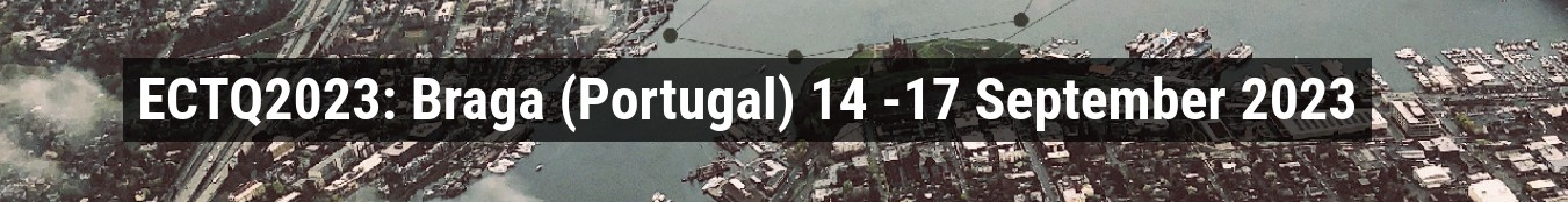
Infering meteorological information at different scales from several sources of data

Didier Josselin, Matthieu Vignal, Nicolas Viaux, Delphine Blanke, Céline Lacaux



Infering meteorological information at different scales from several sources of data

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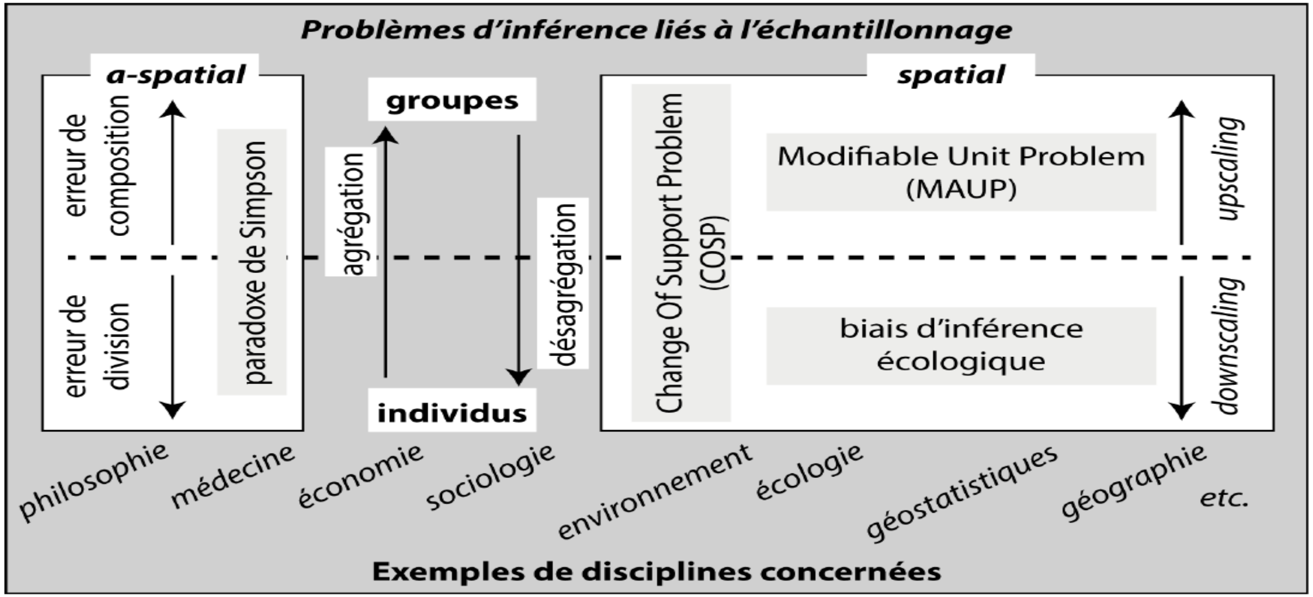
** UMR ESPACE, CNRS, France*
*** Laboratoire de Mathématique d’Avignon, France*

Outline

- Effect of the support on spatial statistics
- Data aggregation through scales
- Eliminating the spatial support effect by resampling and *Relative Scalar Deviation* calculation
- Conclusion

Effect of the spatial support

Spatial (dis)aggregation



[Openshaw, 1974]

[Yule, 1911
Theil, 1972]

[King et al., 2004,
Josselin et al., 2004]

[Robinson, 1950,
Goodman, 1953,
King, 1997]

Josselin & Louvet, 2016

Objectives of the research

- Studying the relationship between climatic statistical data and aggregation scales
- Finding an accurate and relevant scale for climatic data, at a given level (*i.e.* administrative division)
- Generalizing a method of resampling to eliminate the spatial support effect in rescaling procedures

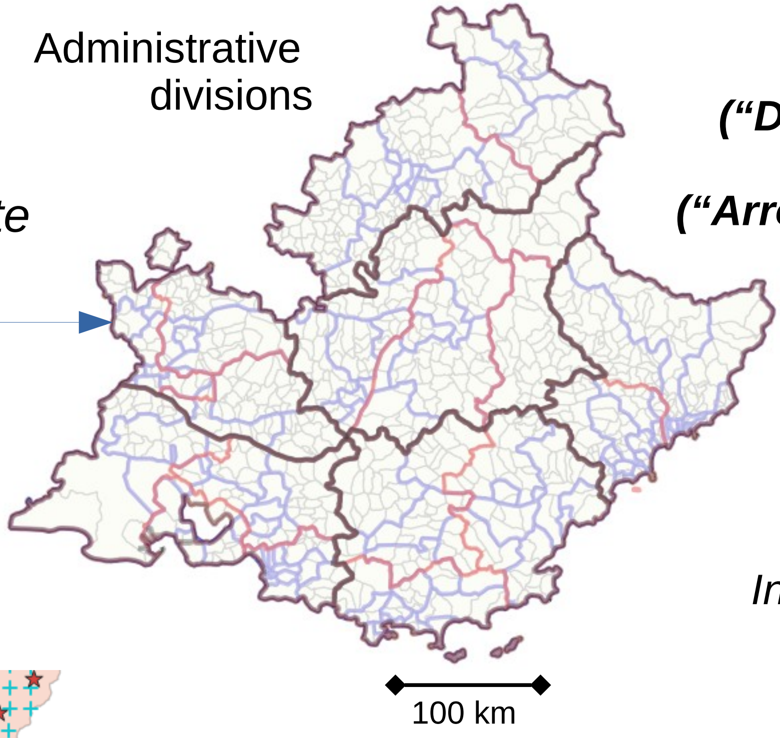
Data aggregation through scales

Data used (over 30 years)

