Neuroscience and Geographic Information Systems to investigate the impact of global warming on mood disorders and brain plasticity in urban areas

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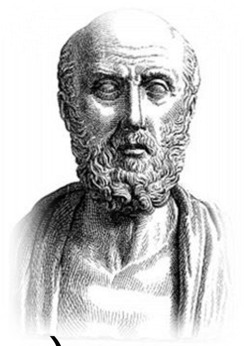
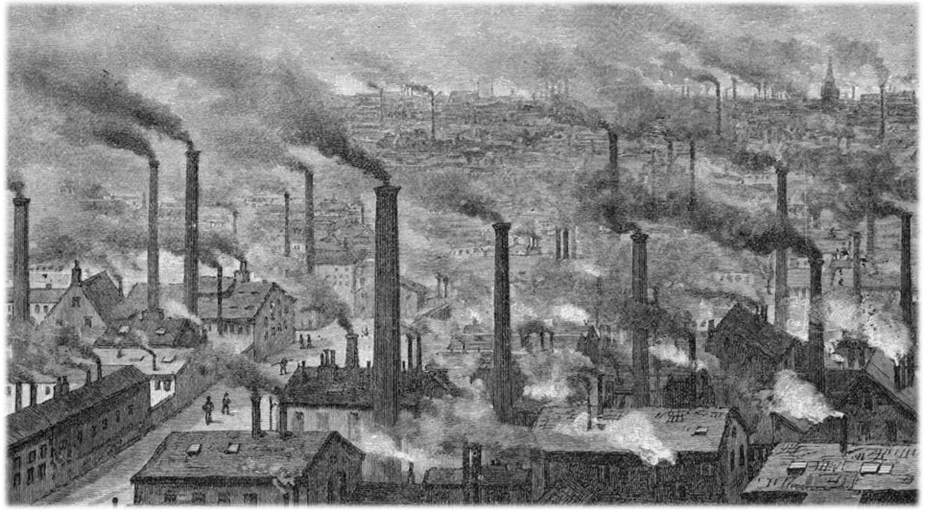
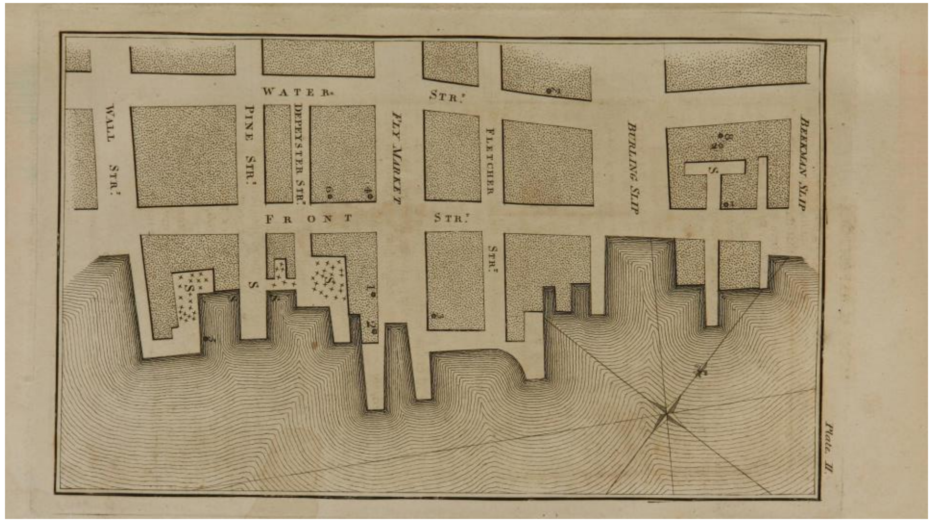
Health and place

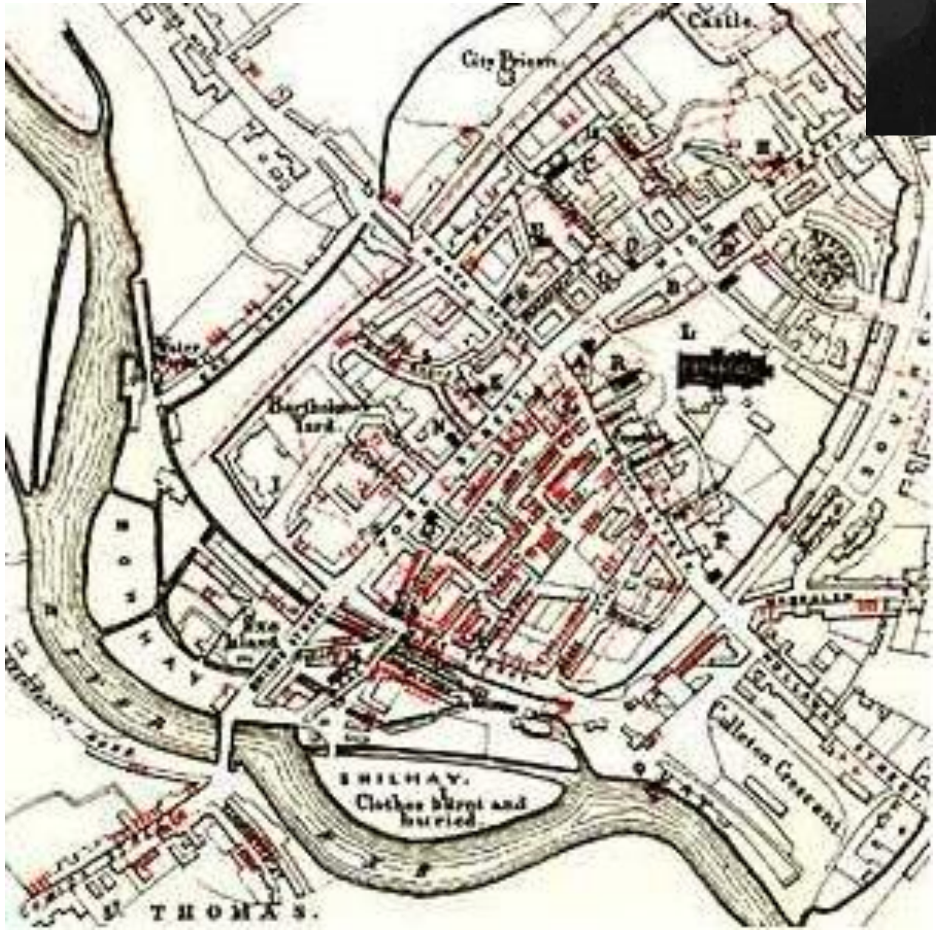


- The study of the relationship between health and place: Hippocrates
- "Airs, waters, and places" influences a whole section of medicine (more than 2,000 years ago)
- Air and water quality must be considered, but also the socio-economic environment and behaviors
- Medical geography: largely based on associations between health and place
- Industrial revolution in the 18th Century: many public health issues
- Emergence of medical cartography
- Need to inform about risk areas where tuberculosis, cholera or yellow fever appear most frequently
- Map by Valentine Seaman, yellow fever cases, 1795



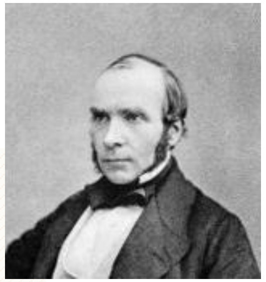


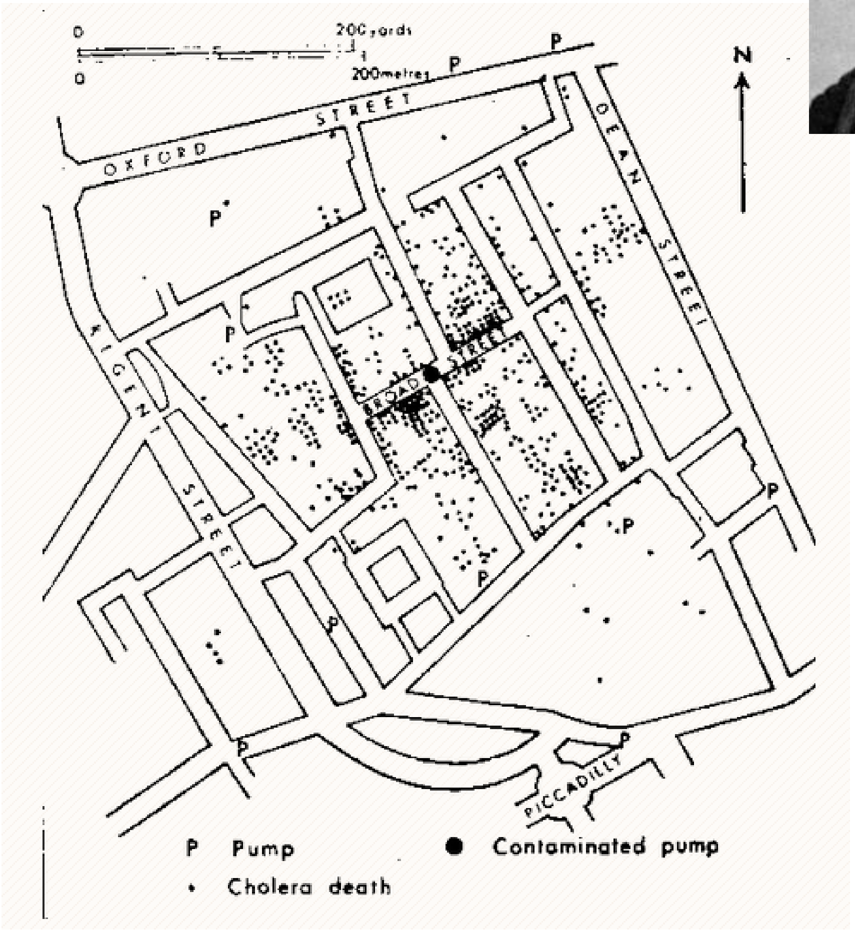
Thomas Shapter



Exeter 1832

John Snow





London, 1854

Jacques May (1896-1975)

- French surgeon
- Notices differences between health status of patients according to the regions from which they came
- Understanding the nature of the relationships between pathogen transmission and geographic factors
- Beginnings of a systematic formulation of **medical geography**
- Cooperation between a medical doctor and a geographer or engineer
- E.g. John Snow (medical doctor) and Edmund Cooper (civil engineer)

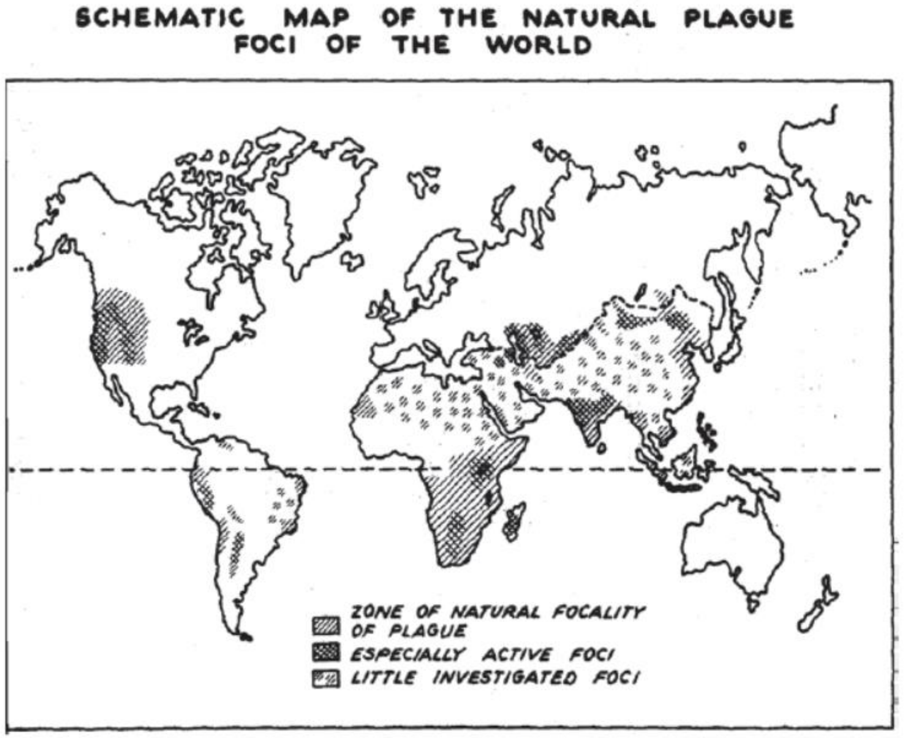


Figure 9.2| May's schematic map of plague foci, distinguishing between environments where plague was known, recurrent, and in some cases, epidemic. Source: May, American Geographical Society (1961).

