Roads, Romans, and River: a Spatial RDD Analysis of the Roman Danubian Frontier in Hungary

Andrew J. Fox*
Hunter College of the City University of New York

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1. Introduction

We tend to think of the fall of the Western Roman empire as a cataclysm, a time of depopulated ruins and marauding barbarians. Another view sees it as a time of transition, where migrating tribes mixed and mingled with the Romanized people of the former empire: a time of adaptation and change rather than a severe disjunction. Just how much continuity is there with this ancient past? How long does history leave its mark on economic development? This paper is an extension on the work done in Wahl (2017), wherein using a spatial RDD with luminosity data, he shows a causal link between the area of modern Germany settled by the Romans and modern economic development.

His hypothesis, and mine as well, is that the presence of the Roman road network encouraged path dependence in Roman areas: even after the collapse of the frontier and the large migrations in late antiquity, the remaining network of roads was a ready-made framework for future economic activity. The spatial RDD technique has been used fruitfully to study other historical subjects, as in Ehrlich (2018), which shows the lasting impact of spatially discontinuous subsidies. The question is broad: just how far back can we detect the impact of history on our times? In fact, Wahl (2017) finds a significant impact of the Roman *Limes Germanicus* on modern Germany. As an extension of Wahl, this paper uses luminosity to show a positive effect along another segment of the frontier: the highly militarized *Limes Pannonicus* of Roman Pannonia, in modern Hungary.

2. (Brief!) Historical Background

What follows is drawn from Christie (1992), University of Pécs CLIR Research Center (2020), Vingo (2010), Burghardt (1079), Molnár (2001).

The Limes Pannonicus

The region of transdanubia in modern Hungary became the Roman province of Pannonia in 11 B.C.E. The course of the Danube became the frontier, and military camps and settlement were founded along it as well as in the interior. The river presented a natural route for

*Email address: andrew.fox29@hunter.cuny.edu. v. 0.0

the transport of goods and military supplies, and thus became a focus for activity. Cities like *Aquincum* (Budapest), *Arrabona* (Gzőr), *Scarbantia* (Sopron), and *Sopianae* (Pécs) suggest continuity between the settlement patterns in ancient and modern times, and there is considerable agreement between Roman settlements, large forts, Roman roads, and modern luminosity data as shown in figure 1.

The actual *Limes Pannonicus* consisted of a series of military camps, watchtowers, and roads stretching along the Danube through central Hungary, connected by the great military road along the Western bank of the river itself. A historical map is supplied as figure 2. Unlike in Germania, were ditches and walls were dug, there is no evidence of a physical barrier in Pannonia, owing to the natural barrier of the river. The Romans weren't entirely restricted to the Western banks, as there is evidence for permanent ferry locations at Csepel and Szentendre islands and when necessary, pontoon bridges were constructed for rapid military crossings as described by Ammianus Marcellinus[1]. While the majority of military sites are along the Western banks of the river, a number of watchtowers and military camps like that at *Transaquincum* and *Contra-Aquincum* were situated on the Eastern side. The camps, forts, and watchtowers were situated so as to allow rapid travel between them by foot in case of incursions.

Starting in the late 2nd century, the Danubian frontier experienced increasing pressure from various Germanic and semi-nomadic peoples. Both the pressure of migrations, and raids and military expeditions led to increased militarization and the settling of Germanic tribes in Transdanubia. A thorough treatment of late antiquity and the continuity (and/or lack there of) of settlement is found in Christie (1992).

After Rome

By the 5th century the *Limes* were in ruins, and Pannonia was repeatedly overrun by the Marcomanni, Quadi, Goths, Alans, and then the Huns, among others. Evidence for continuity of settlement is spotty: finds suggest Langobardic usage of sites like Aquincum and Brigetio. From the 9th century, a new people began to cross the Carpathians into what is now Hungary: the Magyars. These were a nomadic people originally from the Ural mountains, and spoke a Uralic language that would become Hungarian. The Magyars occupied the entire Carpathian basin, becoming the dominant ethnic group. The settling of the Magyars in the Carpathian basin replaced and absorbed the cultures of the pre-Roman, Romanized, and migration period peoples. Hungary would be later invaded by the Mongols, and the Ottoman Turks, but never again would the Pannonian Danube form a significant military or national border.

These waves of invasions, and the disruption they caused to the infrastructure and settlement of Hungary create a region suited to BDD. Elsewhere, the *Limes* still follows ethnic, linguistic, or religious boundaries. In Hungary however, this is not the case. This means the risk of compound treatment, i.e., there is something about the people on one side of the Danube that is different from the others, is reduced. When looking for the impact of Roman settlement on one side, the modern ethnic, linguistic, and religious continuity across

[1] "*the emperor himself quickly moved his camp to Aquincum, joined together boats for the sudden emergency, and having with swift energy made a bridge of planks upon them, crossed through another quarter into the territory of the Quadi.*" (**?**)

the Danube supports its use as an RDD cutoff.

3. Data

For the dependent variable I use NOAA nighttime luminosity data from 2013[2]. These will be used as a proxy for economic development. This raster data is made up of average persistent nighttime luminosity at a resolution of 30 square arc-seconds, which is a little under a kilometer at the equator. The NOAA provides data that has been cleaned of noise from fires, cloud coverage and other interference. I used WGS-84 Mercator projection throughout, converting data files where necessary. The luminosity data is considerably right skewed, with many low light levels and a few very bright regions, as seen in figure 4.

The Roman frontier followed the course of the Danube, so I used the modern course of the river when creating the boundary. The shapefile is supplied free from the EEA. There have been slight shifts in it's course since antiquity, but as the series of military camps and roadways were inland from the banks, this should pose no problem.

