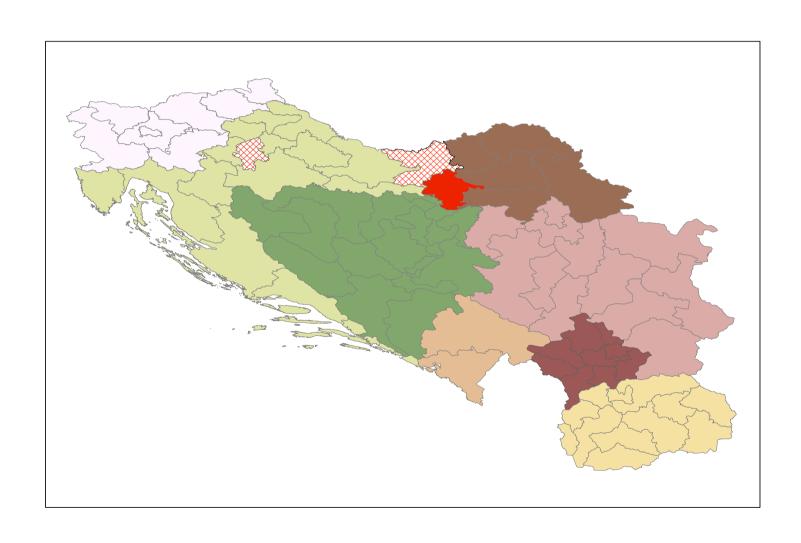
Source: Flowerdew, Manley & Sabel (2008), Social Science and Medicine

MLA with spatially dependent context data

- Banerjee, Carlin and Gelfand (2004) MLA with spatially dependent random effects
- Savitz and Raudenbush (2009) MLA with spatially dependent error term
- These models *neutralise* spatial dependency

Spatially weighted context data approach

- Spatially weighted contextual predictor
- Continuous weighting functions allow to study the impact of collective experiences beyond discrete and (more or less arbitrarily) defined contextual units
- Allow to explore the scale of contextual effects



Spatially weighted context data approach

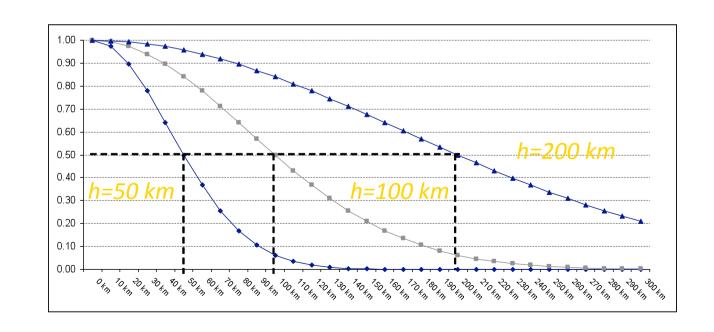
- 4 steps of analysis:
- 1. Creation of spatial weighting matrices
- 2. Construction of spatially weighted context data
- 3. Multilevel modelling with spatially weighted context data
- 4. Computation of estimates of explained spatial dependency

Step 1: Computation of spatial weights

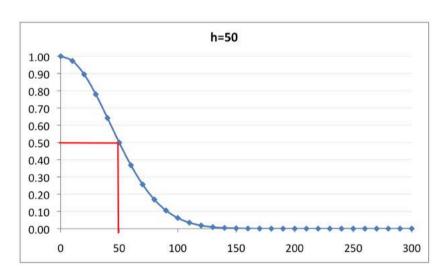
 Spatial weights are computed by applying a kernel function with specified bandwidth value to a distance matrix