Geography and medicine

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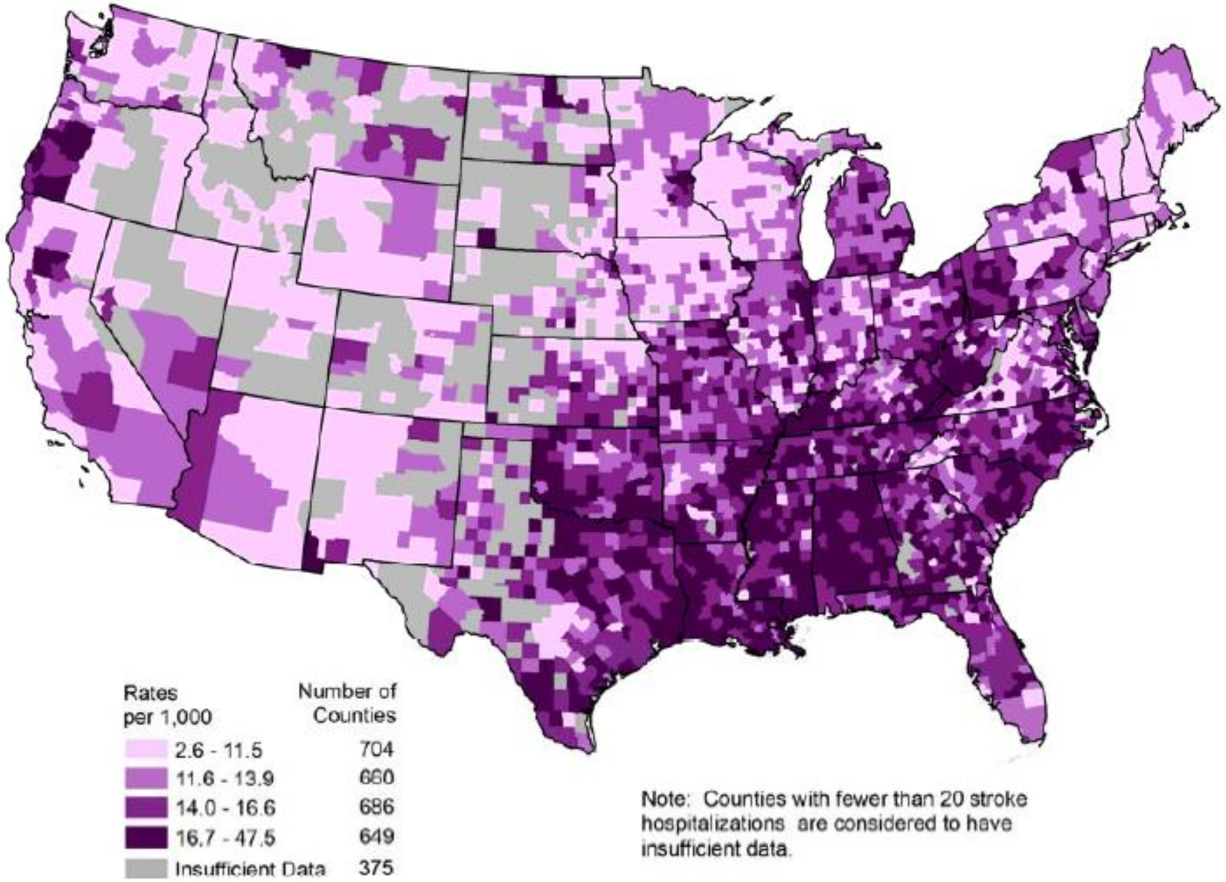
Toward more precision in medical geography

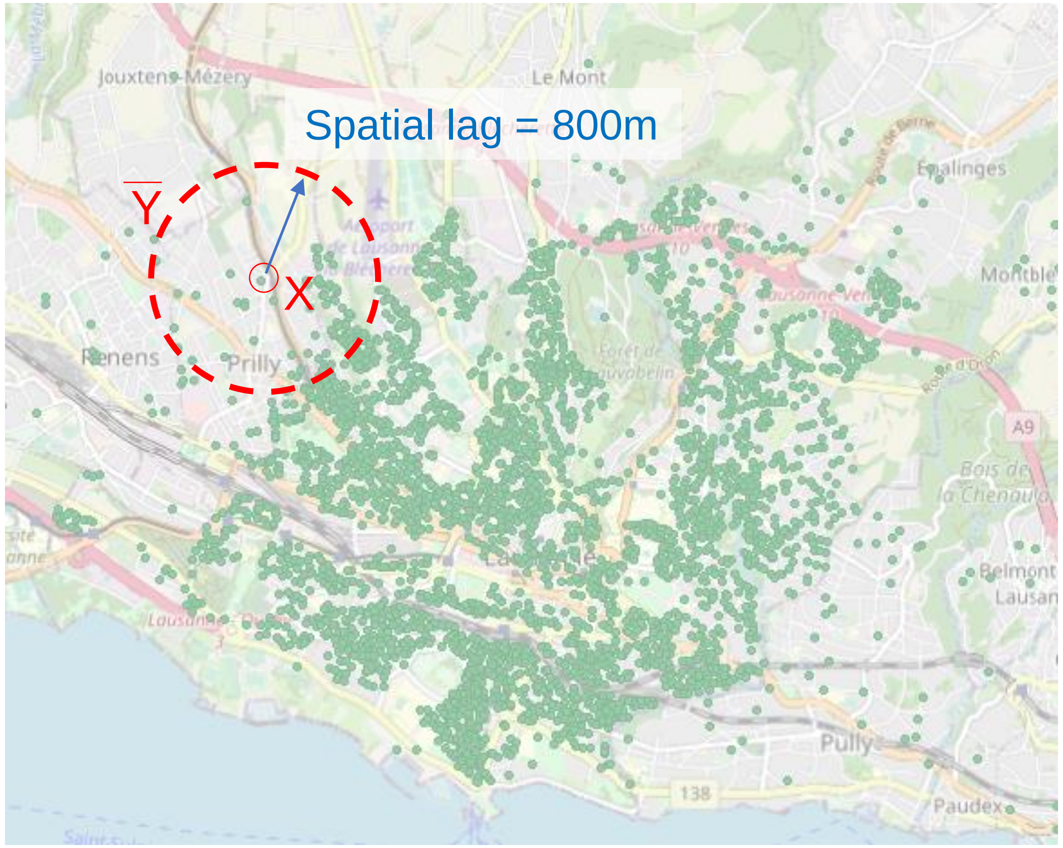
- In spatial epidemiology, geolocated data usually aggregated within administrative units
- Here: stroke hospitalization rates of medicare beneficiaries aged 65 or older in 2005-2006 at the county level
- Poses methodological problems like ecological fallacy or Modifiable Areal Unit Problem (MAUP)
- For what use and effectiveness in public health, in the field of prevention in particular?

- GIRAPH's contribution towards precision public health…



Working with georeferenced individual data

- Participants in medical cohorts precisely located in space
- Method: georeferencing
- X,Y (geographic coordinates) of places of residence (Rue Neuve 14, 1009 Pully)
- First law of geography "Everything is related to everything else, but near things are more related than distant things" (Tobler, 1970)
- Measuring spatial dependence

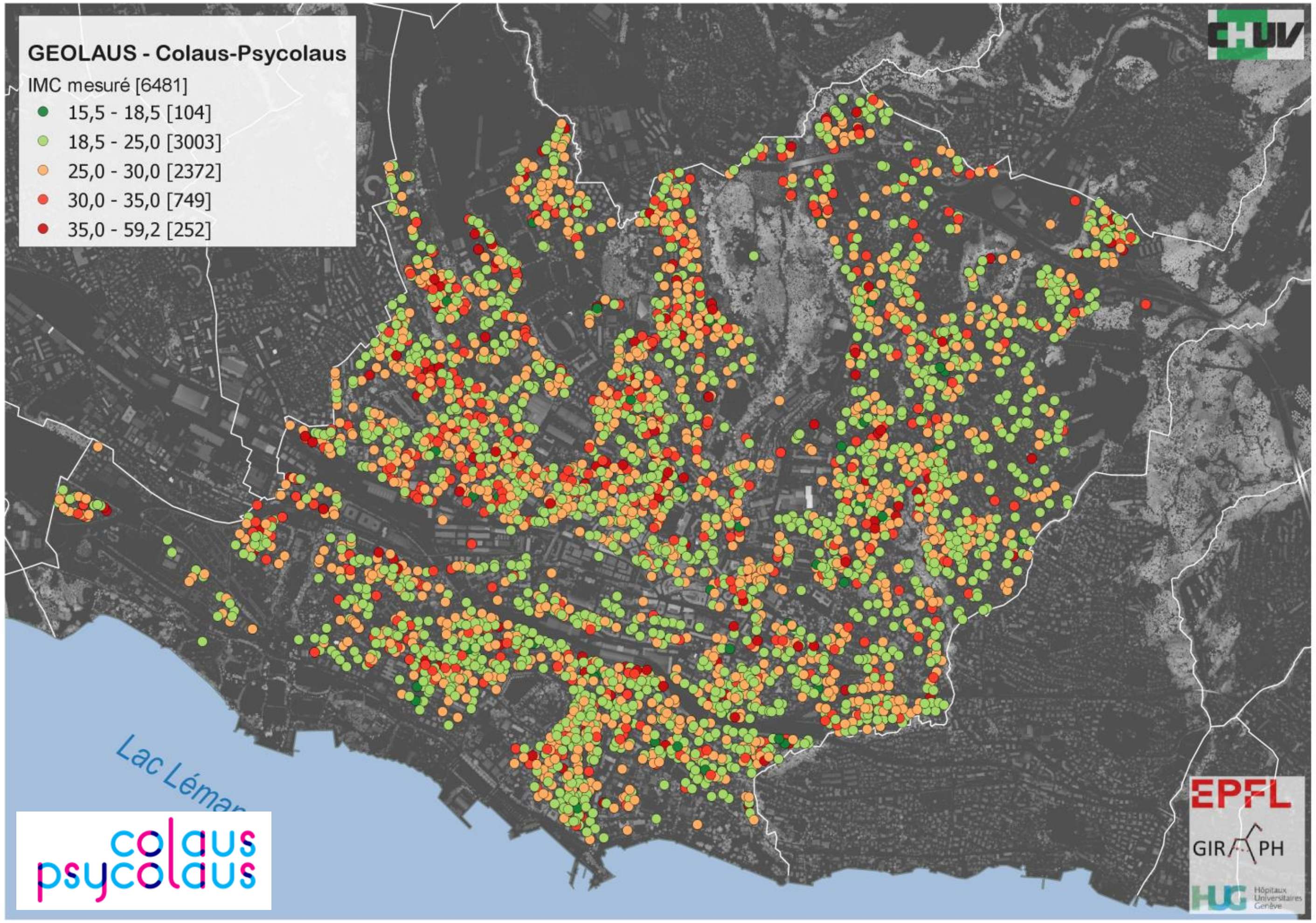


Does X look like $\bar{Y}$?