This boundary has several enticing features. Unlike in Germany and the low countries, where the frontier shifted around and now has to be reconstructed from archaeological data, the frontier in Pannonia followed the Danube and remained unchanged for centuries. The terrain of Hungary is mostly flat, without a distinct change in ruggedness between Roman and non-Roman areas. Finally, the notion of compound treatment is avoided: no border since antiquity has followed this particular section of the Danube, and the Magyar invasions uprooted and replaced the ancient populations. In the case of the Pannonian frontier, I can't separate the effect of the River and the effect of the Roman roads. However the Romans themselves heavily depended on the river, and therefore their settlements and large military camps in Pannonia closely follow it's course.

The locations of some of these settlements can be seen in figure1. I georeferenced locations of major Roman settlements and military camps using the coordinates from Åhlfeldt (2020), in the Digital Atlas of the Roman Empire run by Göteborgs university. Even though the river influenced patterns Roman settlement and thus influences the analysis, it still presents a useful boundary because "treatment" is found primarily on one side.

The shapefiles for Hungary's borders comes from the EEA[3]. The shapefile for the roman roads comes from McCormick (2013). In figure 3 the agreement between Roman roads and modern Hungarian roads is visualized. There is considerable continuity between them, suggesting that later development was influenced by the already established routes.

Soil suitability data is take from Tóth (2015), from the European Soil Data Centre. The centre creates an index measuring suitability for human use. This takes into account slope and altitude. The categories go from 1-4, with 1 being the least suitable. Elevation data is shown in figure 5. The data is freely available from the EEA[4]. Finally, population density is from 2018, and was downloaded from Eurostat[5]. Hungary is mostly flat, with

[2]These are available at https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html

[3]at https://www.eea.europa.eu/data-and-maps/data/eea-reference-grids-2/gis-files/hungary-shapefile

[4]https://www.eea.europa.eu/data-and-maps/datac0=5c11=c5=allb$_start = 0$

[5]https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/population-distribution-demography/geostat

hills in the western and northern regions. When analysis is confined to the region around the Danube, the changes in elevation are small. In this data set, lower elevation is coded with higher numbers.

Summary statistics for these data are below in table 1.

4. Methods

The Roman settlement of Western Hungary presents a nice quasi-experiment. I run robust linear regressions, and then the danube boundary is used to run naive RDD with heteroskedasticity robust errors and data generated bandwidths, and finally fully spatial BDD regressions. Re-centered distance to the Danube is used for the running variable in all discontinuity regressions. Since the luminosity data is a skewed distribution of discrete counts, I also run GLM Poisson regressions to predict luminosity levels in the Roman area.

The unit of analysis is the 30 arc second pixel. I conduct all preliminary geospatial work in QGIS. The luminosity raster data is clipped to Hungary's modern borders, and a vector shapefile representing the course of the Danube used to cut a line representing the boundary discontinuity, roughly following the center of the river. I create a polygon representing the treatment area of Transdanubia as can be seen in figure 4.

I convert each pixel representing luminosity to a point at its centroid. Using the polygon representing the treatment area I then generate a binary variable for each luminosity point value. Then I calculate the closest distance between each point and the boundary line, re-centering the distances so that 0 represented the Danube boundary. Figure 6 illustrates each of these steps.

A similar process involving conversion to points was used to clip, convert then merge the data for population density, elevation, and soil suitability.

5. Results

Both naive and spatial RDD show a positive effect for being on the Roman side of the Danube. RDD shows consistently significant effects, while fully spatial BDD estimates are less statistically significant.

A basic linear regression on a binary variable using the treatment area shows that on average there is lower luminosity on the Roman side of the Danube, while linear regressions with a buffer around the Danube of 3, 5, and 10 km show the effect of being on the Roman side is positive and significant. The linear regression results are in table 2. Elevation and population have small but significant effects.

Table 3 contains the estimates using "naive" RDD. The RDD package in R uses a data-driven method to select widths around the cut-off. Local linear regressions all show significant, positive effects for being on the Roman side of the river. Using all covariates increases the effect, as does using a higher order polynomial for the local regression.

Results for spatial RDD when using 50 divisions are significant at 15% and 10% significance levels. Again, the estimates are positive. These are available in table 3.

Table 5 shows the results of Poisson regressions. For these I used the un-transformed luminosity data. Again, a regression using all of Hungary produces a negative coefficient, although it is not statistically significant. However, restricting the regressions to bands of 3, 5, and 10 km around the cutoff leads to positive and statistically significant coefficients on the treatment variable. Marginal increases are calculated at 2-4 luminosity counts along the right bank within the Roman area, from the 1-63 count measure produced by the NOAA.

Soil suitability has only a small impact, with less suitable soil predicting higher luminosity. Farmland has low luminosity, so this isn't all that surprising. Population density is associated with higher luminosity in all cases, as is expected. Elevation also has the expected sign (in the data, the higher numbers are lower elevation), and this shows that lower areas in general have higher luminosity.

6. Conclusions

This paper shows that there is a positive discontinuity in luminosity along the Roman Danube frontier in Hungary. While I cannot separate the effects of the river from the effects of the Roman settlement, the concentration of settlement along the right bank, coupled with the continuity between the Roman and modern road systems are highly suggestive of increased economic development on the Roman side. The infrastructure built in ancient times plausibly gave Western Hungary a head start. This demonstrates the considerable time persistence of transport networks, both road and river, and the very long run impact of economic development.

References

[1] Burghardt, A. F. (1979). The origin of the road and city network of Roman Pannonia. *Journal of Historical Geography*, 5(1):1–20.

[2] Christie, N. (1992). The Survival of Roman Settlement Along the Middle Danube: Pannonia From the Fourth to the Tenth Century AD. *Oxford Journal of Archaeology*, 11(3):317–339.

[3] EEA. EEA Data, Maps, and GISShapefiles.