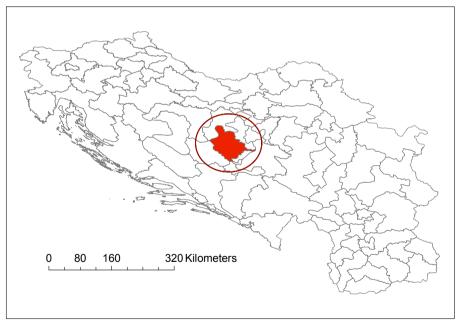
Implemented kernel function

$$w_{ij} = \left(\frac{1}{2}\right)^{\frac{d^2}{h^2}}$$

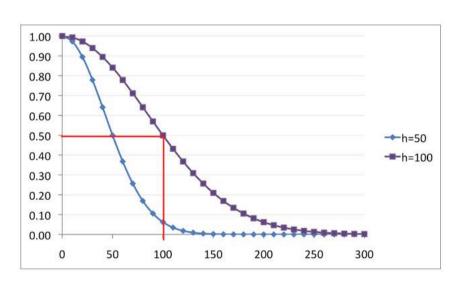


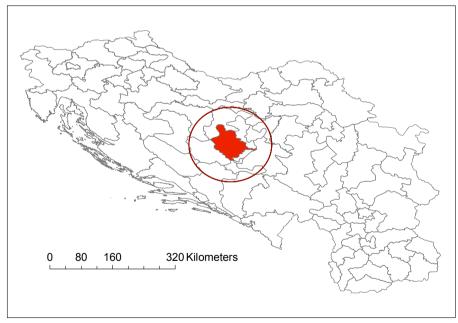
Step1: Computing spatial weights, bandwith value (h) = 50 km



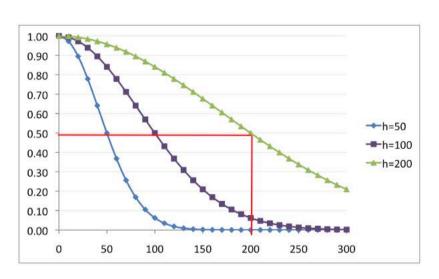


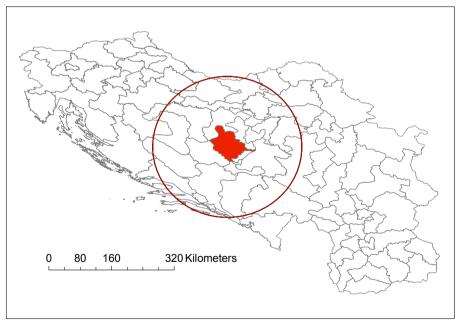
Step1: Computing spatial weights, bandwith value (h) = 100 km





Step1: Computing spatial weights, bandwith value (h) = 200 km





Step 2: Spatially weighted contextual indicator

- Weighting performed on the individual level
- Spatially weighted mean

Spatially weighted risk of war victimization

$$Risk_{i}^{weighted} = \frac{\sum_{k=1}^{80} Risk_{k} \times w_{ik}}{\sum_{k=1}^{80} w_{ik}}$$

Step 2: Spatially weighted contextual indicator

- N areas
- **n** individuals
- a a vector of area codes of length n
- x a vector of predictor values of length n
- w^s a N x N matrix of geographical weights where w^s_{IJ} is the spatial weight of values in area I on values in area J
- w^d a vector design weights of length n

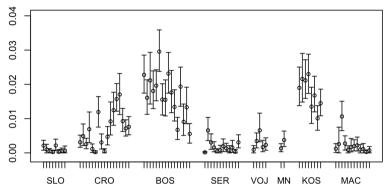
\boldsymbol{a}	$oldsymbol{x}$	$oldsymbol{w}^d$	• • •	$oldsymbol{w}_c^I$
a_1	x_1	w_1^d		:
a_1	x_2	w_2^d	• • •	:
a_1	x_3	w_3^d	• • •	:
:	Ė		• • •	:
a_I	x_i	w_i^d		$w_i^d w_{a_I i}^s$
a_I	x_{i+1}	w_{i+1}^d	• • •	:
a_I	x_i	w_i^d		:
:	:	į	• • •	• 100
a_N	x_n	w_n^d		:

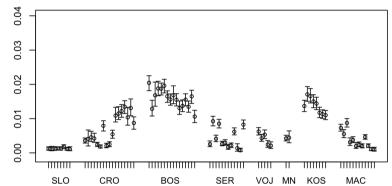
Step 2: Collective war experiences and scale