France

Provence Alpes Côte d'Azur region

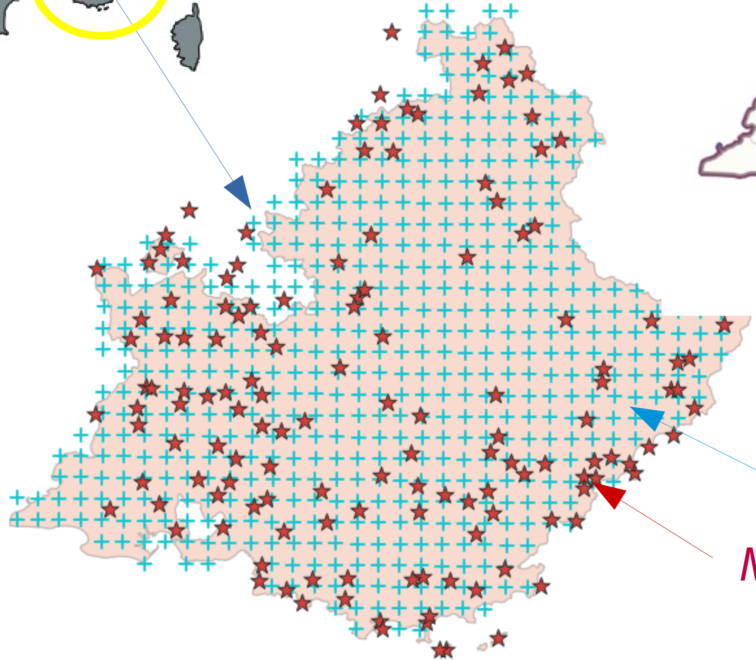
Administrative divisions



Department (“Départements”)
Districts (“Arrondissement”)
County (“Canton”)
Municipality (“Commune”)

\+

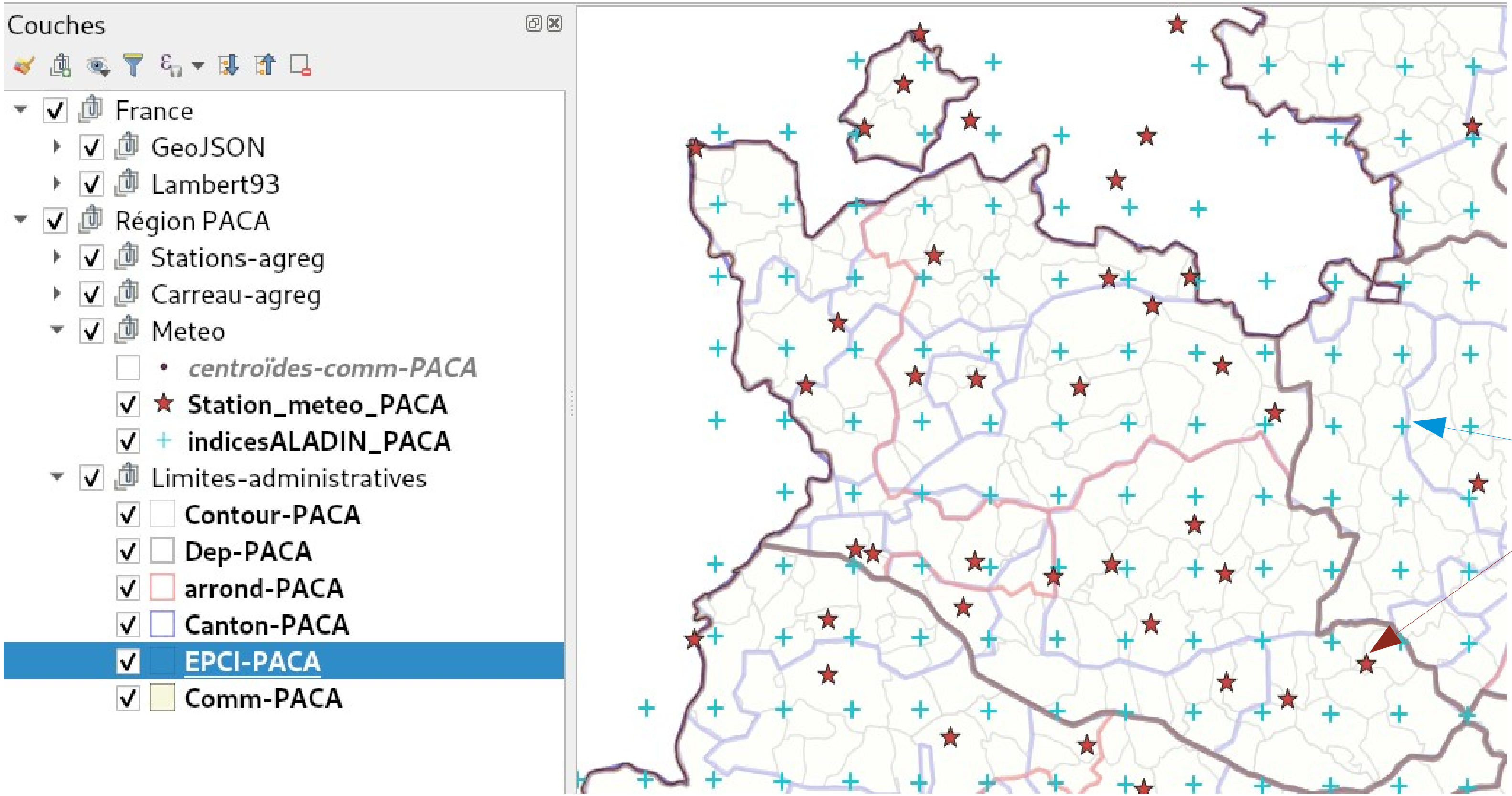
Inter-municipality structures (“EPCI”)