Without Tobler’s law

- No detectable signal through standard thematic mapping

Classification en fonction de l'indice de masse corporelle	
Insuffisance pondérale	< 18.5
Éventail normal	18.5 - 24.9
Surpoids	⩾ 25.0
Préobésité	25.0 - 29.9
Obésité	⩾ 30.0
Obésité, classe I	30.0 - 34.9
Obésité, classe II	35.0 - 39.9
Obésité, classe III	⩾ 40.0



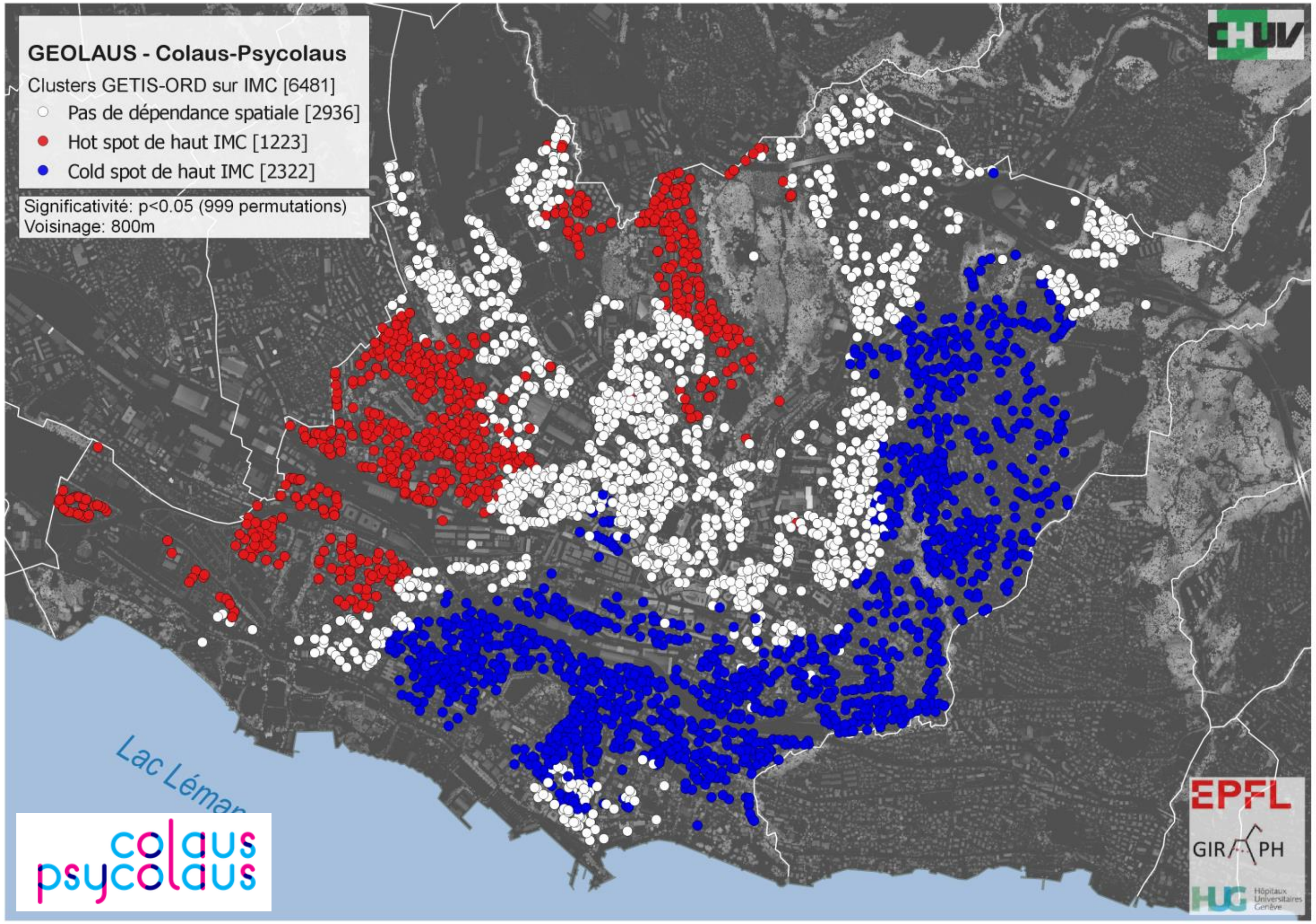
Body Mass Index, Colaus-PsyColaus cohort

Joost et al. 2016

Spatial statistics based on spatial dependence concept

- Specific statistical tools
- Key to make the invisible visible!
- Open doors for spatial data exploration

- Potential to develop targeted prevention actions where needed!

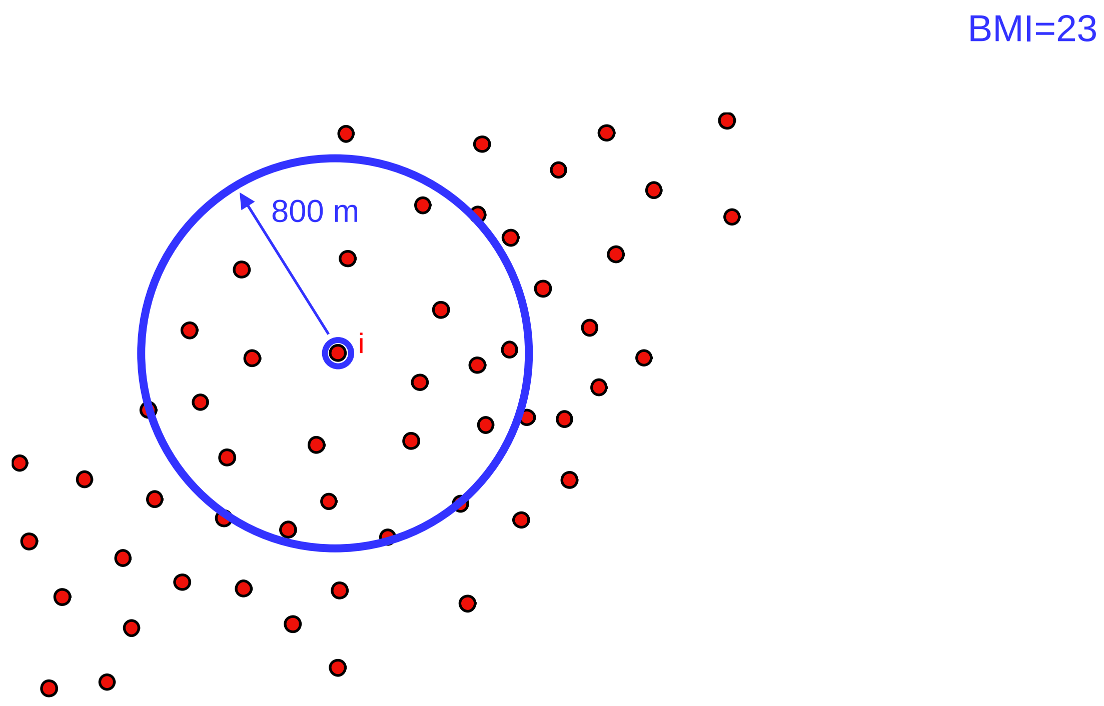


Body Mass Index, Colaus-PsyColaus cohort

Joost et al. 2016

How to measure spatial dependence?

- Use neighborhood relationships
- "How much" an individual resembles his neighbors in a given neighborhood (e.g. 800m)
- Example with body mass index (BMI) and Getis-Ord statistics (Getis & Ord, 1992)
- BMI = $\frac{Weight}{(Height)^2}$



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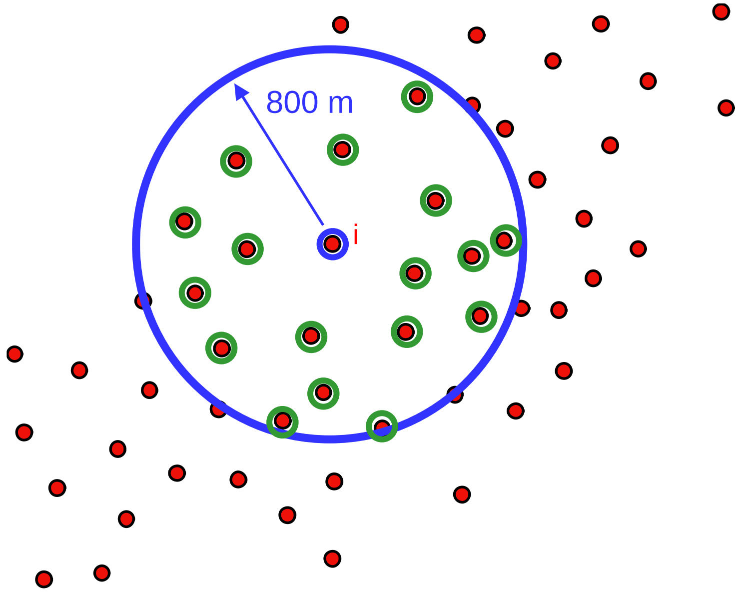

BMI=23
BMI=21
BMI =27
BMI =23
BMI =29
BMI =23
BMI =33
BMI =35
BMI =18
BMI =23
BMI =22
BMI =26
BMI =27
BMI =27
BMI =25
BMI =21

$\overline{BMI}_i = 25.18$

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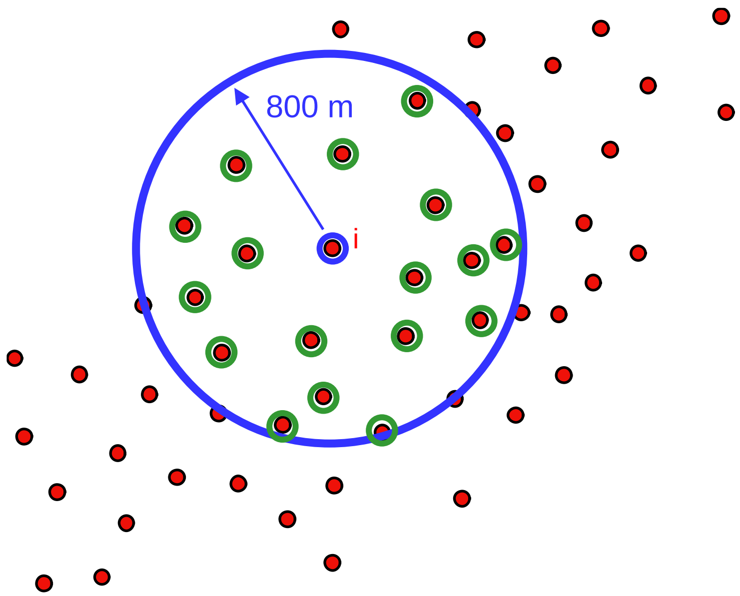

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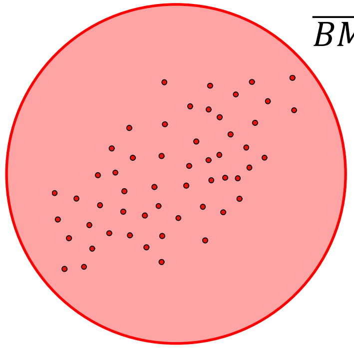