Unweighted h=50 km h=200 km h=100 km

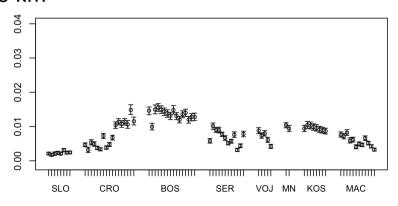
Step 2: Scale and precision of estimates



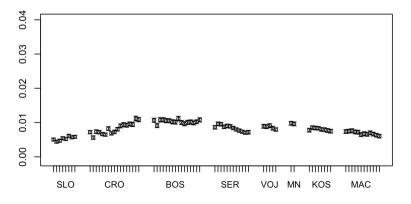




h=100 km



h=200 km



$$Y_{ij} = \beta_{0j} + \beta_{1j} X_1 + \dots + \beta_{nj} X_n + e_{ij}$$
$$\beta_{0j} = \gamma_{00} + \gamma_{01} Z_j + u_{0j}$$

$$Y_{ij} = \beta_{0j} + \beta_{1j} X_1 + ... + \beta_{nj} X_n + e_{ij}$$

$$\beta_{0j} = \gamma_{00} + \gamma_0 W^g Z_j + u_{0j}$$

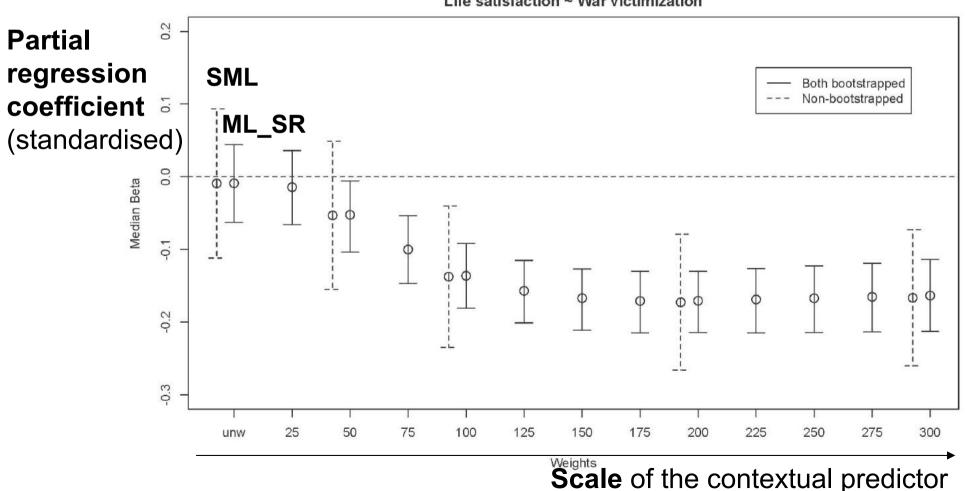
Spatially weighted contextual indicator

- Standard MLA assumes:
- contextual units are a random sample of the underlying population
- contextual indicators are measured without an error
- problematic estimates of standard errors

- SML standard multilevel analysis
- ML_SR
 - multilevel analysis with stratified resampling: resampled both individual data and contextual indicator (n_{resamples}=1000)
 - generates robust point estimates for regression coefficients and model fit indicators, and computes confidence intervals adjusted for measurement dependency and measurement error of the aggregate estimates.