[4] Ehrlich, M. v. and Seidel, T. (2018). The Persistent Effects of Place Based Policy: Evidence from the West German Zonenrandgebiet. *American Economic Journal: Economic Policy*, 10(4):344–374.

[5] Marcellinus, A. (1935). *Rerum Gestarum*. Harvard University Press, Cambridge, Mass. John C. Rolfe, trans.

[6] McCormick, M., Huang, G., Zambotti,G., and Lavash, J. (2013). Roman Road Network (version 2008).

[7] Molnár, M. (2001). *A Concise History of Hungary.* Cambridge University Press.

[8] NOAA. Version 4 dmsp ols nighttime lights time series. Image and Data processing by NOAA's National Geophysical Data Center. DMSP data collected by the US Air Force Weather Agency.

[9] University of Pécs CLIR Research Center, Neményi, R., University of Pécs CLIR Research Center, Szabó, M., and University of Pécs CLIR Research Center (2020). *The Danube Limes in Hungary: Archaeological Research Conducted in 2015–2020.* CLIR Research Center.

[10] Vingo, P. (2010). Shifting populations in Late Antiquity. Germanic populations, nomads and the transformation of the Pannonianlimes. *Acta Archaeologica AcademiaeScientiarum Hungaricae*, 61(1):261–282.

[11] Wahl, F. (2017). Does European development have Roman roots? Evidence from the German Limes. *Journal of Economic Growth*, 22(3):313–349.

[12] Åhlfeldt, J. (2020). Digital Atlas of the Roman Empire. Göteborgs Universiteit.

[13] Tóth G. and Hermann T. (2015). European map of soil suitability to provide a platform for most human activities (EU28). Harvard Dataverse. Version = IV.

[14] GEOSTAT - GISCO - Eurostat, ec.europa.eu/eurostat/web/gisco/geodata/reference-data/population-distribution-demography/geostat.

7. Tables

Table 1. Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Raw Luminosity	74985	12.23	11.37	4.00	63.00
Log Luminosity	74985	2.267	0.602	1.386	4.143
Distance to River (m)	74985	99646.37	67730.65	2.43	282566.73
Elevation	74985	50.40	21.73	12.0	147.0
Soil Suitability	74985	3.66	NA	1	4
Population Density	74985	306.21	861.30	1.0	32186.0

Note: soil suitability is a factor variable

Table 2. Pooled Linear Regressions

	Dependent variable:				
	Ln of Luminosity				
Buffer			3km	5km	10km
	(1)	(2)	(3)	(4)	(5)
Roman Area	−0.071***	−0.031***	0.108***	0.113***	0.054***
	(0.004)	(0.004)	(0.033)	(0.027)	(0.021)
Elevation		−0.001***	−0.007***	−0.002**	0.001*
		(0.0001)	(0.001)	(0.001)	(0.001)
Pop. Density		0.0003***	0.0001***	0.0001***	0.0002***
		(0.00000)	(0.00001)	(0.00001)	(0.00000)
soil (2)		0.123***	0.012	0.123	0.711***
		(0.013)	(0.379)	(0.345)	(0.233)
soil (3)		0.167***	0.083	0.189	0.265
		(0.015)	(0.376)	(0.341)	(0.232)
soil (4)		0.156***	0.164	0.397	0.500**
		(0.011)	(0.372)	(0.339)	(0.231)
Constant	2.298***	2.109***	2.840***	2.421***	2.114***
	(0.003)	(0.012)	(0.380)	(0.343)	(0.234)
Observations	74,985	74,985	2,059	3,290	5,818
R^2	0.003	0.176	0.203	0.203	0.193
Adjusted R^2	0.003	0.176	0.200	0.202	0.192
Residual Std. Error	0.601	0.547	0.739	0.755	0.758
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 3. Naive RDD Results

	Dependent variable:				
	Ln of Luminosity				
	(1)	(2)	(3)	(4)	(5)
Coefficient	0.096*	0.101*	0.146***	0.145***	0.189***
	(0.039)	(0.041)	(0.036)	(0.037)	(0.036
Polynomial Order	1	1	1	1	2
Treated obs	3561	3237	3364	3299	6545
Untreated obs	3828	3438	3597	3511	7069
Elevation	No	Yes	Yes	Yes	Yes
Population	No	No	Yes	Yes	Yes
Soil	No	No	No	Yes	Yes
Rho	0.470	0.451	0.430	0.441	0.414

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4. Spatial BDD Results

	Dependent variable:		
	Ln of Luminosity		
	(1)	(2)	(3)
ATE	0.0472	0.0374	0.0426*
P-value	(0.111)	(0.1244)	(0.0690)
Boundary Divisions	50	50	50
Elevation	No	Yes	Yes
Population	No	Yes	Yes
Soil	No	No	Yes

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5. Poisson Regressions

	Dependent variable:			
	Luminosity			
	(1)	(2)	(3)	(4)
Buffer		(3km)	(5km)	(10km)
Roman	−0.003	0.138***	0.145***	0.082***
	(0.002)	(0.009)	(0.007)	(0.006)
Elevation	−0.001***	−0.009***	−0.002***	0.001***
	(0.0001)	(0.0004)	(0.0002)	(0.0001)
Pop. Density	0.0001***	0.0001***	0.0001***	0.0001***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Soil (2)	0.175***	0.020	0.207	0.930***
	(0.007)	(0.136)	(0.128)	(0.092)
Soil (3)	0.202***	0.223*	0.389***	0.502***
	(0.009)	(0.135)	(0.127)	(0.092)
Soil (4)	0.217***	0.347***	0.609***	0.775***
	(0.007)	(0.134)	(0.126)	(0.092)
Constant	2.309***	3.066***	2.580***	2.223***
	(0.007)	(0.136)	(0.127)	(0.092)
Observations	74,985	2,059	3,290	5,818
Log Likelihood	−382,884.900	−17,623.780	−29,308.140	−52,198.040
Akaike Inf. Crit.	765,783.800	35,261.550	58,630.280	104,410.100