ALADIN grid (8 x 8 km)

Meteorological stations (Météo France)

Aggregation process



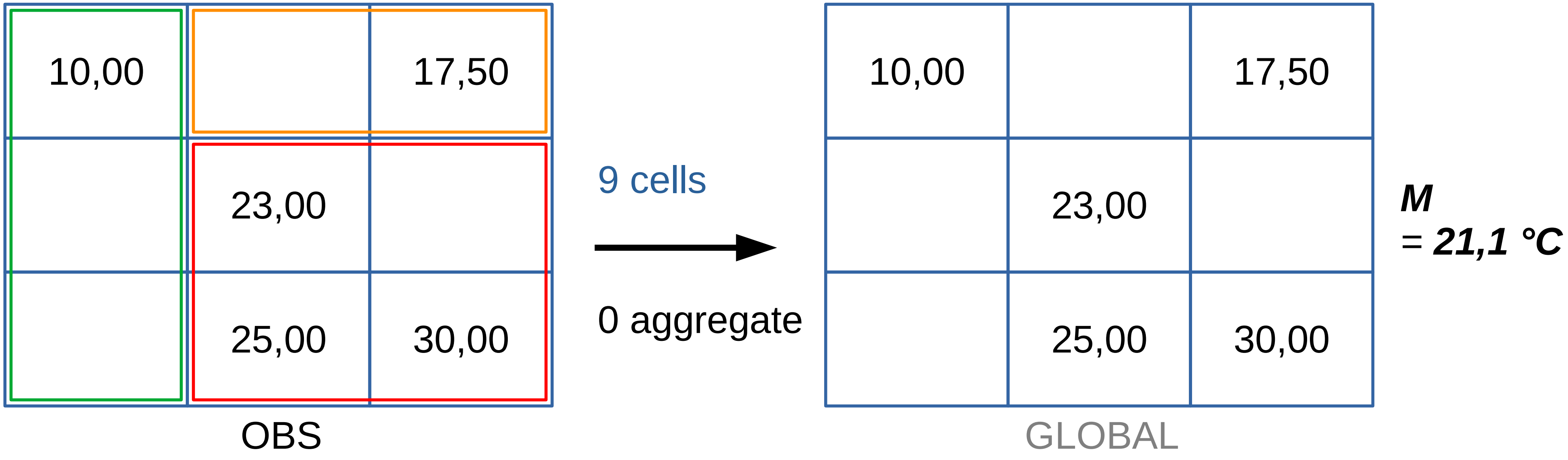
For each aggregate of a given spatial partition, we calculate central values and dispersion statistics of *mean temperature* on both series of:

the points on the grid

the local stations

Calculation without partition
(*e.g.* global average M)

No resampling, we compute the clue on observed data without spatial partition



N=5
N_Agreg=3

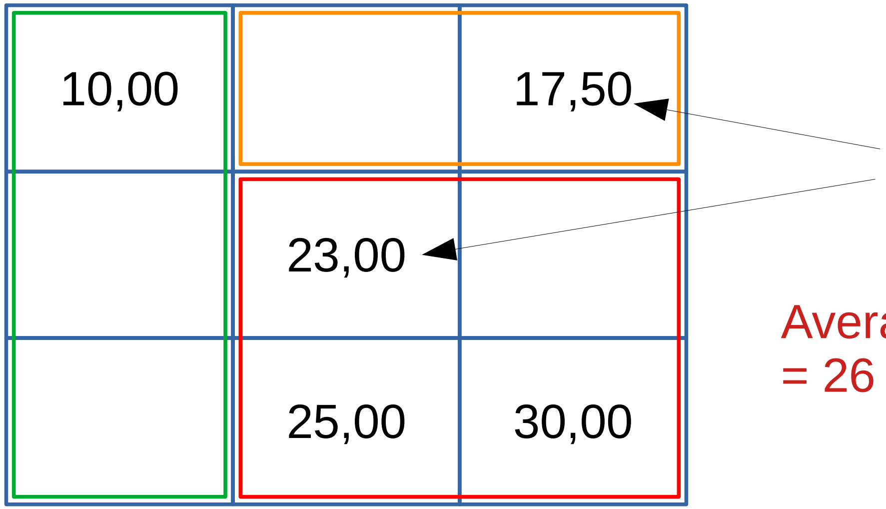
N=5
N_Agreg=0

Calculation considering the partition (*e.g.* aggregated average M)

We compute the clue on the observed data for each aggregate, and then aggregate them