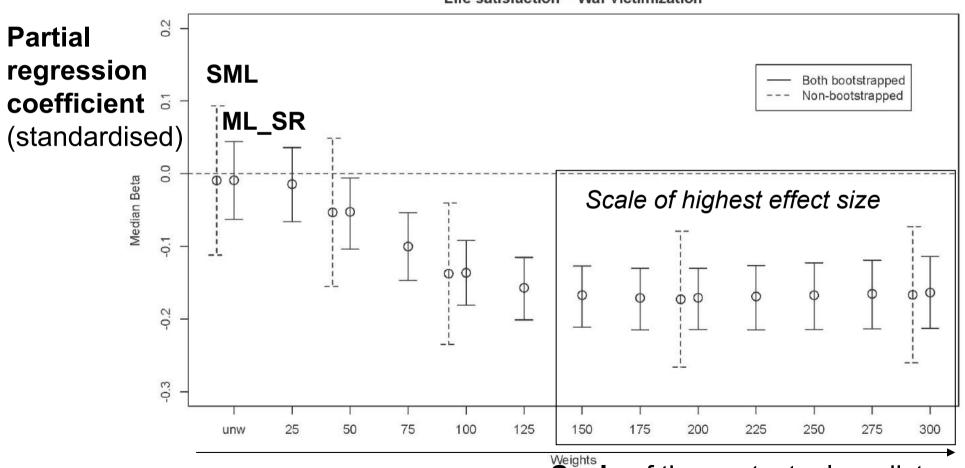
Step 3: Modelling scale effects

Comparison of Median Beta and CI for different geographical weights
Non-bootstrapped and Both bootstrapped
Life satisfaction ~ War victimization



Step 3: Modelling scale effects

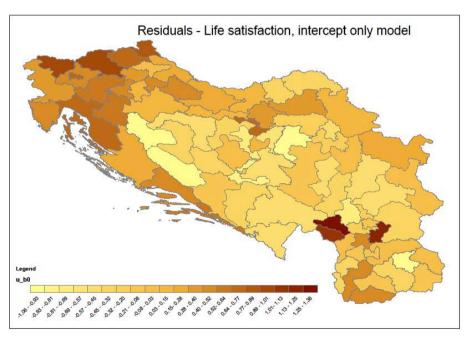
Comparison of Median Beta and CI for different geographical weights
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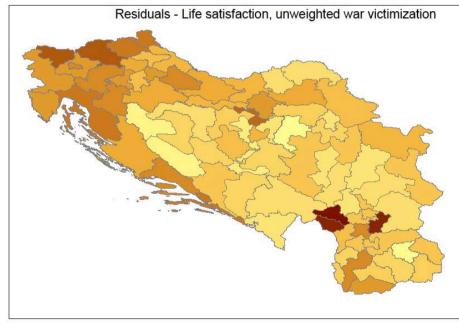


Scale of the contextual predictor

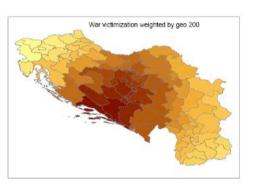
Step 4: Residual spatial dependency

Area-level residuals: « no predictor » & «unweigthed predictor »



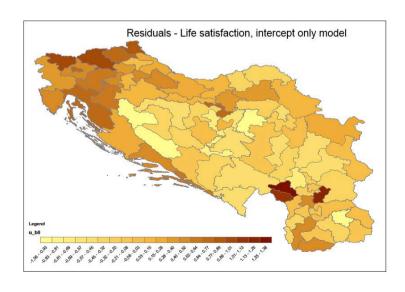


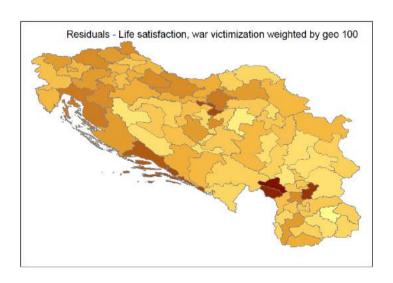
Step 4: Explained and unexplained spatial dependency



Univariate distribution: Predictor at optimal scale

Area-level residuals: « no predictor » & «predictor weighted at optimal scale »