$\overline{BMI_g} = 22$

As $25.18 > 22$ $\rightarrow$

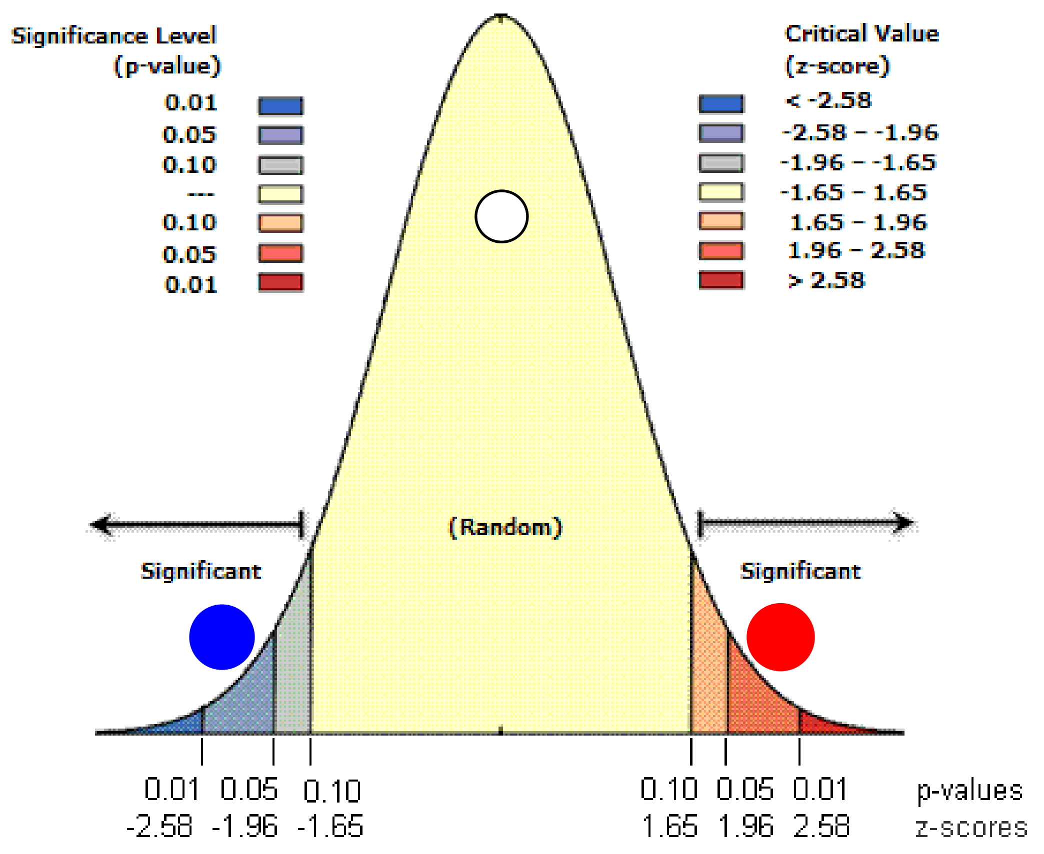
If $IMC_i < 22$ $\rightarrow$

Idem for all points in the dataset

Spatial dependence or random distribution?

- Null hypothesis: the observed local value is not different from the general mean
- T-test* to compare the means of two groups, random permutations

- **Significantly lower than the general average**, the value depends on its geographical location
- **Random value**, does not depend on its geographical location
- **Significantly higher than the general average**, the value depends on its geographical location



Impact of global warming on human health

- The impact of global warming on human health was investigated in various studies
- It is likely to affect not only physical but also mental health (Padhy et al., 2015)
- Previous research has shown evidence connecting mental disorders, specifically <u>anxiety</u>, with extreme weather events (Palinkas & Wong, 2020)
- The fact of merely contemplating climate change and its potential consequences in the future can also contribute to mental distress (Palinkas & Wong, 2020)

Rising Land Surface Temperature (LST)

- Rising land surface temperature (LST) has resulted in more prolonged and intense heatwaves
- In urban areas, air temperature is higher compared to rural areas, especially during the summer months (heat island effect)
- During nighttime, urban areas show temperatures that are 5-7°C higher than natural surroundings (Wicki et al. 2018; MeteoSwiss, 2023)
- Risk to human well-being (Berry et al., 2010) and health (Hondula et al., 2015)
- Association is observed between heatwaves and mental disorders (Thompson et al., 2018)
- A temperature increase of 1°C over five years is linked to a 2% rise in mental health problems (Obradovich et al. 2018)

Effect of rising temperatures on brain structures

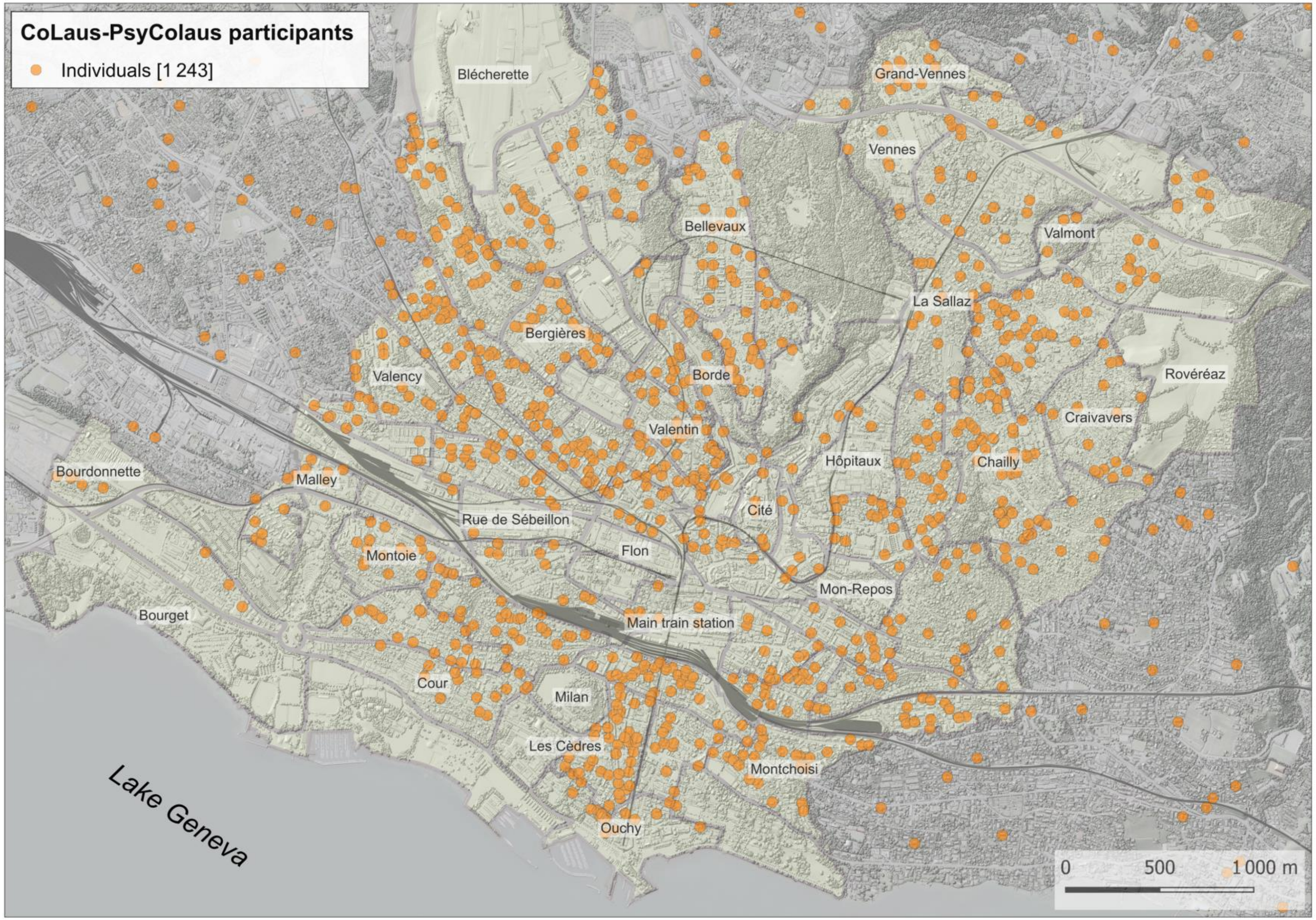
- Rising temperatures also have an effect on brain structures
- Difficult to clearly identify the influence of global warming on neurological disorders (Amiri et al., 2021)
- Evidence available to date indicates that climate change will have a significant impact on the prevalence of major neurological diseases (Louis et al., 2023).

Impact of increased LST on mood disorders & brain white matter

- Use of georeferenced information (place of residence), GIS and spatial statistics to investigate relationships between LST, mental health, and brain plasticity
- Population-based data collected in Lausanne (Firmann et al., 2008; Preisig et al., 2009)
- Examine the impact of increased LST on mood disorders, on brain white matter characteristics recorded by means of Magnetic Resonance Imaging (MRI)
- Hypotheses: a) high LST values are associated with low mental health and high anxiety; b) relationships exist between global warming (as translated by higher LST) mood disorders and white matter microstructure

Data

- Study area: dense Lausanne urban area (mainly Lausanne municipality)



Health data

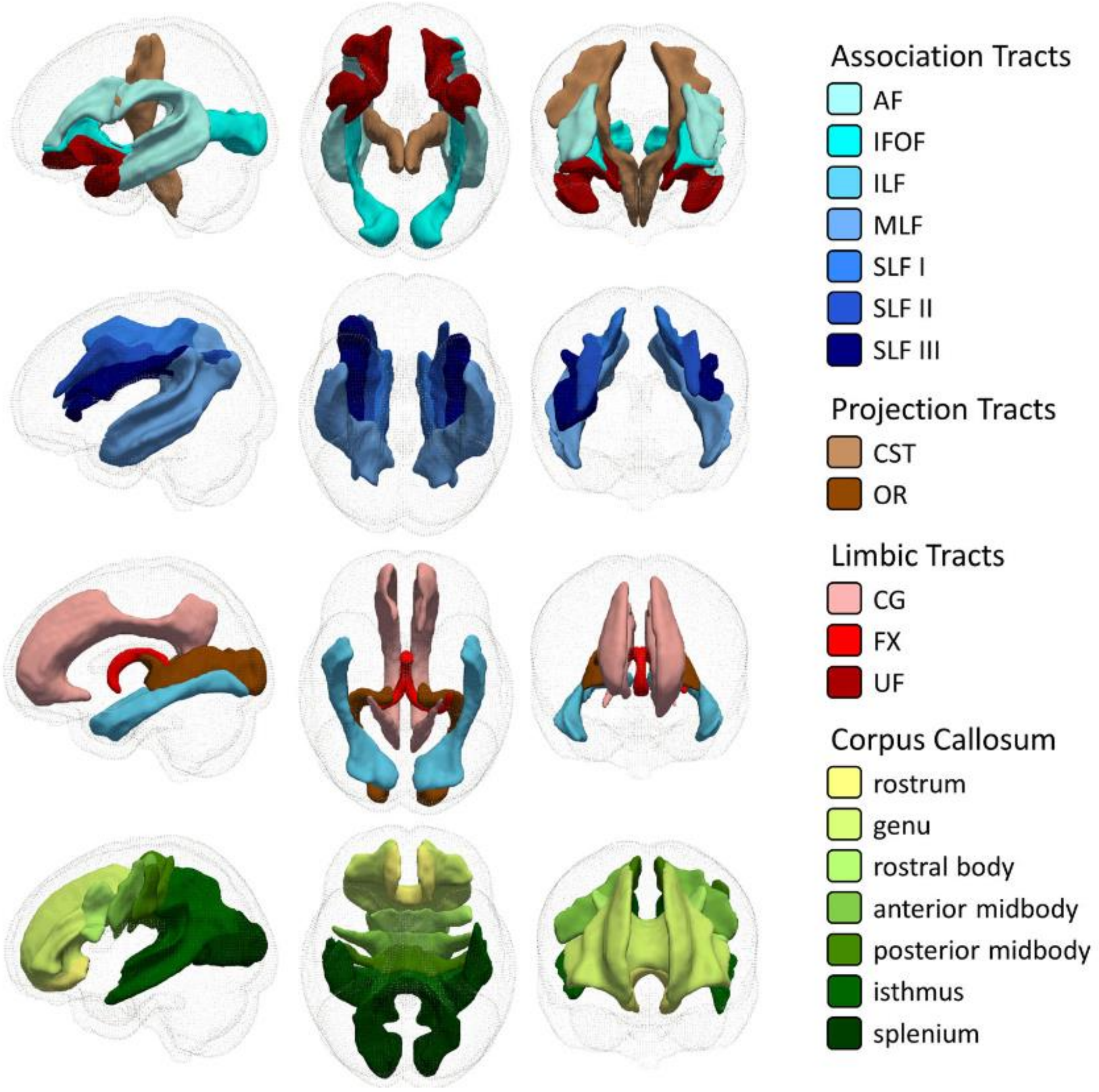
- CoLaus-PsyColaus longitudinal study initiated in 2003 with 5-yearly follow-ups (FU1: 2009-2012; FU2: 2014-2017; FU3: 2018-2021)
- At baseline, 6733 individuals aged 35 to 75 years old (Firmann et al., 2008; Preisig et al., 2009)
- Mood data used were collected during the second follow-up (FU2)
- MRI was used to acquire brain structure data from subjects during follow-ups 2 and 3

