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Mixture kriging for granular data: The case of energy performance certificate prediction

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ABSTRACT

Energy transition planning requires an in-depth knowledge about a the building stock. To achieve this, data is collected from multiple sources, at multiple scales, with constraints such as privacy policies. This results in data being available for given areas of space such as a land plot. This is the case of Energy Performance Certificate (EPC) database which is anonymized and geo-localized with postal address. EPC prediction has been studied up to now mostly by heat engineers resulting in an effort to classify buildings into typologies. These approaches give good results at a statistical scale (not less than neighbourhood) but poor results at building scale. This paper presents a way to treat EPC as a geo-localized information.

In this paper, we first show that it is possible to apply Kriging methodology to random fields observed at random locations. This new model is referred to as Mixture Kriging. While the usual Gaussian setting is lost, conditional mean, variance and covariance can still be derived. This new model gives interesting results in EPC prediction at building level which is a prerequisite to target renovation efforts. The specific case of a French city is taken as an example.

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Figures and tables

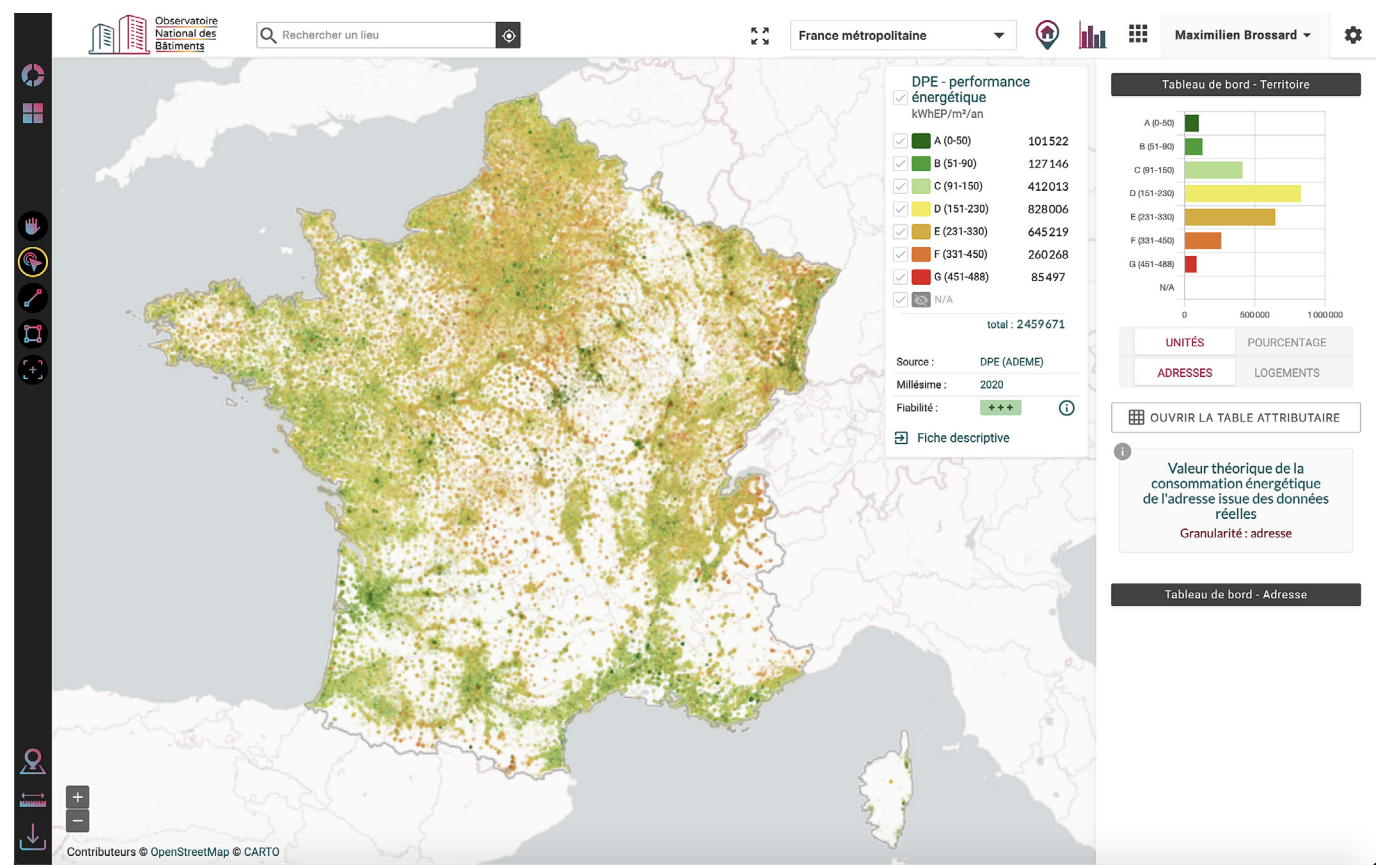


Fig. 1. Screen capture of the National Building Observatory (ONB) giving the distribution of buildings' energy performances in France.