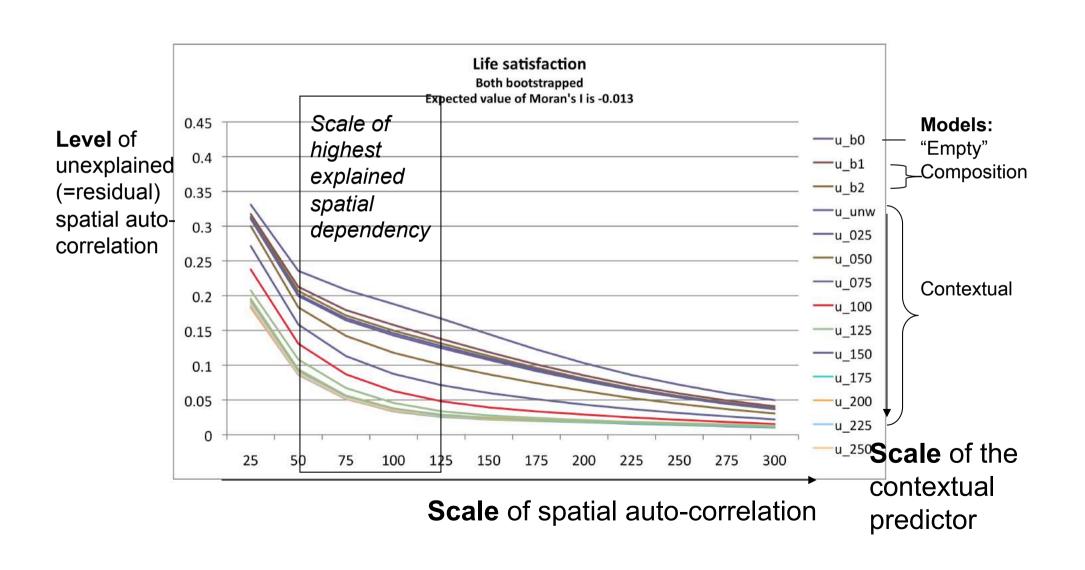
Step 4: Quantifiying spatial autocorrelation

Moran's I coefficient:

$$I = \frac{N}{\sum_{i} \sum_{j} w_{ij}} \frac{\sum_{i} \sum_{j} w_{ij} (X_{i} - \bar{X})(X_{j} - \bar{X})}{\sum_{i} (X_{i} - \bar{X})^{2}}$$

Spatial weighting matrix

Step 4: Spatial variogram



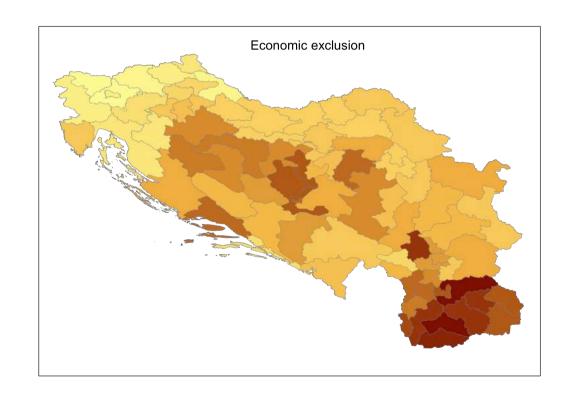
Exposure to war and well-being

- Contrary to MLA, a significant impact of collective experiences of war on well-being
- Different impact at different scales
- Bootstrap confidence intervals vs ML standard errors
- Explained spatial dependency

Different scale effect of different collective experiences

Risk of economic exclusion

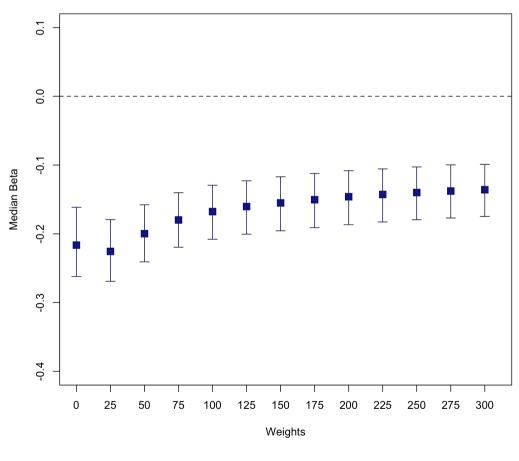
- life events calendar
- two events:unemployment andpoverty during the1990-2006 period



Step 3: Different scale effect of different collective experiences

Comparison of Median Beta and CI for different geographical weights Life satisfaction ~ Economic exclusion

Partial regression coefficient (standardised)