Mood data

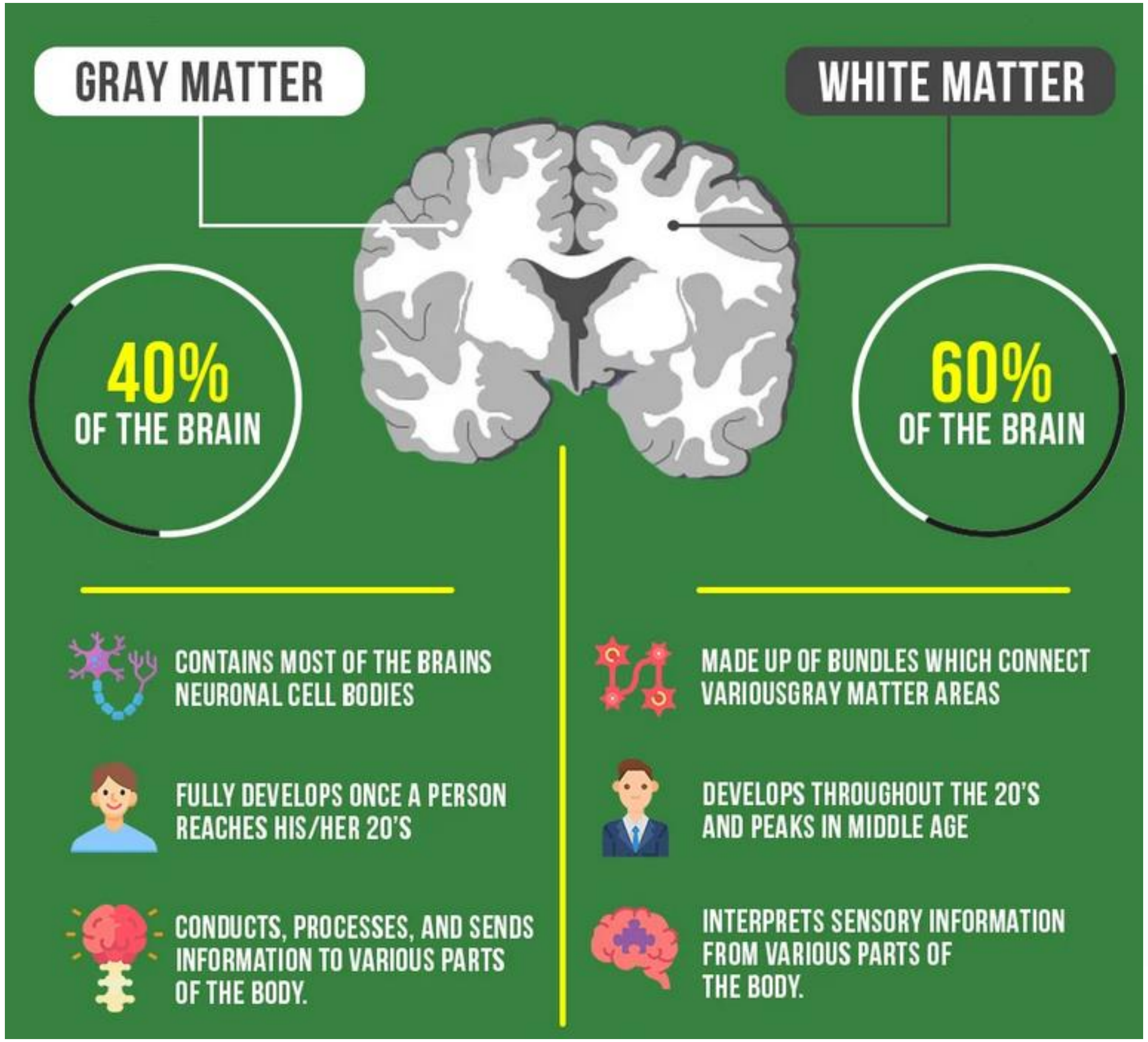
- Anxiety levels → State Trait Anxiety Inventory (STAI) (Spielberger's et al. 1983)
- Score ranging between 20 and 80, with higher values corresponding to higher levels of anxiety – data collected through questionnaires
- Affective components of social, occupational, and psychological well-being → Global Assessment of Functioning (GAF) (Bell, 1994)
- GAF scores range from 1 to 100, higher scores translate into a better overall well-being – data collected through questionnaires
- STAI state and GAF scores were adjusted for age, gender, and neighborhood median income

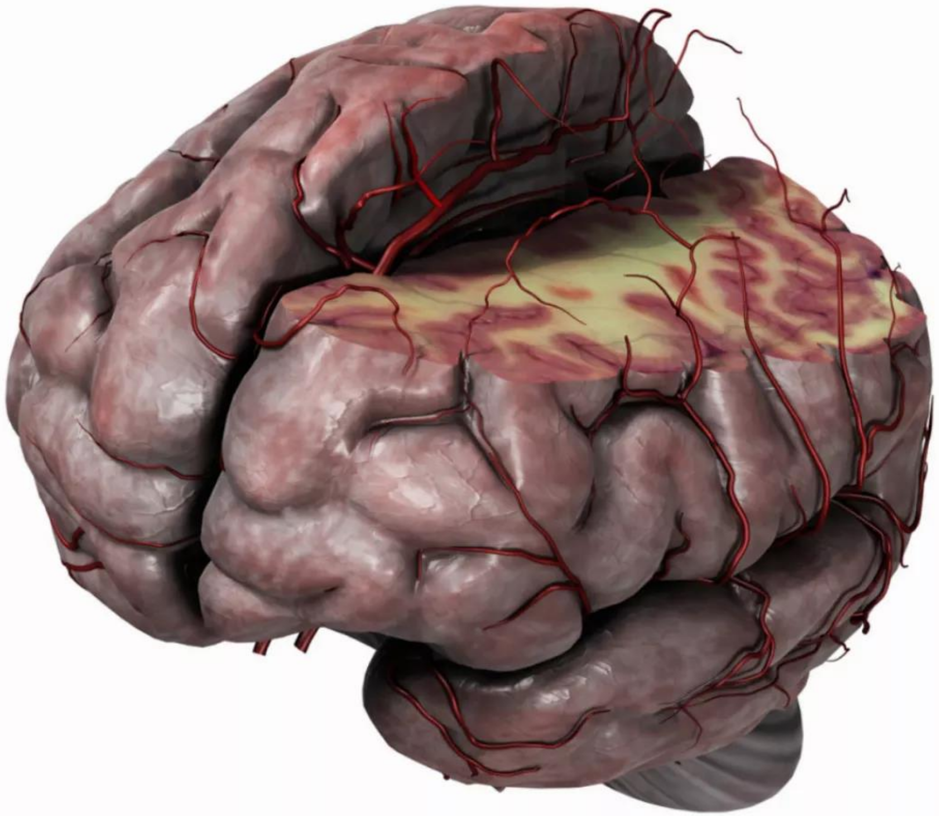
Brain data

- Brain white matter (WM) microstructure
- Investigation of 31 brain tracts identified from MRI-derived maps (Trofimova et al., 2023)
- The maps correspond to measurements of myelin content (MTsat), axonal density (ICVF), free water (ISOVF) and tract volume (number of voxels)



White vs gray matter





Environmental data

- Two types of Land Surface Temperature (LST) measurements
- Characterize the place of residence of the participants

  a) LST for the examination year;
  b) LST delta between two periods: 2004-2012 and 2014-2021

- For each year analyzed, LST was calculated using values from June, July, and August
- Atmospherically Resistant Vegetation Index (ARVI)
  - *(NIR - RED - y * (RED - BLUE))/ (NIR + RED - y*(RED-BLUE))*
  - y = quotient derived from components of atmospheric reflectance in the blue and red channels (Bannari, 1992)

Land Surface Temperature (LST) calculation

- LST was calculated using Landsat satellite imagery (https://landsat.gsfc.nasa.gov/) from the United States Geological Survey (USGS)
- Google Earth Engine platform (GEE; https://earthengine.google.com/) for processing the satellite imagery (Statistical Mono-Window algorithm, Ermida et al. 2020)
- Landsat 5 imagery before 2012, and Landsat 8 for the subsequent years
- 14 images per year to create a single composite image for each summer (median value for each pixel)
- The median images were further aggregated by calculating the mean value over several years

Methodology

- <u>Mood data</u>: calculate the spatial dependence of the variables of interest (GAF and STAI) to identify geographic clusters of high versus low mood values
- Then variance analysis to determine if significant differences exist in LST variables - a) year of examination and b) delta - between the different mood cluster classes identified
- <u>White matter data</u>: first calculation of a linear regression between the MRI-derived maps and LST measurements for each of the 31 tracts
- We only considered significant associations for spatial and variance analysis across identified clusters