9 cells
in 3 aggregates

Aggregates
1, 2 et 3



Temperature

OBS

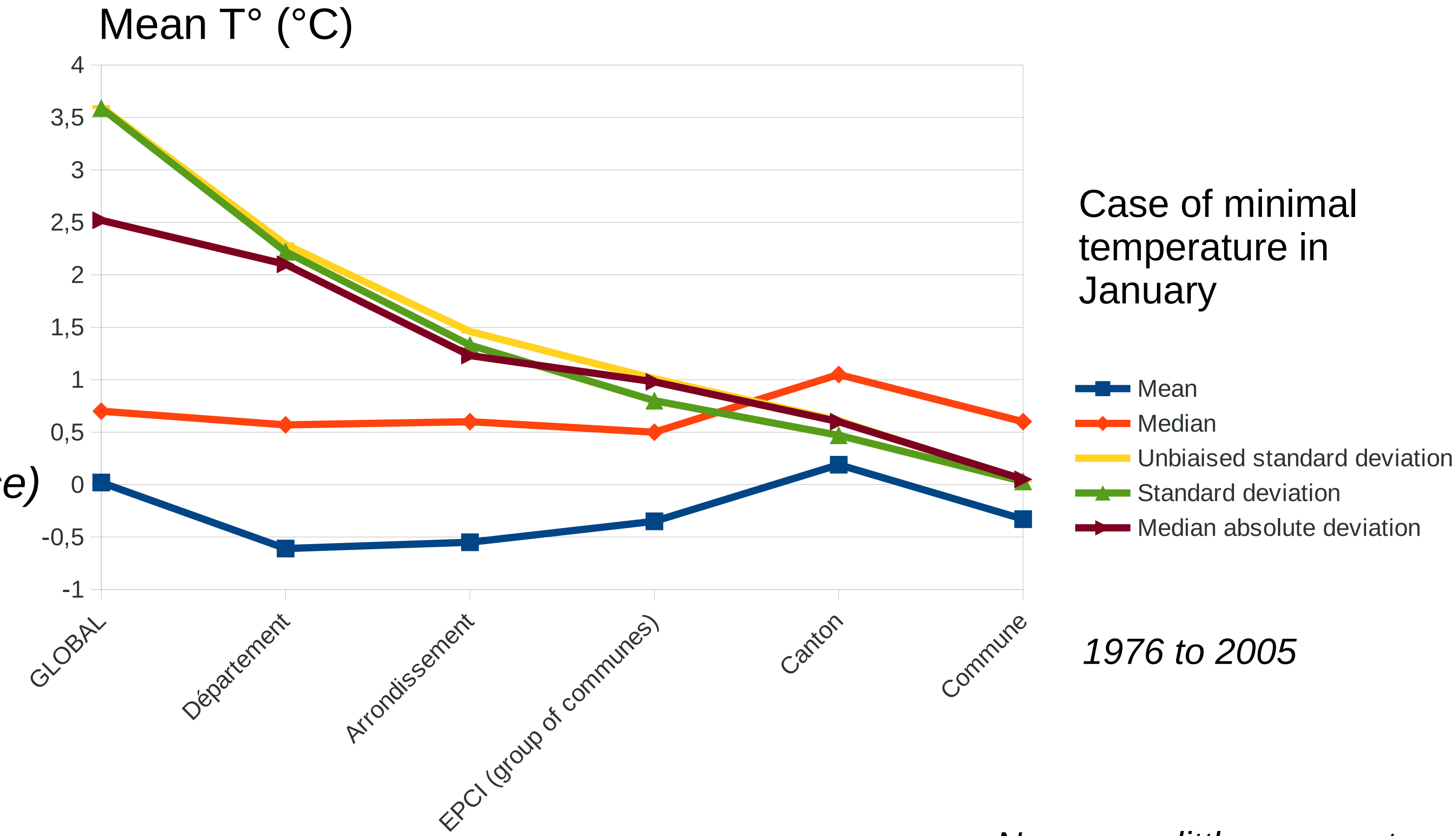
N=5
N_Agreg=3

Average T° of the aggregate 3
= 26 °C

Example :
Mean of the average T°:
***M** = (10,00+17,50+26,00)/3*
*= **17,83 °C***