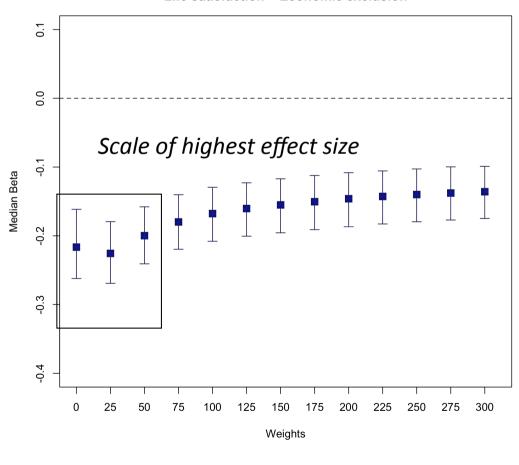


Scale of the contextual predictor

Step 3: Different scale effect of different collective experiences

Comparison of Median Beta and CI for different geographical weights
Life satisfaction ~ Economic exclusion

Partial regression coefficient (standardised)

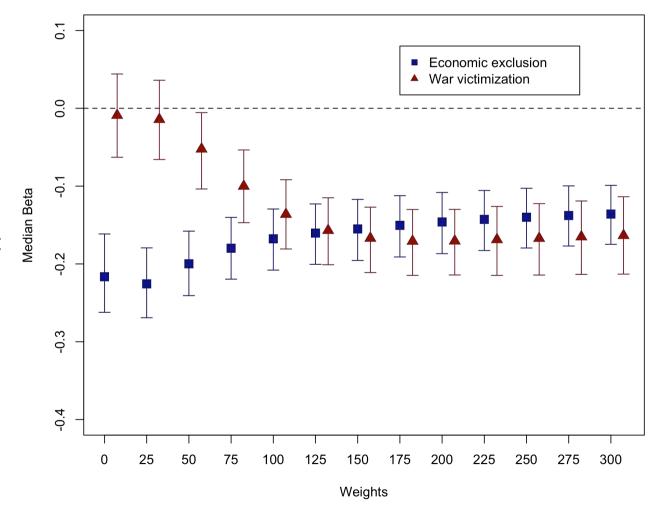


Scale of the contextual predictor

Step 3: Different scale effect of different collective experiences

Comparison of Median Beta and CI for different geographical weights Life satisfaction ~ War victimization and Economic exclusion

War Victimization has the highest impact on the large scale, while Economic Exlcusion has the highest impact on the small scale



spacom – Structure of the package

	Step of analysis	Functions in spacom	
1.	Create weights	WeightMatrix()	
2.	Create spatially weighted contextual indicator	SpawExact() SpawAggregate()	
3.	MLA with spatially weighted contextual indicator	MLSpawExact() ResampleMLSpawExact() ResampleMLSpawAggregate()	
4.	Residual spatial autocorrelation	MLSpawResidMoran()	
	Exploratory analysis	ExploreMLExact()	
	Data in package	Name of dataset	
Distance matrices		d_geo, d_ident, d_ethnic, d_migr	
Individual level dataset		traces_ind	
Contextual indicator for aggregation		traces_event	
Precise contextual indicator		homog_census	

Extensions: Socialising spatial dependency

Distance as demographic dissimilarity

$$d_{ij} = \sum_{g=1}^{6} \left| \hat{r}_{ig} - \hat{r}_{jg} \right|$$

Distance as lack of common identification

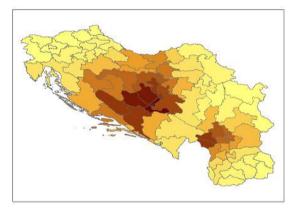
$$d_{ij} = MIN \left(\sqrt{y_i \times y_j}, \sqrt{r_i \times r_j} \right)$$

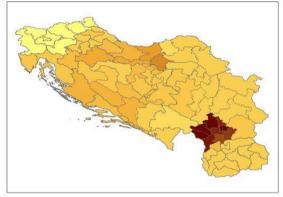
Distance as lack of contact

$$d_{ij} = \frac{(N_i + N_j)/2}{\hat{n}_{i \to j} + \hat{n}_{j \to i}} \times \frac{4}{\ln(n_{i \to j} + n_{j \to i}) + 1}$$

Comparing spatial patterns across different social definitions of 'proximity'