Methods

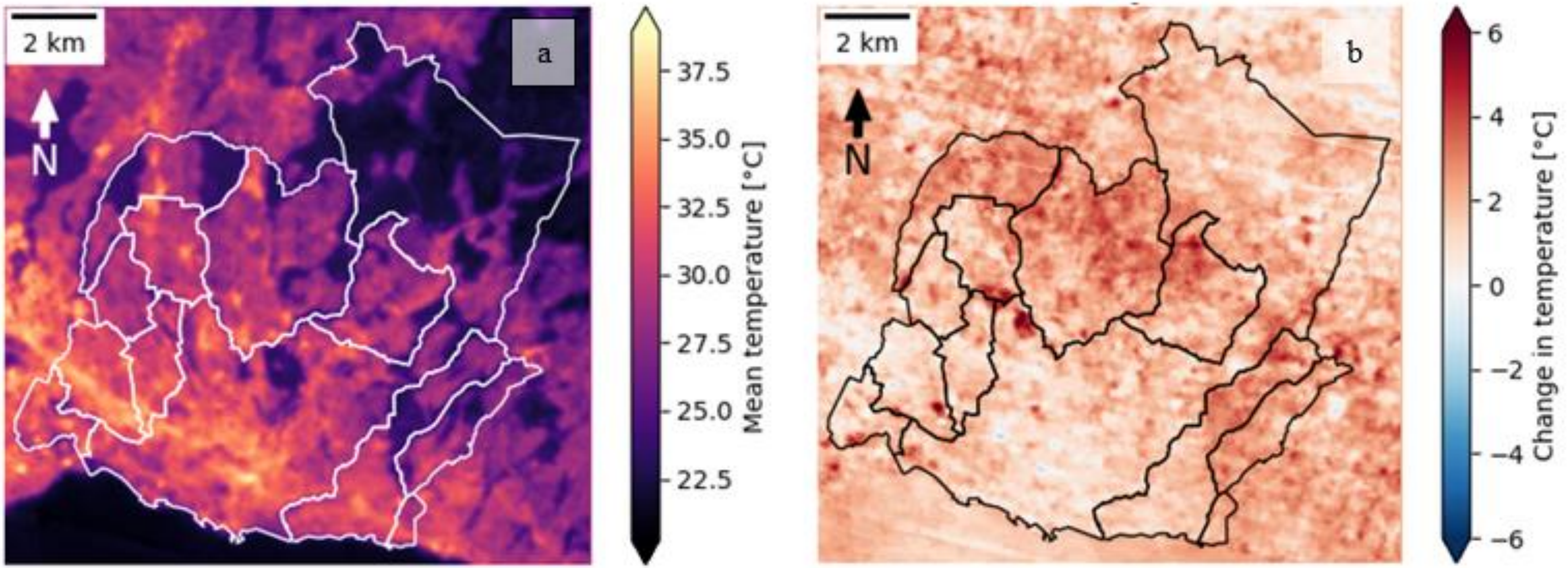
- Georeferencing to assign XY coordinate to home addresses
- Overlay and intersection of home addresses with corresponding LST raster pixel values (30 x 30 m pixels)
- Getis-Ord Gi* statistics to detect spatial clusters of high vs low values of mental health/brain variables
- Variance analysis: is the mean significantly different between clusters? (Levene’s test, Tukey HSD test, Kruskal-Wallis test)
- Linear regression (OLS) to calculate the associations between the MRI-derived maps (myelin content, axonal density, free water and tract volume) and LST of the examination year and LST delta

Results – Participant's characteristics for each health variable

	GAF	STAI	Brain
Follow-Up	F2	F2	First examination in F2 and F3
Total number of subjects	3647	2470	1582
# of subjects analyzed	2991	2174	1258*
% Men/Women**	43.7 / 56.3	42.8 / 57.2	47.6 / 52.4
Mean Age (sd) [years]**	62.9 (10.3)	63.5 (10.1)	63.5 (9.5)

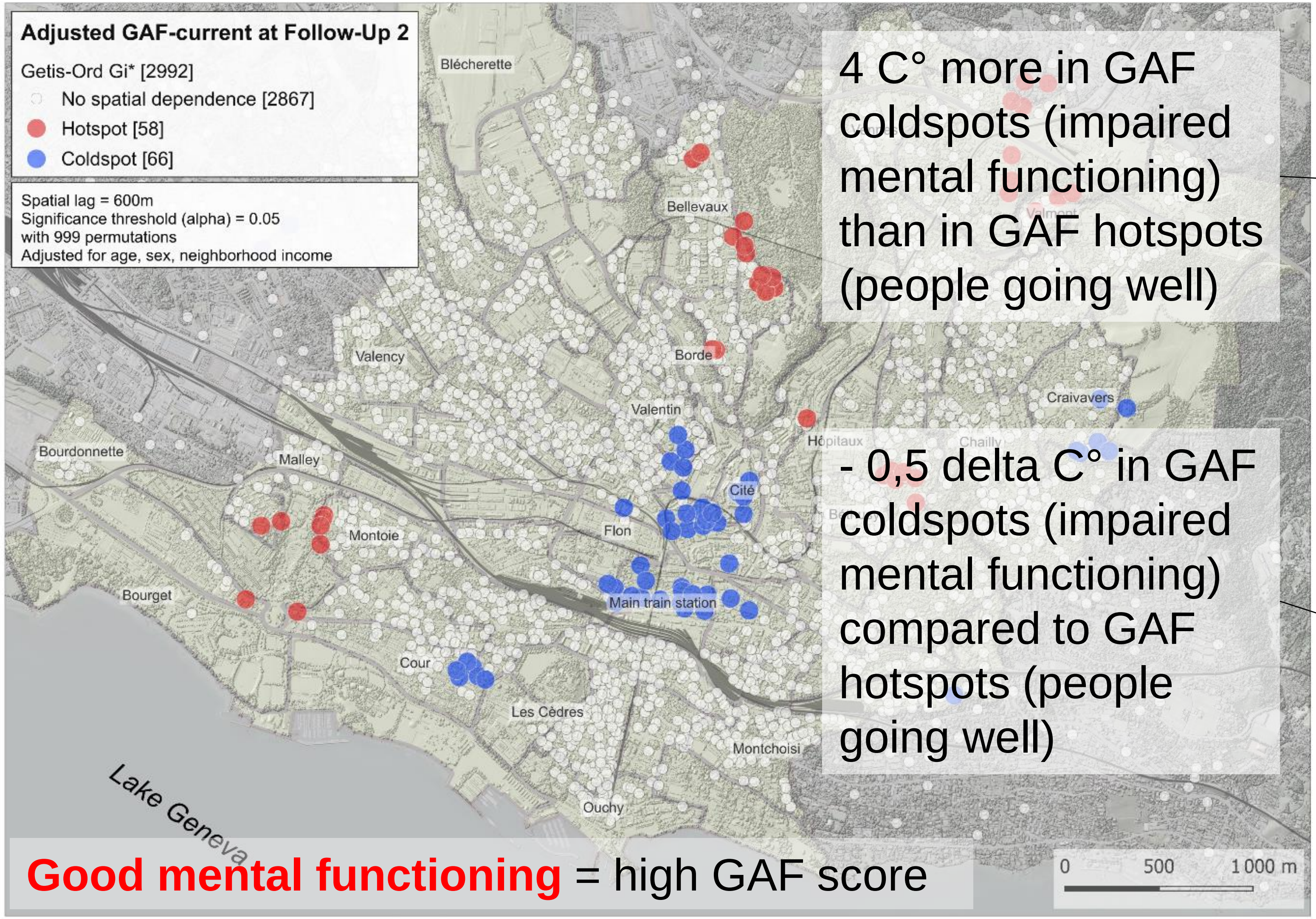
* Depending on the tract and map, subjects with outstanding values (outside the 3-sigma interval around the mean) were excluded from the analysis (on average, 98.9% of the values were within the interval)
** Referring to the number of subjects analyzed

Results – LST and delta LST



On the left (a), average Land Surface Temperature (LST) calculated for each pixel (30m x 30m) between 2014 and 2021 during the months of June, July and August. On the right, average difference in LST between 2014 and 2021. Delta LST = mean(2014-2021) - mean(2004-2012).