Scalogram of temperatures

Stations (Meteo France)
In the region
Provence Alpes
Côte d'Azur

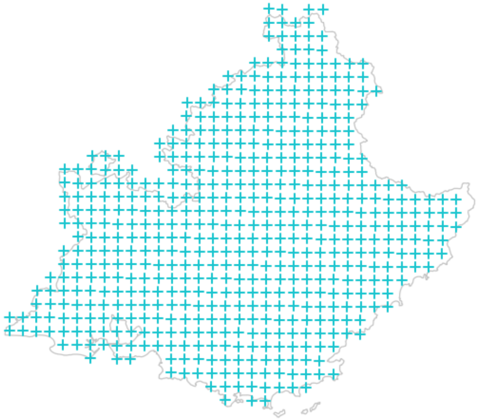


Case of minimal temperature in January

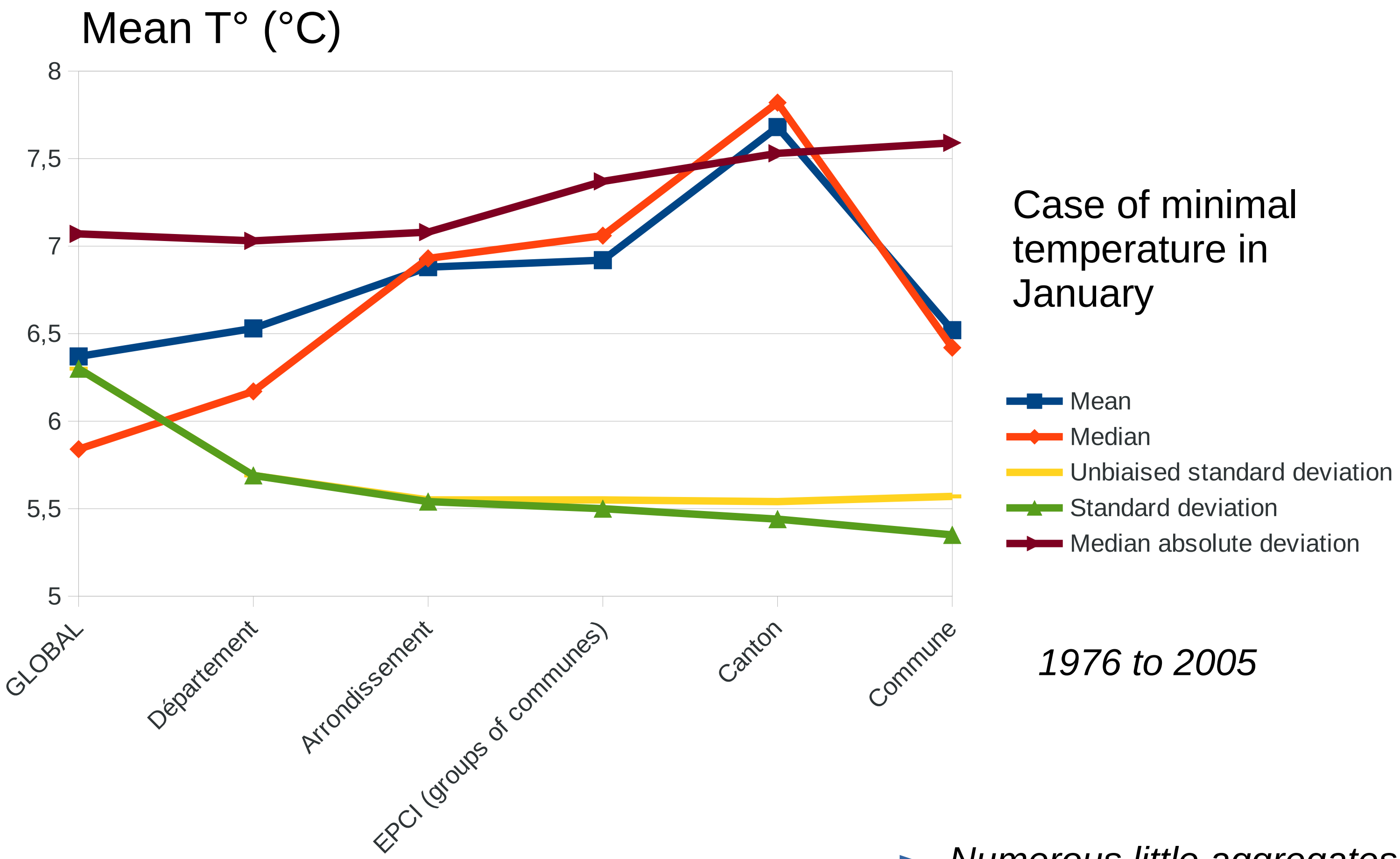
1976 to 2005

A few large aggregates ◄──► *Numerous little aggregates*

Scalogram of temperatures



ALADIN climatic model from CRNM in region Provence Alpes Côte d'Azur



Case of minimal temperature in January

1976 to 2005

A few large aggregates ◄———► *Numerous little aggregates*

Observations

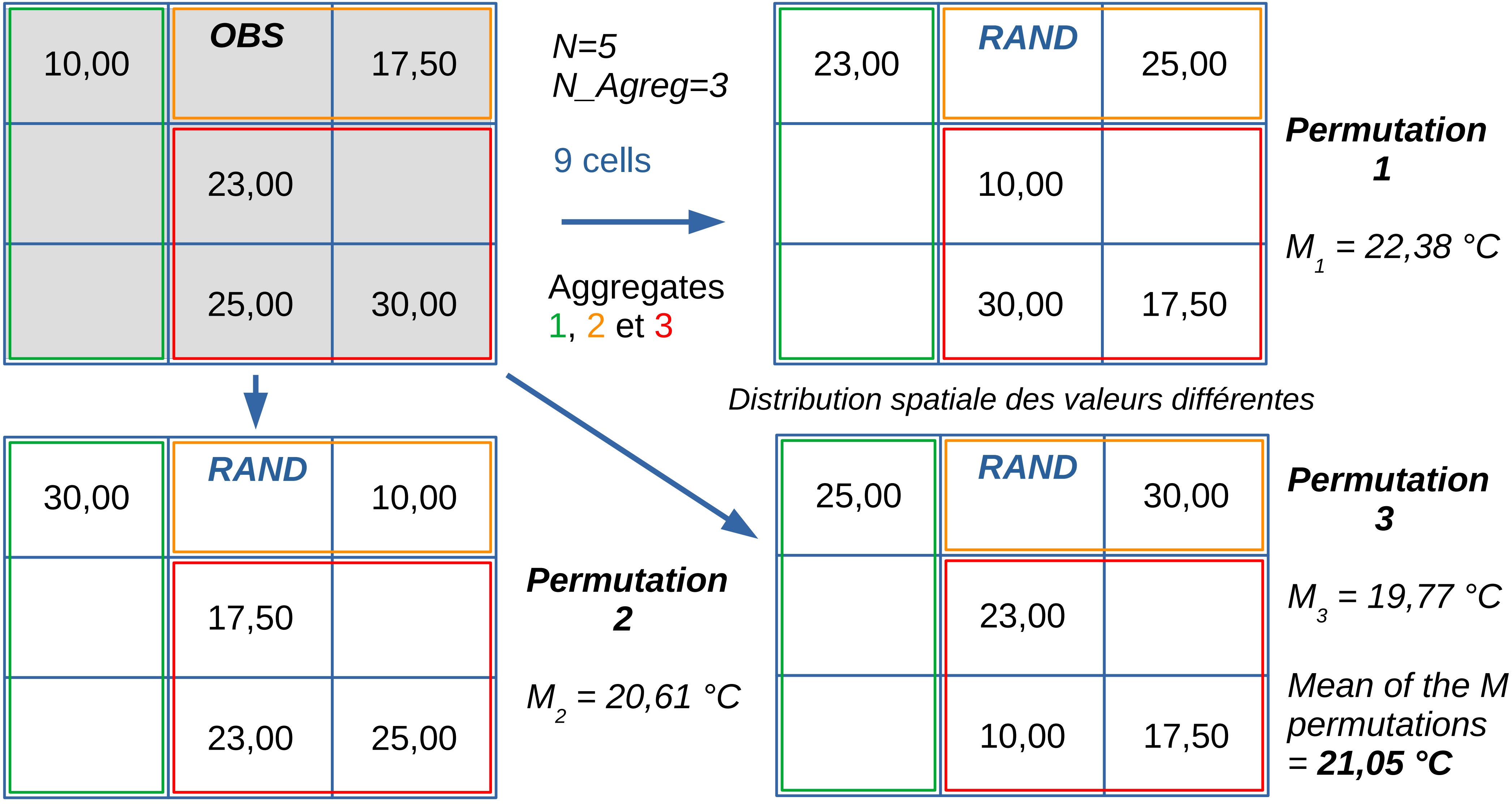
- There are significant gaps of mean temperatures according to partitions (up to 3.5 or 8 °C)
- Statistical dispersion decreases when number of aggregates increase
- We observe a peak where mean T° is maximal
- *But: we need a reference to allow comparison between partitions*