Note: *p<0.1; **p<0.05; ***p<0.01

8. Figures

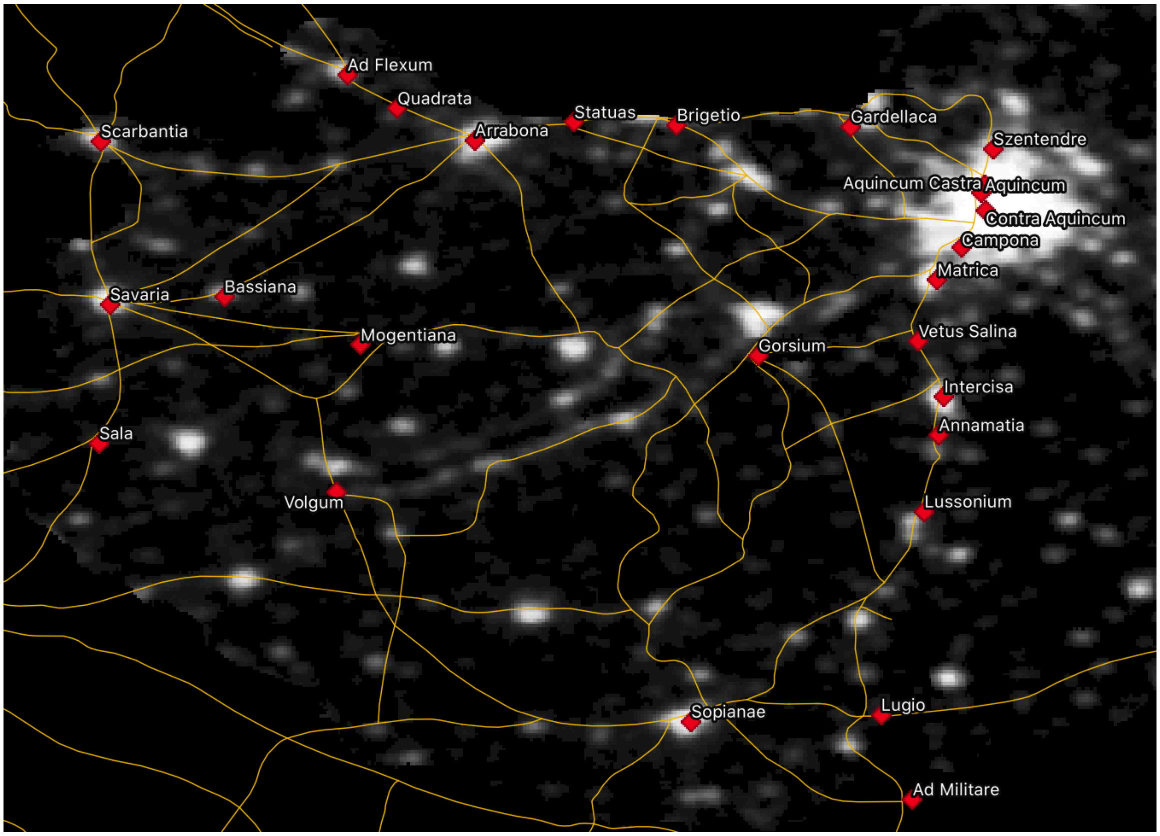

Figure 1. Major Roman settlements and forts in the area of interest.