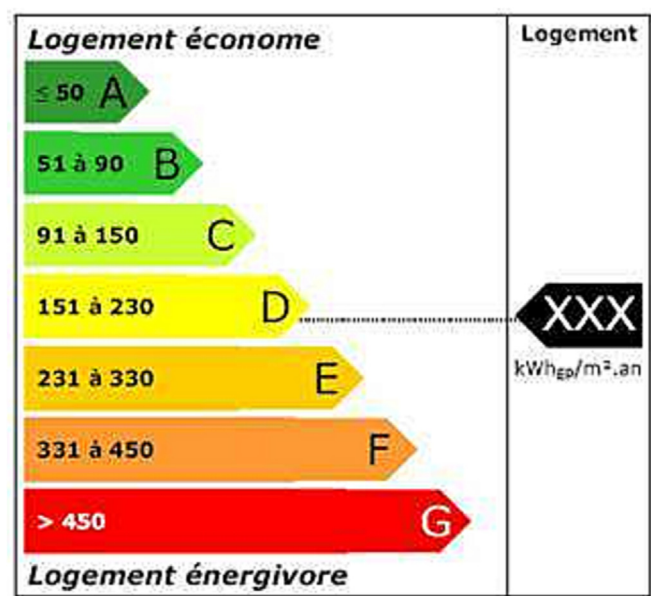


Fig. 2. French EPC vignette.



True values	Predicted values						
	A	B	C	D	E	F	G
A	2	1	1	2	2	0	0
B	1	3	3	9	2	2	0
C	1	3	3	26	15	4	0
D	3	5	5	80	33	5	1
E	4	2	2	36	36	5	1
F	0	3	3	4	5	3	0
G	0	0	0	1	1	0	0

Fig. 5. Confusion matrix of predicted values vs true values using Mixture Kriging. Data comes from a neighbourhood of Angers (France).

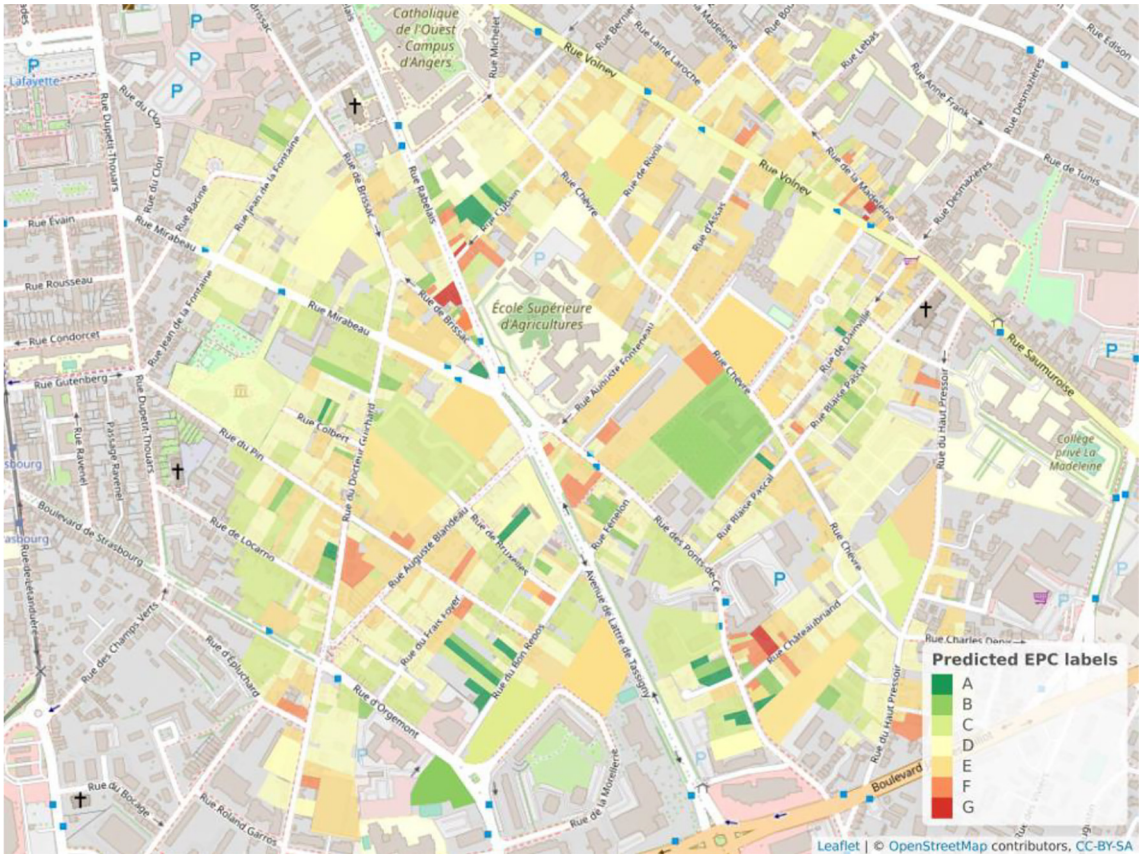


Fig. 6. Map of predicted EPCs in an urban area.

Data availability

Data will be made available on request.

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Further reading

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