Eliminating the spatial support effect by resampling and Relative Deviation calculation

(Josselin et al., 2012, 2023)

Resampling procedure

- We randomly permute *N times* the observed temperatures without changing the spatial partition
- We re-compute statistical clues for each partition
- *This is our "control tube" that draws a random spatial distribution of the temperature, without spatial autocorrelation any more*



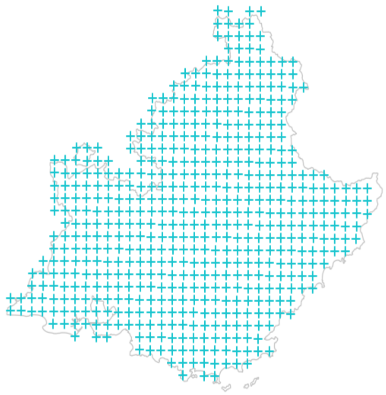
Spatial structure of measures does not change, but values are permuted (drawing without replacement)

Relative Scalar Deviation

$$RSD(\%) = 100 * \frac{T_{obs} - T_{rand}}{T_{rand}}$$

- Due to permutations, the **normalized difference between the observed and the randomized clue allows to eliminate the change of support problem because its effect is similar in both cases** (for a given scale/partition)
- **The Relative Scalar Deviation reflects the effective part of the geography in the measured values** (e.g. Temperature), **because the random process deleted all the spatial autocorrelation**

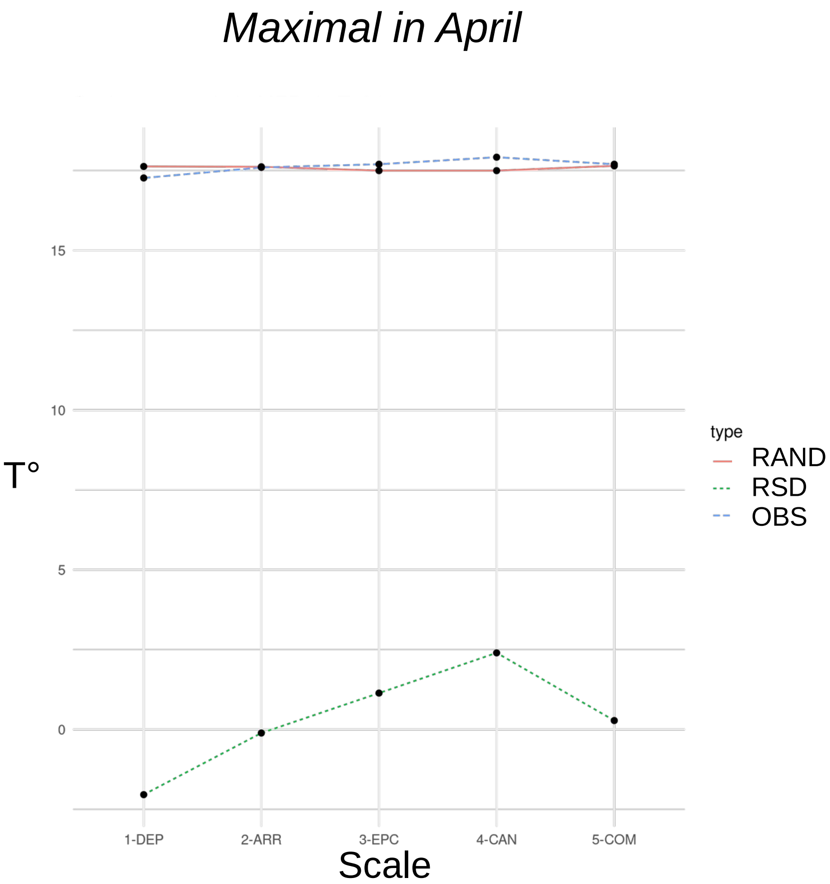
Scalogram with Relative Scalar Deviation