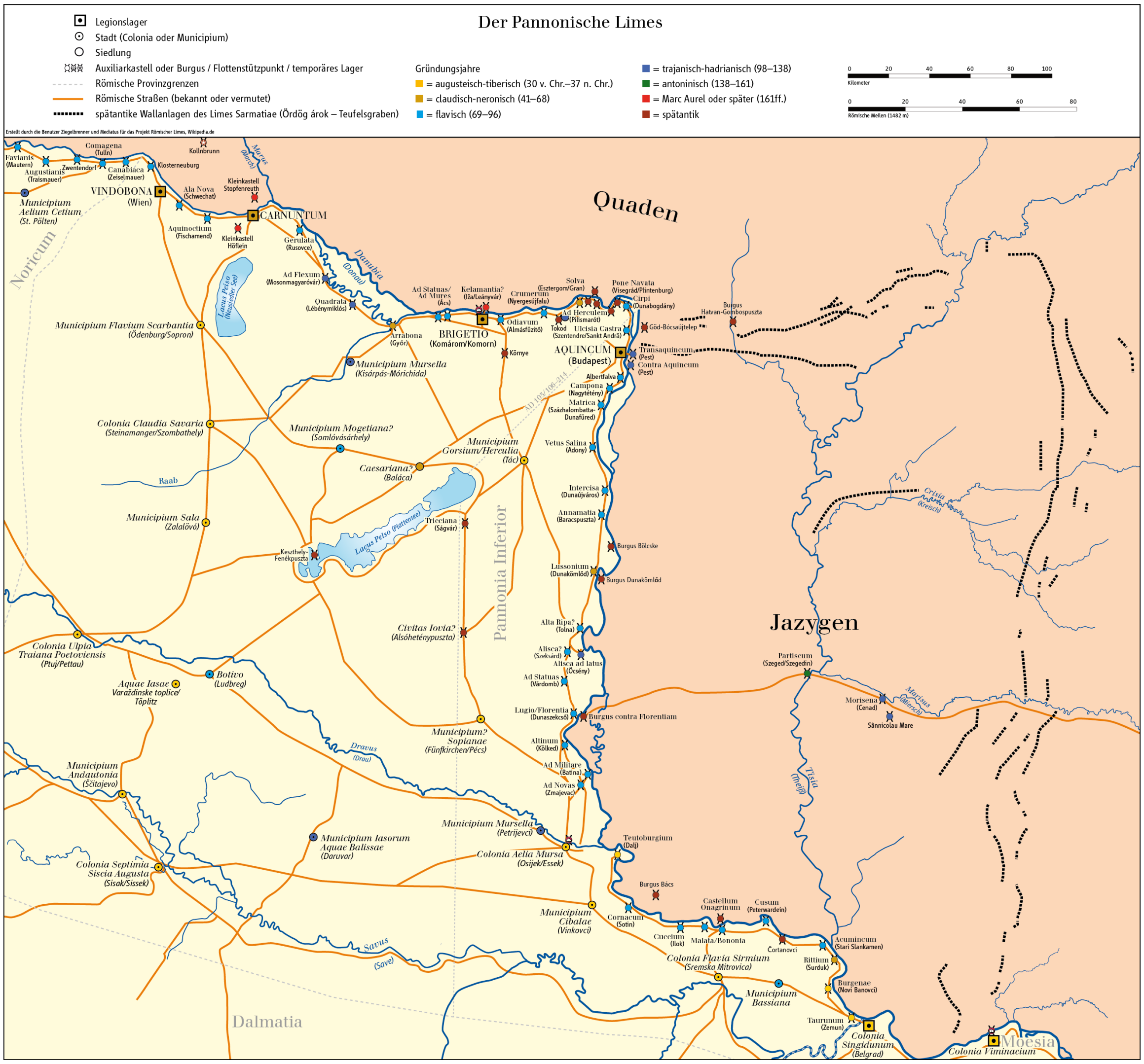

Figure 2. Pannonian Limes. Source: wikimedia commons (creative commons)