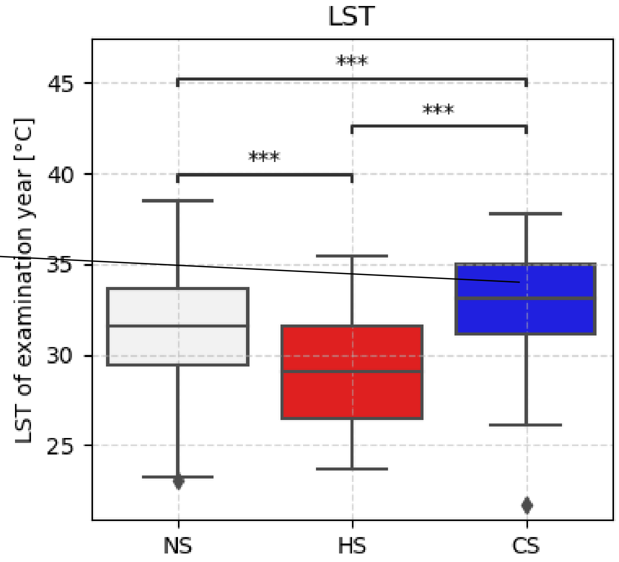
Results – spatial dependence of GAF

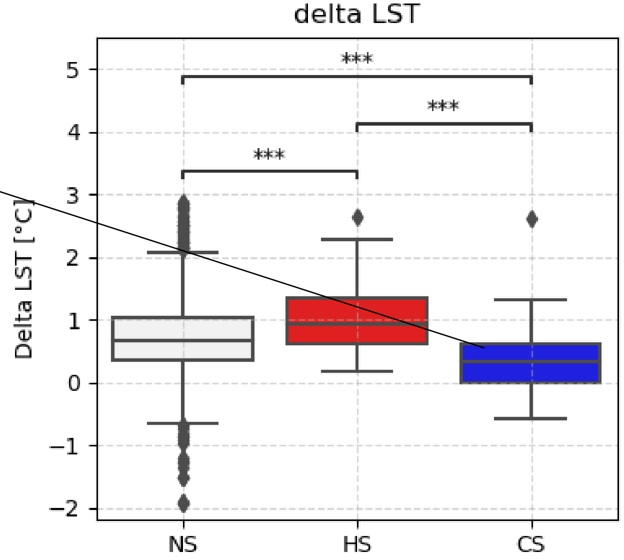


4 C° more in GAF coldspots (impaired mental functioning) than in GAF hotspots (people going well)

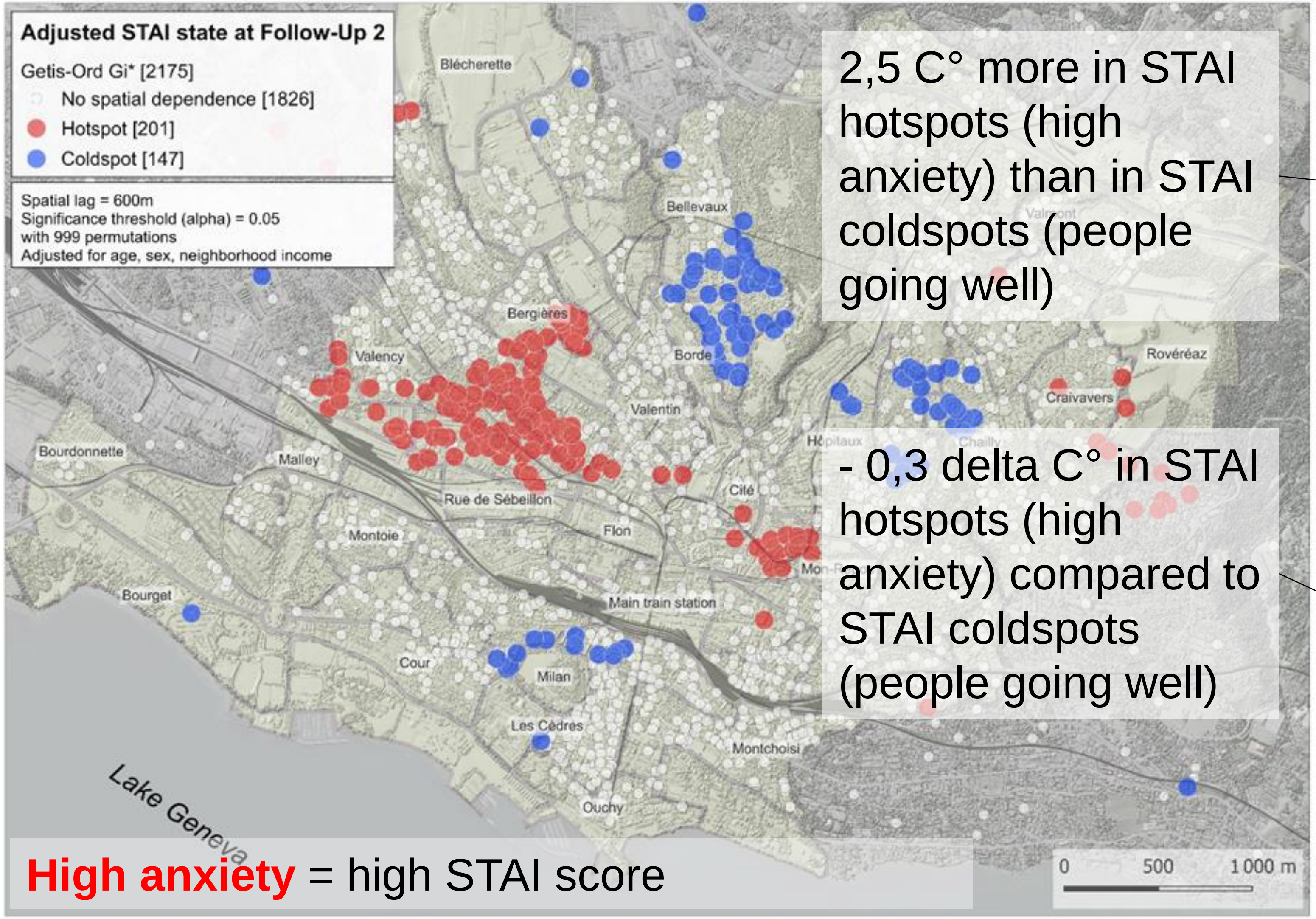
- 0,5 delta C° in GAF coldspots (impaired mental functioning) compared to GAF hotspots (people going well)

Good mental functioning = high GAF score





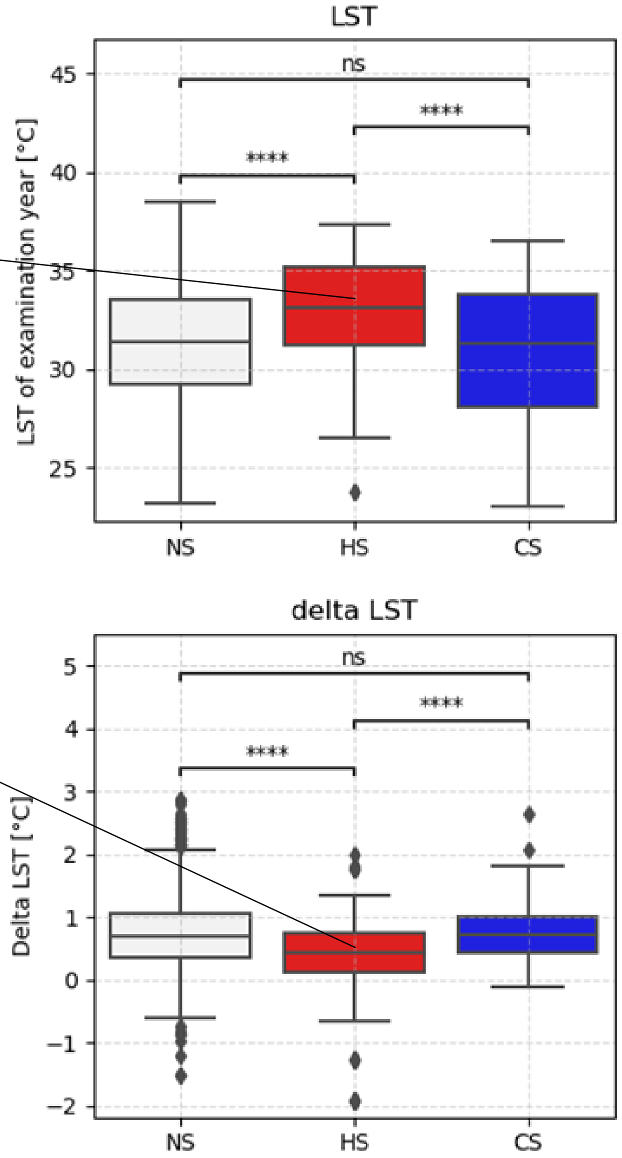
Results – spatial dependence of STAI



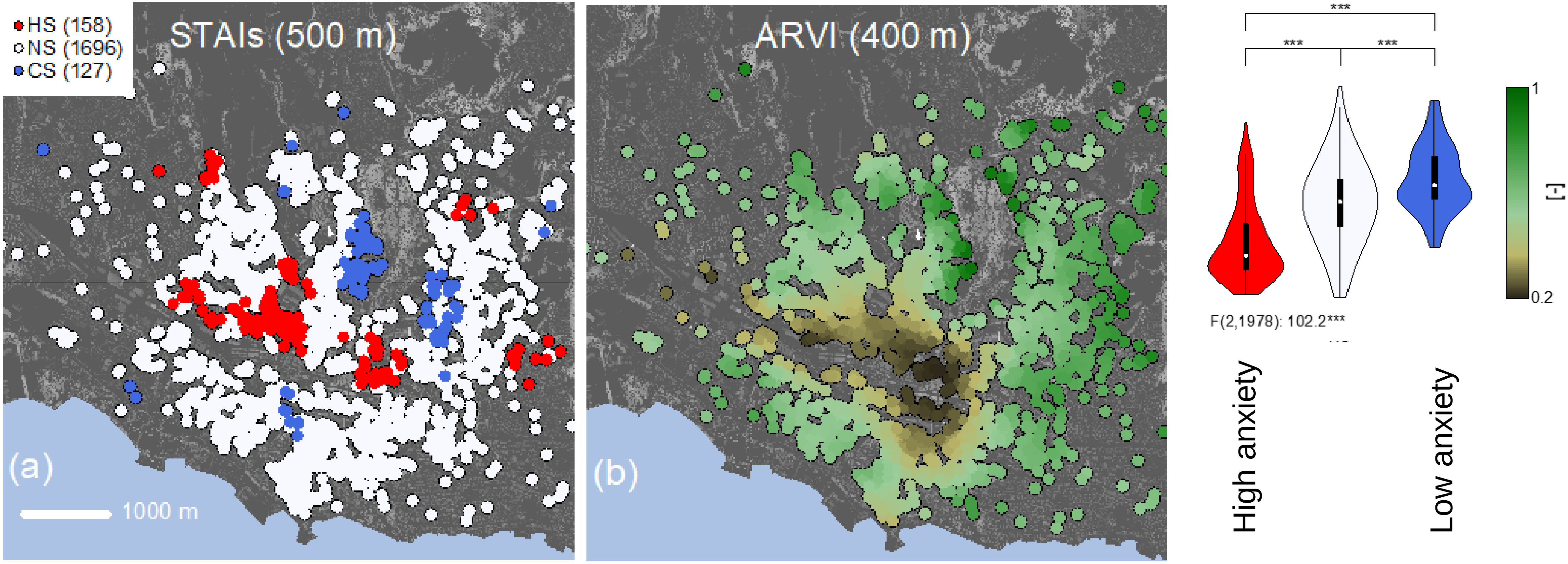
2,5 C° more in STAI hotspots (high anxiety) than in STAI coldspots (people going well)

- 0,3 delta C° in STAI hotspots (high anxiety) compared to STAI coldspots (people going well)

High anxiety = high STAI score

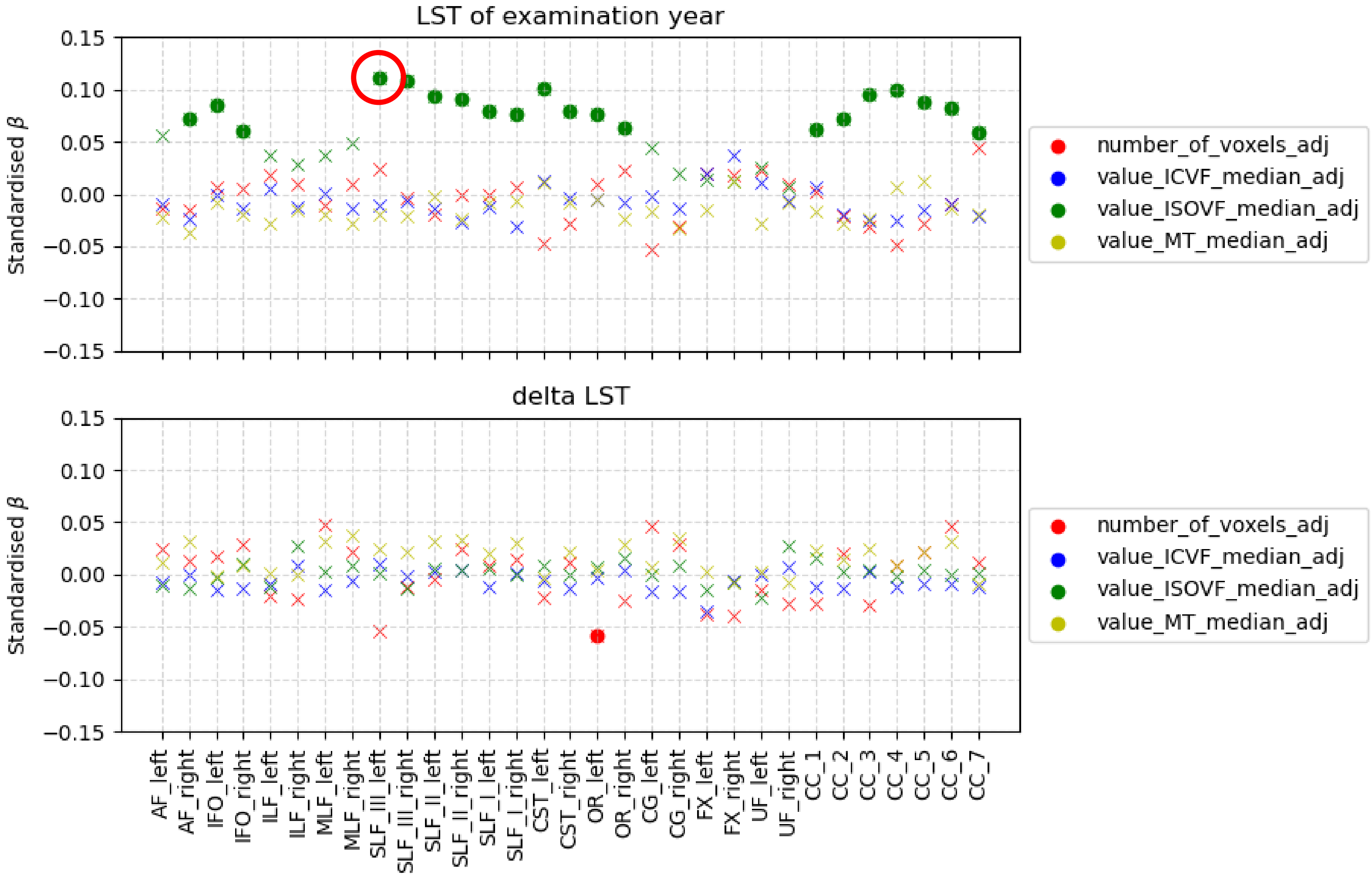


Results – Anxiety and vegetation (ARVI index)