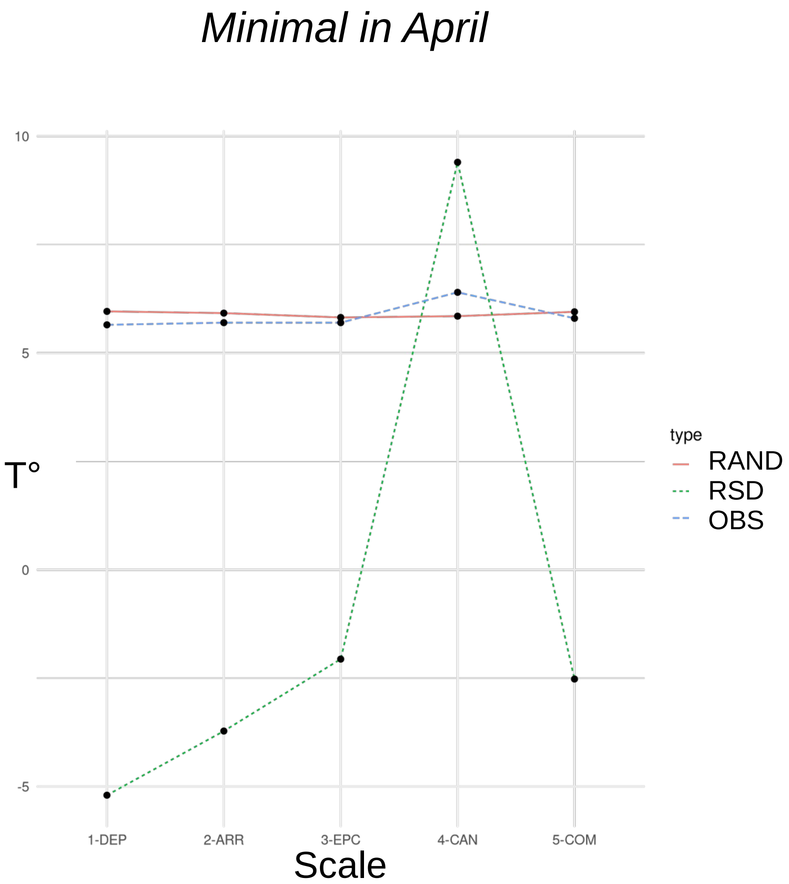


ALADIN climatic model from CRNM in region Provence Alpes Côte d'Azur

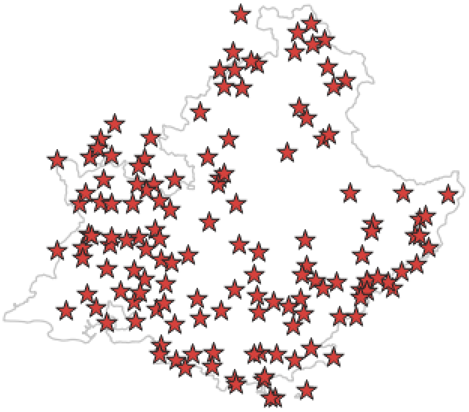
1976 to 2005

Median Temperature (°C)





Scalogram with Relative Scalar Deviation

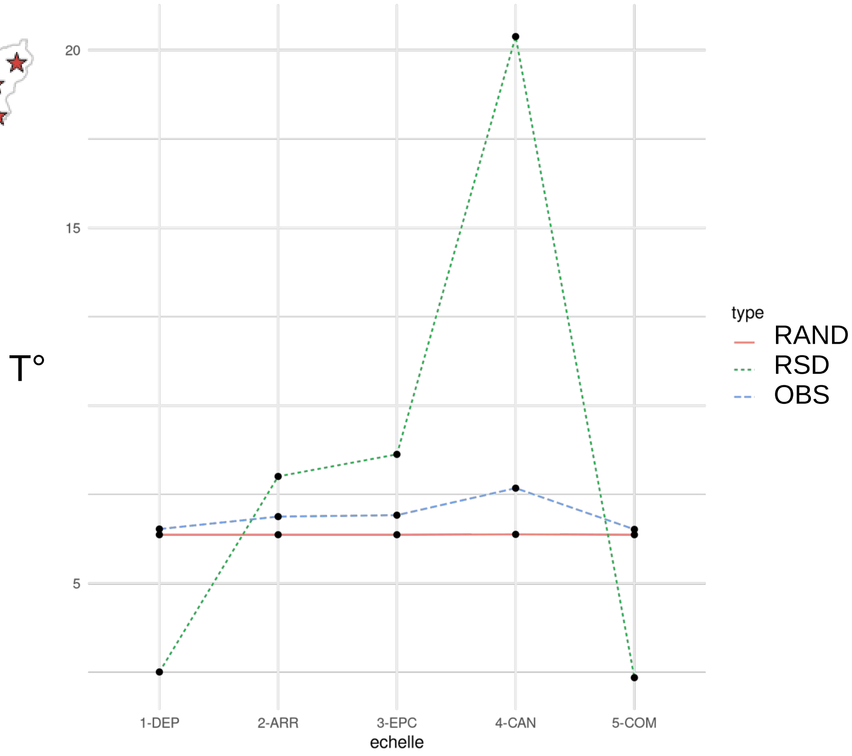


Stations (Meteo France) en région Provence Alpes Côte d'Azur

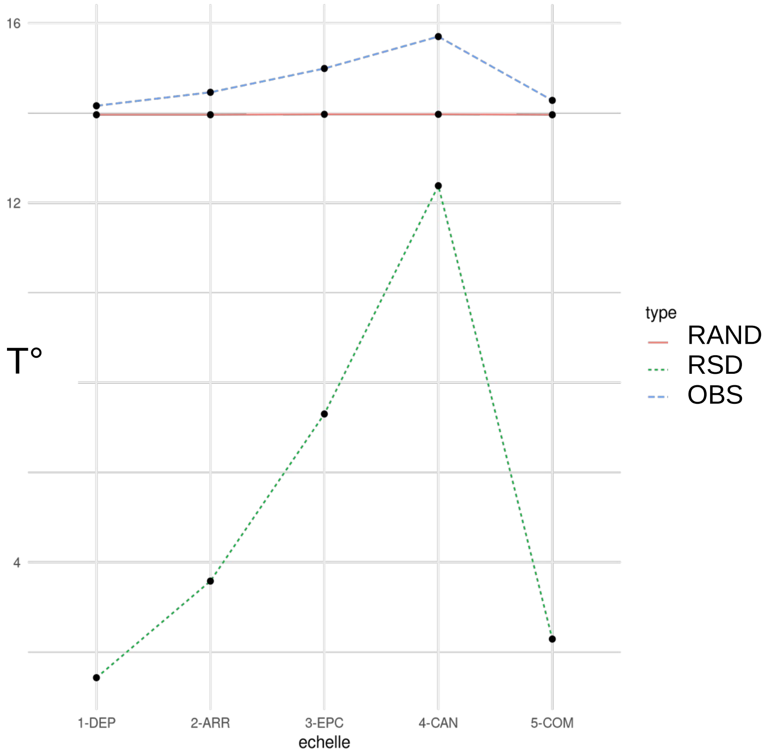
1976 to 2005

Mean Temperature (°C)