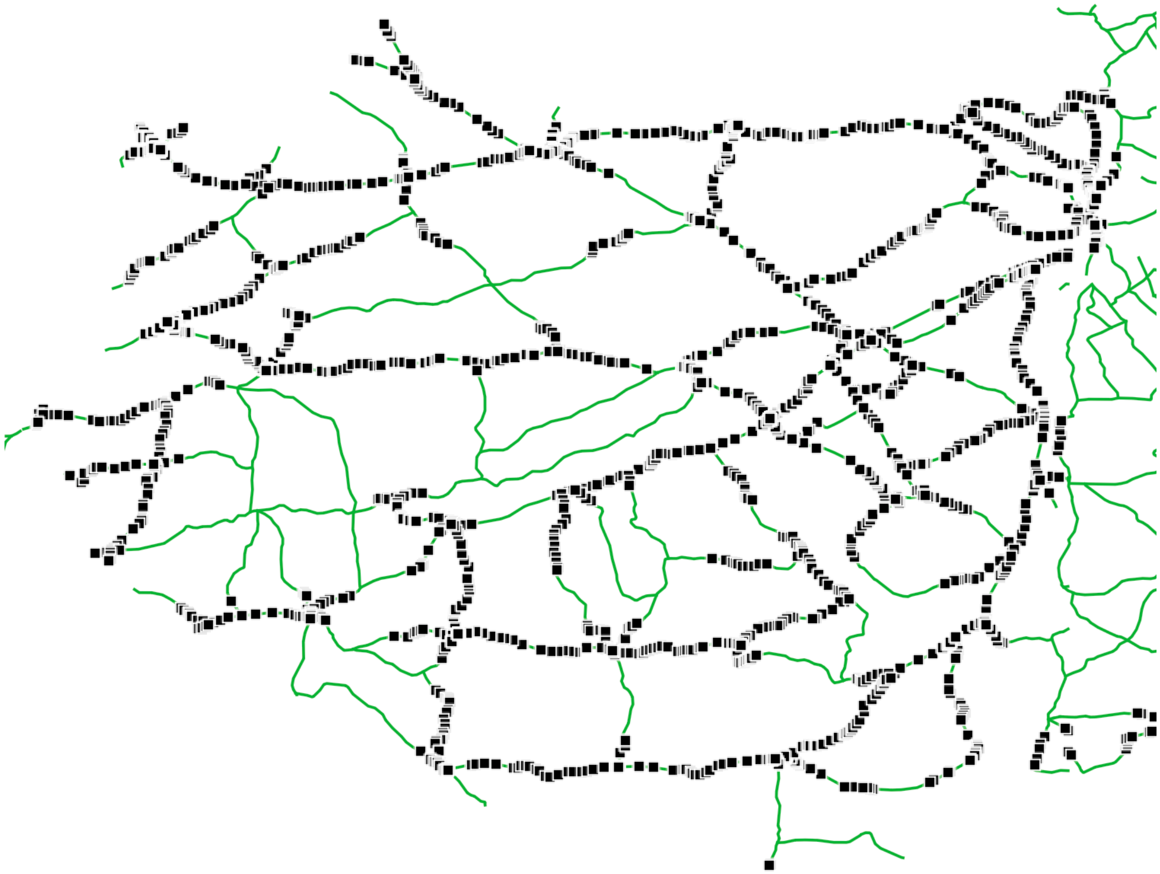

Figure 3. Modern Hungarian Roads within 5km of a Roman road

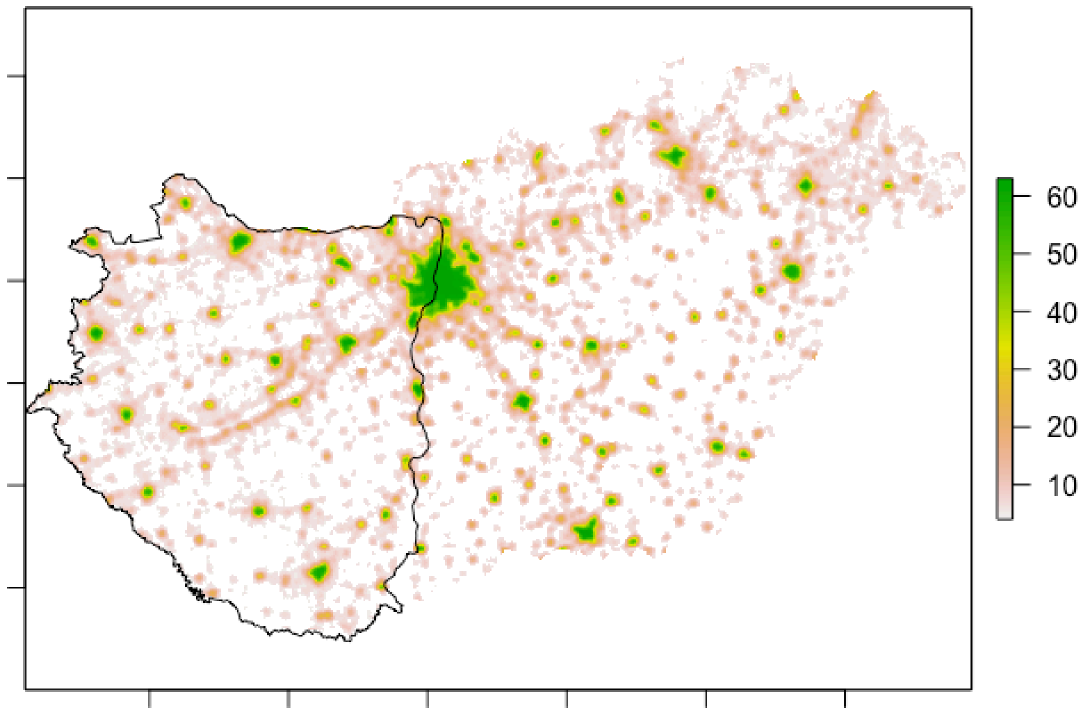

Figure 4. Luminosity within Hungary with outlined treatment area (Transdanubia)

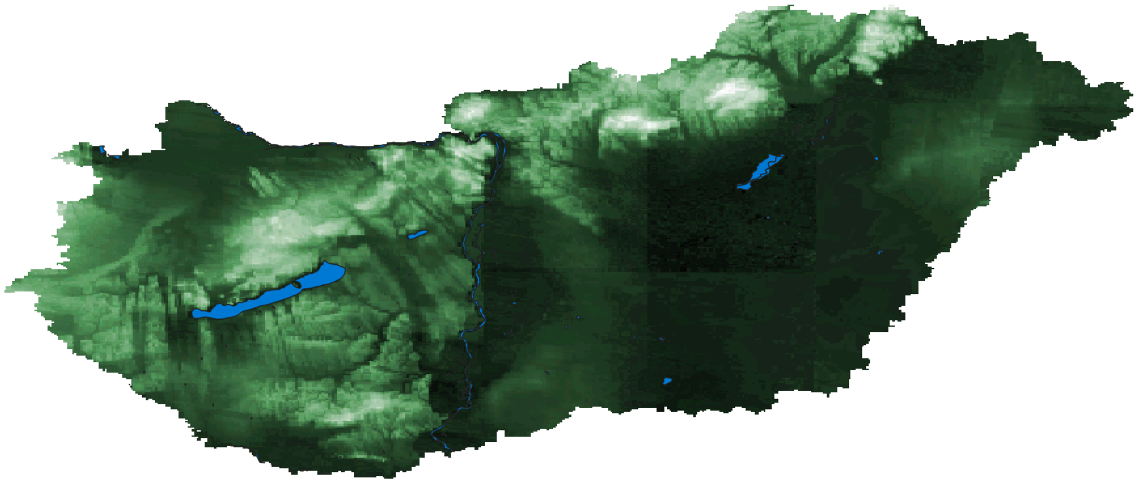

Figure 5. Elevation with major waterways in blue. Danube valley in center.