High anxiety = high STAI score

Results – Brain’s white matter

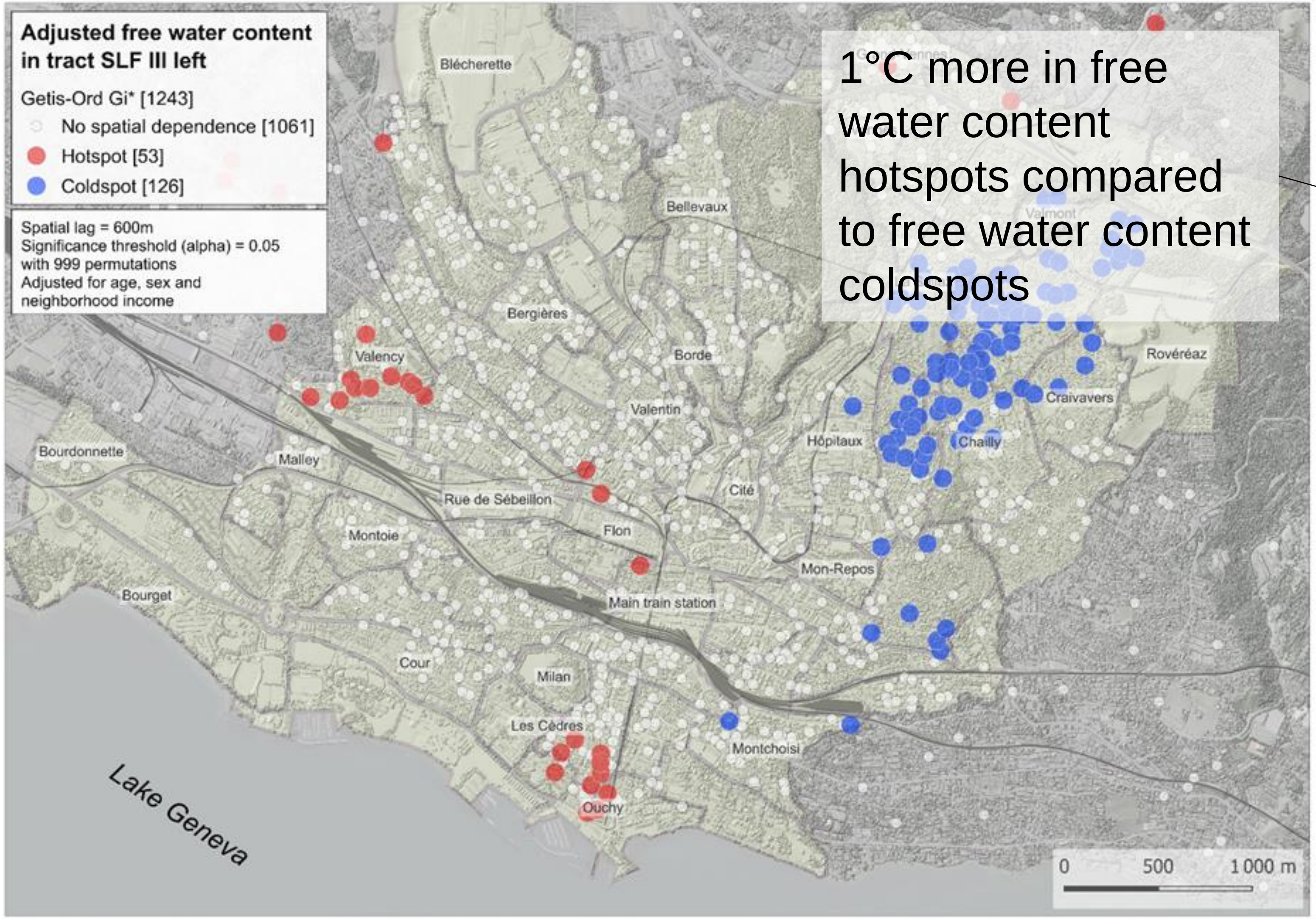


Relationship between the Land Surface Temperature (LST) (top) and delta LST (bottom)

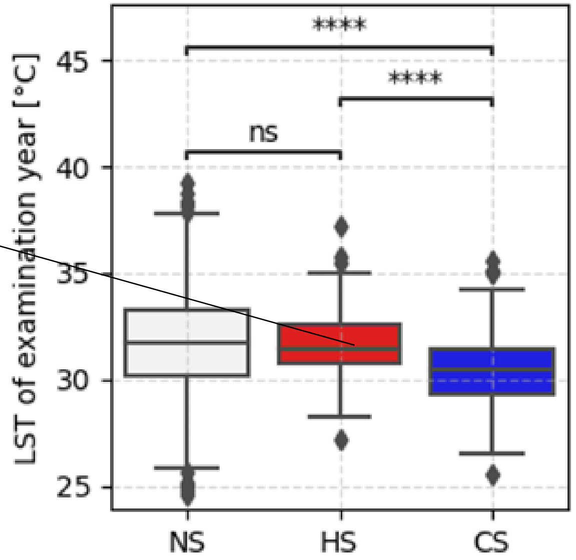
A cross indicates that the parameter estimate for the corresponding map in that tract is not significant, and a dot means that the relationship is significant

Only free water content (ISOVF) in white matter is significantly associated with LST the year of examination [in tract superior longitudinal fasciculus (SLF) III left]

Results – Adjusted free water content in tract SLF III left



1°C more in free water content hotspots compared to free water content coldspots



Discussion – more warming in peripheral areas

- Densely built-up areas exhibit higher soil temperatures. Conversely, vegetated areas show lower soil temperatures, consistent with literature (Gago et al., 2013)
- However, the city center experience a lower temperature increase compared to surrounding areas
- Contrasting temperature dynamics between densely built downtown areas where high LST values already existed in 2004, and its more vegetated surrounding regions
- While the urban core maintained consistently high temperatures, peripheral areas underwent warming mainly because of urban expansion, extensive construction activities of new housings and new industrial zones (Dutta et al. 2019)

Discussion – Mental health variables

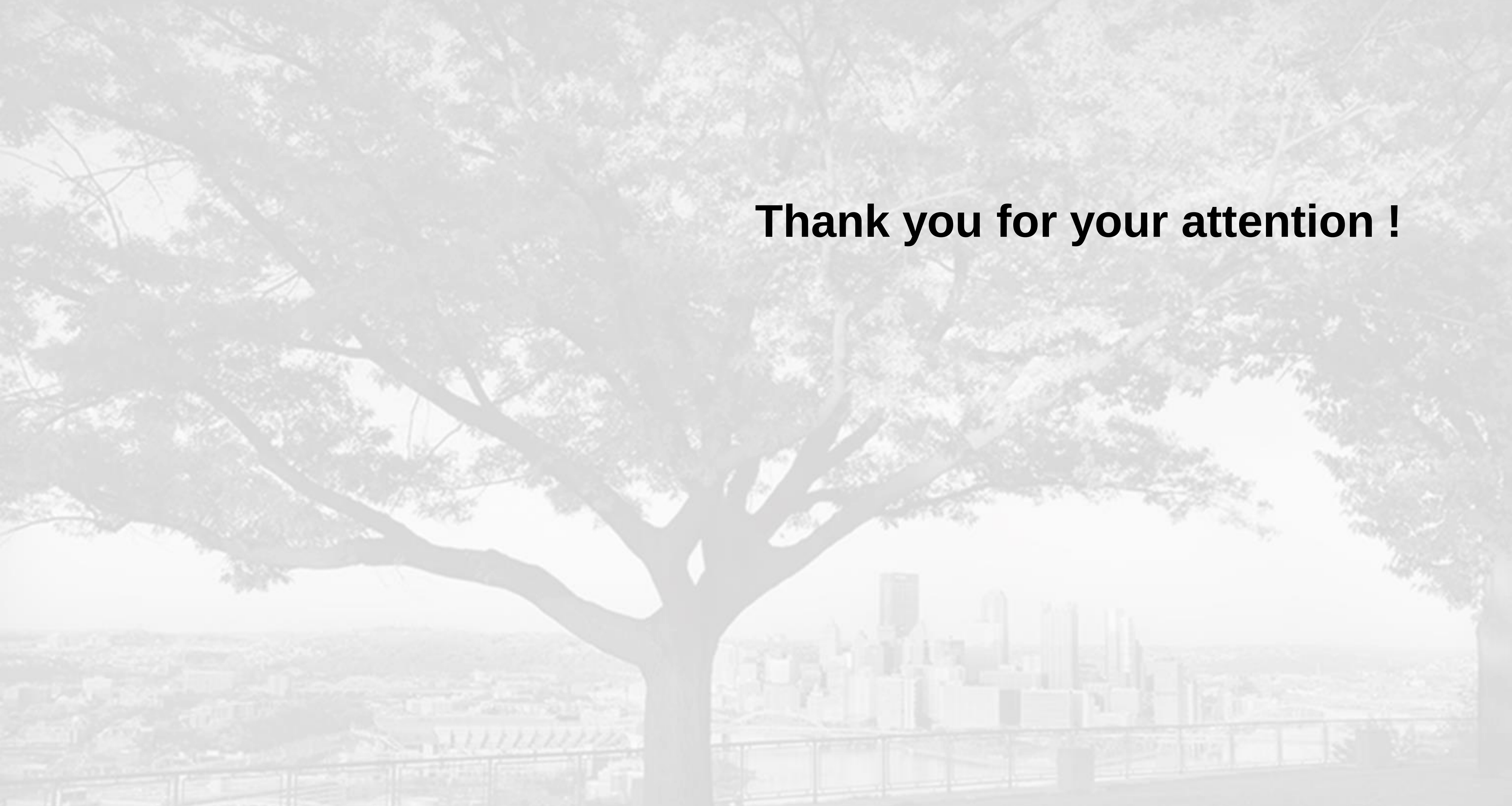
- Both GAF coldspots and STAI hotspots, which denote impaired mental functioning and high anxiety, are the areas with the highest LST (as expected)
- Acute events are likely to act through mechanisms similar to traumatic stress (Obradovich et al., 2018)
- When we consider the LST delta C°, we observe the opposite phenomenon, i.e. better mental health and moderate anxiety where the delta is highest
- On the contrary, people are worse off where the LST delta is lower
- Possible mechanism of (mental) adaptation to a gradual increase in delta LST over decades?
- Effects of climate change can be direct or indirect, and short-term or long-term (Cancioni et al. 2020).

Discussion – white matter and free water content

- Spatial statistics showed that spatial clusters of lower free water content values were found in areas with lower LST
- Higher free water content values where LST is higher
- Increased free water is associated with chronic bipolar disorders (Tuozzo et al., 2018)
- Confirms the link between mental disorders and high LST

Conclusion

- Merit of this study : analyzing mental health variables and cerebral tracts in a geographic context, quantifying spatial dependence
- Geography facilitates the integration of environmental and neurological information to better understand health challenges associated with the accentuation of the climate warming phenomenon particularly affecting urban populations
- Makes it possible to target specific urban areas where LST is high and where the mental health of people is impaired
- Permanent monitoring recommended (i.e. through web-based platforms to collect mental health data through questionnaires)
- Implementation of environmental actions to remedy the lack of vegetation and of permeable soils in affected neighborhoods



Thank you for your attention !