Minimal during the year



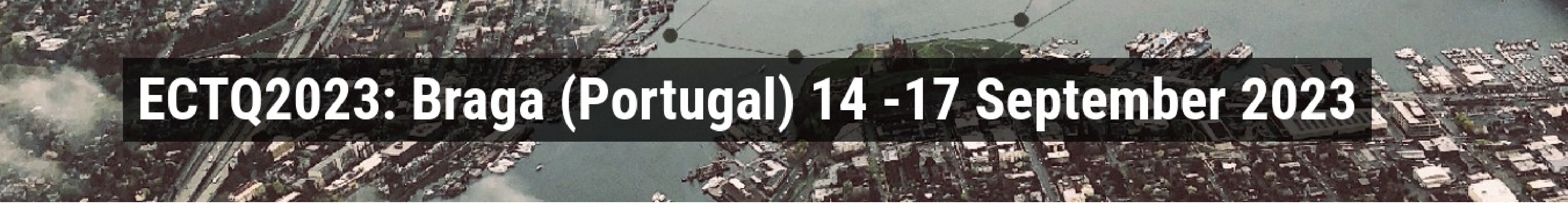
Maximal during the year



Conclusion

- A proposition to eliminate the Change of Spatial Support Problem
- The County scale seems to be the partition the furthest from a random distribution of mean T°
- It was shown that different scales can appear as relevant depending on the tackled topic
- The Relative Scalar Deviation being generalized

Josselin *et al.*, 2023, Uncertainties related to real estate price estimation scales, in *Geographic Data Imperfection 2* (Eds.: Batton-Hubert & Pinet) ISTE Wiley



UNIVERSIDADE DE COIMBRA

Thank you for your attention

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AVIGNON UNIVERSITÉ

cnrs advancing the frontiers

ESPACE

Simpson paradox

ONE SAMPLE

	Sick due to pesticide	**Not sick**	TOTAL
Orsini Viper	200	800	*1000*
Apollon Butterfly	50	950	*1000*
TOTAL	*250*	*1750*	*2000*

Probability to be sick for vipers: 200/1000 = 0,20 = 20 %

Probability to be sick for butterflies: 50/1000 = 0,05 = 5 %

Relative Risk = 0,20/0,05 = 4

(4 times more for vipers)

Simpson paradox

TWO
SEPARATED SAMPLES

Sample 1	**Sick**	**OK**	TOTAL
Viper	193	224	*417*
Butterly	39	45	*84*
TOTAL	*232*	*269*	*501*

Relative Risk = (193/417) / (39/84) = 1

Sample 2	**Sick**	**OK**	TOTAL
Viper	7	576	*583*
Butterfly	11	905	*916*
TOTAL	*18*	*1481*	*1499*

Relative Risk = (7/583) / (11/916) = 1

Simpson paradox

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Aggregated Relative Risk = 1 ←

(same risk)

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Simpson paradox

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≠ !

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(same risk)

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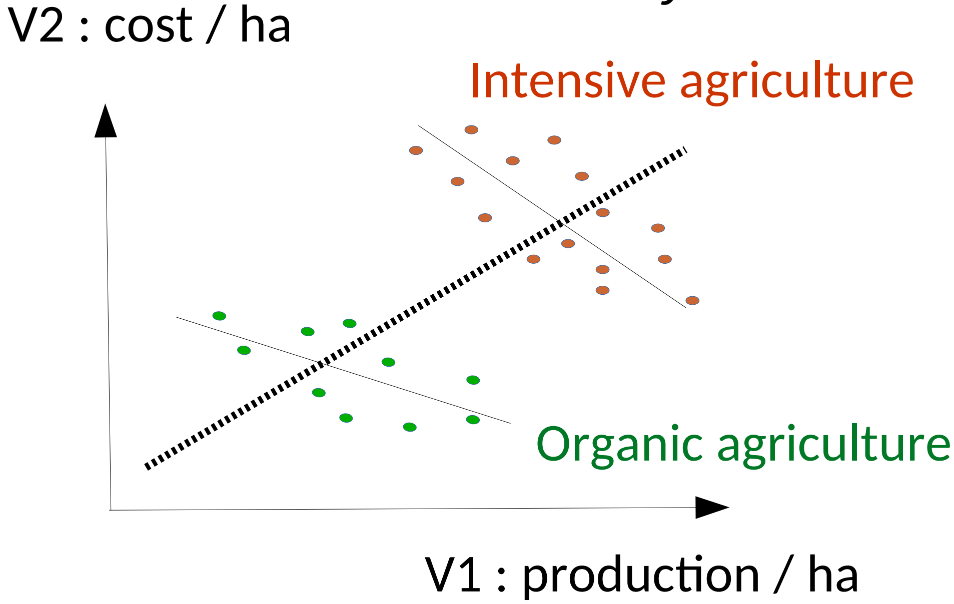
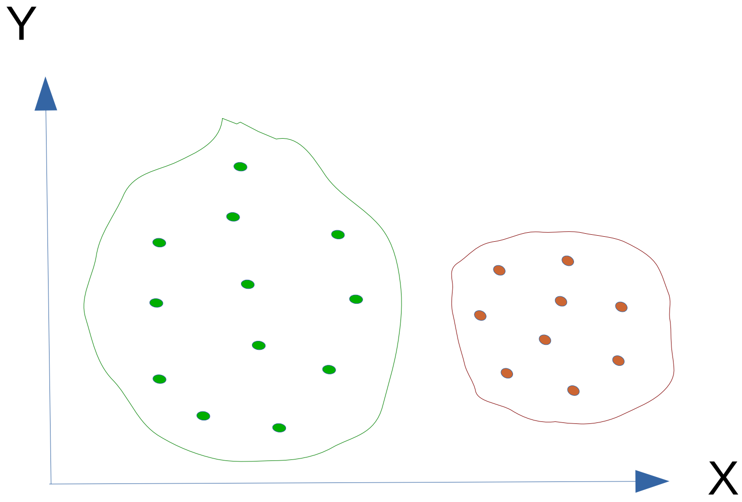
(Spatial) aggregation bias

2 parcels of vine
described by V1 et V2



In a point plot

Located measures
on a map



In geographical space