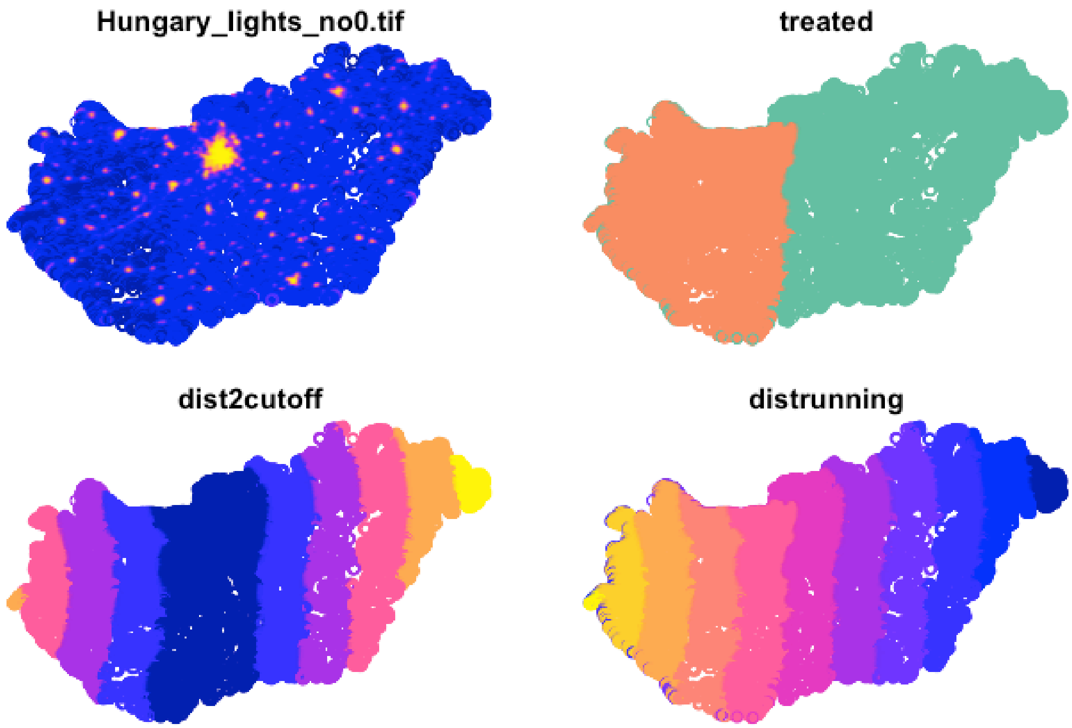

Figure 6. Visualizations showing lights as point geometries, with treated area, distance to the cutoff, and cutoff centered at zero.