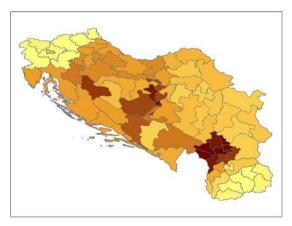
Geographic Proximity

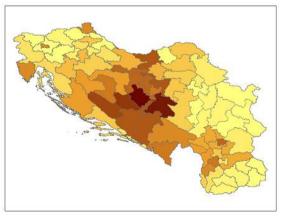




Proximity as common identification

Proximity as similarity





Proximity as contact

Modelling the social mediation of spatial patterns

	<u>Model A</u> "Geographic space"	Model B "Territorial identification"	Model C "Combined spaces"
Individual-level predictors			
Personal experience of war trauma	0.08	0.07	0.07
	(0.03 - 0.13)	(0.02 - 0.11)	(0.02 - 0.12)
Combatant	0.04	0.04	0.04
	(-0.01 - 0.08)	(0.00 - 0.09)	(0.00 - 0.09)
Male	0.04	0.04	0.04
	(0.00 - 0.08)	(0.00 - 0.08)	(0.00 - 0.08)
Age in 1990	0.00	0.00	0.00
	(-0.03 - 0.05)	(-0.04 - 0.04)	(-0.04 - 0.04)
Level of education			
- Secondary	0.03	0.04	0.04
	(-0.02 - 0.08)	(-0.01 - 0.09)	(-0.01 – 0.09)
- Tertiary	-0.01	-0.01	-0.01
	(-0.06 - 0.04)	(-0.06 - 0.04)	(-0.06 - 0.04)
Contextual-level predictors Collective experience of war trauma			
- Weighted by geographic space	0.09	_	-0.04
	(0.03 - 0.14)		(-0.10 - 0.03)
- Weighted by territorial	-	0.21	0.23
		(0.17 - 0.25)	(0.17 - 0.27)

Conclusion (I): Why is classic MLA insufficient?

- Multilevel regression analysis: statistical inferences based on assumptions that cannot be met in comparative survey research?
 - The contextual system is composed of independent units
 - Contextual units are randomly drawn from an underlying population
 - Contextual values are measured without error
- Spatial auto-regressive analysis: "keeping the bathwater and throwing out the baby"? (Gould, 1970)

Conclusion (II): What do spatially weighted context data add?

- Spatially weighted data enable to...
 - explore the spatial structure of collective experiences that generate context effects
 - describe how contextual effects, and spatial dependency explained by contextual models, vary as a function of scale
 - identify social interdependences or influences that mediate observable geographic spatial patterns between contextual units,
 - produce estimates of contextual effects and associated confidence intervals that rely on realistic assumptions

Conclusion (III): When to use spatially weighted context data? Boundary conditions

- Spatially weighted context data presuppose...
 - contextualised research questions: relational inference within the system, no inference beyond the system
 - a complete set of contextual units, defined below the scale of the contextual effects of interest
 - a complete matrix of distances between contextual units on relevant dimensions
 - precise contextual measures or appropriate microlevel data for aggregation-with-error
 - stratified sampling designs

Future applications

- LIVES IP 15: Stephanie Glaeser & Guy Elcheroth
- Spatially weighted indicators of inequalities

Acknowledgement and references

Full paper:

- Elcheroth, G., Penic, S. Fasel, R., Giduici, F., Gläser, S., Le Goff, J.-M., Joye, D., & Spini, D. (conditional acceptance). Spatially weighted contextdata and their application to collective war experiences, Sociological Methodology
- Working paper version: http://www.lives-nccr.ch/en/page/lives-working-papers-n40
- R-package (including replication data):
- Junge, T., Penic, S., Cossuta, M., & Elcheroth, G. (2013). Spacom: Spatially weighted context data for multilevel modelling. R package version 1.0-0.
 http://cran.r-project.org/web/packages/spacom/
- TRACES dataset:
- Accessible through the Swiss data archives: <u>www.uni.ch/daris</u>
- Data documentation: Spini, D., Elcheroth, G., & Fasel, R. (2011). TRACES: Methodological and technical report. *LIVES Working Paper, 4.*
- Substantive background (edited book):
- Spini, D., Elcheroth, G., & Corkalo, D. (forthcoming). War and Community: Collective experiences in the former Yugoslavia. Berlin & New York: Springer.

Thank you!