9. Appendix

```
library(tmap)
library(maptools)
library(raster)
library(SpatialRDD)
library(ggplot2)
library(sf)
library(stars)
library(rgdal)
library(rdrobust)
library(xtable)
library(stargazer)
library(lwgeom)
library(margins)


#loading tif files into stata
hungary <-raster("~/Desktop/DFP/tif files/Hungary_lights_no0.tif")
hungary
plot(hungary)
col = heat.colors(63)
cellStats(hungary, range)
image(hungary, col=col)

# creating plot of hungary lights
hungary2 <- as.data.frame(hungary)
hist(hungary2$Hungary_lights_no0)

# plot of the brightest regions
image(hungary, zlim=c(50,63), col=col)

# loading as a stars object to convert to sf object
hungary_stars <- read_stars("~/Desktop/DFP/tif files/Hungary_lights_no0.tif")
plot(hungary_stars)
# this converts all pixels to point geometries
hungary.sf <- st_as_sf(hungary_stars, as_points = TRUE,
  merge = FALSE, long = TRUE, crs = 4326, coords = c("x", "y"))
plot(hungary.sf)

#importing discontinuity/danube. For some reason "~" doesn't work here
danube <- readOGR(dsn="/Users/andrewfox/Desktop/DFP/danube", layer="discont")
plot(danube)

danube.sf <- st_read("/Users/andrewfox/Desktop/DFP/danube", layer = "discont")
ggplot()+geom_sf(data=danube.sf)

# loading elevation data and merging with luminosity
hungary_elev_stars <- read_stars("~/Desktop/DFP/tif files/Hungary_elevation.tif")
plot(hungary_elev_stars)
hungary.elev.sf <- st_as_sf(hungary_elev_stars,
  as_points = TRUE, merge = FALSE, long = TRUE, crs = 4326, coords = c("x", "y"))
hungary.sf <- st_join(hungary.sf, hungary.elev.sf, join = st_nearest_feature)

# loading and merging population density data
hungary_pop_stars <- read_stars("~/Desktop/DFP/hungary.pop.tif")
```

```
hungary.pop.sf <- st_as_sf(hungary_pop_stars,
  as_points = TRUE, merge = FALSE, long = TRUE, crs = 4326, coords = c("x", "y"))
hungary.sf <- st_join(hungary.sf, hungary.pop.sf, join = st_nearest_feature)

# loading and merging soil data
hungary_soil_stars <- read_stars("~/Desktop/DFP/soil.tif")
hungary.soil.sf <- st_as_sf(hungary_soil_stars,
  as_points = TRUE, merge = FALSE, long = TRUE, crs = 4326, coords = c("x", "y"))
hungary.sf <- st_join(hungary.sf, hungary.soil.sf, join = st_nearest_feature)

# coding as factor variable
hungary.sf$soil.tf.f <- factor(hungary.sf$soil.tif)
is.factor(hungary.sf$soil.tf.f)

# a plot with the boundary
plot(hungary)
plot(danube, add = TRUE)

#importing the treatment polygon cut in QGIS
treat <- readOGR(dsn="/Users/andrewfox/Desktop/DFP/treatment", layer="treat")
plot(hungary)
plot(treat, add = TRUE)

treat.sf <- st_read("/Users/andrewfox/Desktop/DFP/treatment", layer = "treat")
ggplot()+geom_sf(data=treat.sf)
# setting the coordinate system, so they are consistent
st_crs(treat.sf) = 4326
st_crs(hungary.sf) = 4326
st_crs(danube.sf) = 4326

# creating the treatment area
hungary.sf$treated <- assign_treated(hungary.sf, treat.sf, id = "geometry")
# a warning appears, but for this small area, it shouldn't be a problem
summary(hungary.sf$treated)

# creating ln of luminosity
hungary.sf$log_lights <- log(hungary.sf$Hungary_lights_no0.tif)

# a first simple pooled binary variable regression
lm1 <- lm(log_lights ~ treated, data = hungary.sf)
lm2 <- lm(log_lights ~ treated + Hungary_elevation.tif
          + hungary.pop.tif + soil.tf.f , data = hungary.sf)

# calculating distance between each point and the danube
hungary.sf$dist2cutoff <- as.numeric(sf::st_distance(hungary.sf, danube.sf))
summary(hungary.sf$dist2cutoff)

# simple pooled regression within 3,5,10 km distance
lm4 <- lm(log_lights ~ treated + Hungary_elevation.tif
          + hungary.pop.tif, data = hungary.sf[hungary.sf$dist2cutoff < 5000, ])
lm5 <- lm(log_lights ~ treated + Hungary_elevation.tif
          + hungary.pop.tif + soil.tf.f, data = hungary.sf[hungary.sf$dist2cutoff <
                                                          10000, ])
lm6 <- lm(log_lights ~ treated + Hungary_elevation.tif
          + hungary.pop.tif + soil.tf.f, data = hungary.sf[hungary.sf$dist2cutoff <
                                                          3000, ])
lm7 <- lm(log_lights ~ treated + Hungary_elevation.tif
```

```
          + hungary.pop.tif + soil.tf.f, data = hungary.sf[hungary.sf$dist2cutoff <
                                                                5000, ])
lm8 <- lm(log_lights ~ treated + Hungary_elevation.tif
          + hungary.pop.tif + soil.tf.f, data = hungary.sf[hungary.sf$dist2cutoff <
                                                                10000, ])

stargazer(lm1, lm2, lm6, lm7, lm8, title="Pooled Linear Regressions", align=TRUE)

# note that around the border, the effect is positive

lm3 <- lm(Hungary_lights_no0.tif ~ treated, data = hungary.sf[hungary.sf$dist2cutoff <
                                                                15000, ])
coef(summary(lm3))[, "Std. Error"]


# re-centering data at zero
hungary.sf$distrunning <- hungary.sf$dist2cutoff
hungary.sf$distrunning[hungary.sf$treated == 0] <- -1 *
    hungary.sf$distrunning[hungary.sf$treated == 0]

# plot of lights around Danube
ggplot(data = hungary.sf, aes(x = distrunning, y = Hungary_lights_no0.tif))
+ geom_point() + geom_vline(xintercept = 0, col = "red")

# "naive" rdd with local linear estimation
covs1 <- cbind(hungary.sf$Hungary_elevation.tif, hungary.sf$hungary.pop.tif)
covs2 <- cbind(hungary.sf$Hungary_elevation.tif, hungary.sf$hungary.pop.tif,
               hungary.sf$soil.tf.f)
rd1 <- rdrobust(hungary.sf$log_lights, hungary.sf$distrunning, c = 0)
rd1.1 <- rdrobust(hungary.sf$log_lights, hungary.sf$distrunning, c = 0, p = 2)
rd2 <- rdrobust(hungary.sf$log_lights, hungary.sf$distrunning, covs =
                  hungary.sf$Hungary_elevation.tif, c = 0)
rd3 <- rdrobust(hungary.sf$log_lights, hungary.sf$distrunning, covs = covs1, c = 0)
rd4 <- rdrobust(hungary.sf$log_lights, hungary.sf$distrunning, covs = covs2, c = 0)
rd5 <- rdrobust(hungary.sf$log_lights, hungary.sf$distrunning, covs = covs1, c = 0, p=2)
rd6 <- rdrobust(hungary.sf$log_lights, hungary.sf$distrunning, covs = covs2, c = 0, p =2)

rdplot(hungary.sf$log_lights, hungary.sf$distrunning, covs = covs2, c = 0, p =2,
       y.label = "Luminosity", x.label = "distance to border")

rdplot(hungary.sf$log_lights, hungary.sf$distrunning, covs = covs2, c = 0, p =1,
       y.label = "Luminosity", x.label = "distance to border")

rdplot(hungary.sf$log_lights, hungary.sf$distrunning, covs = covs2, c = 0, p =6, h = 60,
       y.label = "Luminosity", x.label = "distance to border")

rdplot(hungary.sf$Hungary_lights_no0.tif, hungary.sf$distrunning, c = 0, ci = 95,
       kernel = "triangular", y.label = "Luminosity", x.label = "distance to border")

# for a nice 4-part plot
plot(hungary.sf)

# discretize border (approx every 6 kilometers)
borderpoints.sf <- discretise_border(cutoff = danube.sf, n = 50)
borderpoints.sf$id <- 1:nrow(borderpoints.sf)

# approx every 1 kilometer
```

```
borderpoints.sf2 <- discretise_border(cutoff = danube.sf, n = 10)
borderpoints.sf2$id <- 1:nrow(borderpoints.sf2)

# looping over boundary points with spatialrd(), with 50 sections. non-parametric estimate
bdd1 <- spatialrd(y = "log_lights", data = hungary.sf, cutoff.points = borderpoints.sf,
treated = "treated", minobs = 10, spatial.object = F)
knitr::kable(bdd1)
bdd2 <- spatialrd(y = "log_lights", data = hungary.sf, cutoff.points = borderpoints.sf,
                  treated = "treated", minobs = 10, covs = covs1, spatial.object = F)
bdd3 <- spatialrd(y = "log_lights", data = hungary.sf, cutoff.points = borderpoints.sf,
                  treated = "treated", minobs = 10, covs = covs2, spatial.object = F)
```

```
plotspatialrd(bdd2, map = T)

#calculating average treatment effect
mean(bdd1$Estimate)
mean(bdd1$pvalR)

# poisson regressions
m1 <- glm(Hungary_lights_no0.tif ~ treated + Hungary_elevation.tif
          + hungary.pop.tif + soil.tf.f, family="poisson", data=hungary.sf)

m2 <- glm(Hungary_lights_no0.tif ~ treated + Hungary_elevation.tif
          + hungary.pop.tif + soil.tf.f, family="poisson",
          data=hungary.sf[hungary.sf$dist2cutoff < 3000, ])

m3 <- glm(Hungary_lights_no0.tif ~ treated + Hungary_elevation.tif
          + hungary.pop.tif + soil.tf.f, family="poisson",
          data=hungary.sf[hungary.sf$dist2cutoff < 5000, ])

m4 <- glm(Hungary_lights_no0.tif ~ treated + Hungary_elevation.tif
          + hungary.pop.tif + soil.tf.f, family="poisson",
          data=hungary.sf[hungary.sf$dist2cutoff < 10000, ])

# seeing marginal effects
margins(m1)
margins(m2)
margins(m3)
margins(m4)

# compiling to LaTeX table!
stargazer(m1,m2,m3,m4)

# woohoo!
```