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Supplementary Material

Modelling wildfire activity in wildland–urban interface (WUI) areas of Sardinia, Italy

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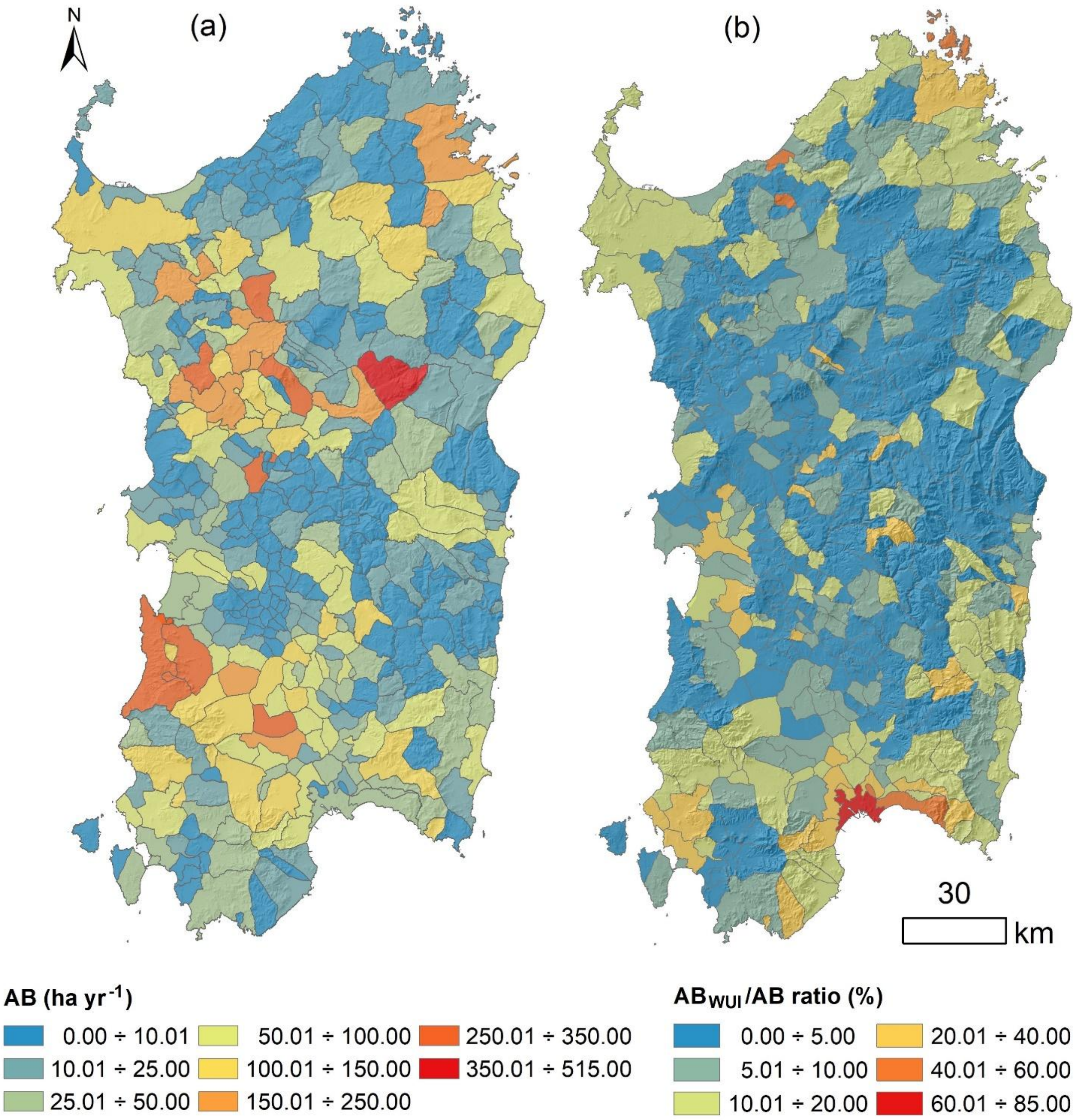
Suppl. Table S1. Description of the socio-economic, vegetation, climatic and zootechnical variables used for this study. ISTAT census data refer to the National Institute of Statistics data (http://dati-censimentopopolazione.istat.it/Index.aspx#); EEA 2012 (https://www.eea.europa.eu/data-and-maps/data/clc-2012-raster/link); WorldClim (https://doi.org/10.1002/joc.5086); National Veterinary Registry (https://www.vetinfo.it/j6_statistiche/#/new-list)

Variable Group	*Acronym*	*Description*	*Units*	*YEAR*	*Source*
SOCIO-ECONOMIC	COMM	Number of commuters in the municipality	%	2010	ISTAT census
	ILLITER	Number of illiterate people in the municipality	%	2010	ISTAT census
	MASCUL	Masculinity ratio (=100: balance between gender; <100: ♀ predominance, >100: ♂ predominance)	%	2010	ISTAT census
	POPINC	Net taxable income in the municipality	€	2010	ISTAT census
	POPURB	Resident population inside urban areas	%	2010	ISTAT census
	RAIL	Linear meters of railways in the municipal area	m km^{-2}	2010	ISTAT census
	ROADS	Linear meters of roads in the municipal area	m km^{-2}	2010	ISTAT census
VEGETATION	FOR	WUI area covered by forests	%	2011	EEA, 2012
	HERB	WUI area covered by herbaceous vegetation	%	2011	EEA, 2012
	NAT	Municipal area subject to landscape-naturalistic restrictions and protection	%	2011	EEA, 2012
	SHR	WUI area covered by shrublands	%	2011	EEA, 2012
CLIMATIC	PREC	Total annual municipal precipitation	mm	1970-2000	WorldClim
	SRAD	Annual average municipal solar radiation	kJ m^{-2}	1970-2000	WorldClim
	TMAX	Annual average municipal maximum temperature	°C	1970-2000	WorldClim
	WS	Annual average municipal wind speed	m s^{-1}	1970-2000	WorldClim
ZOOTECHNICAL	BF	Bovine breeding farms in the municipality	# km^{-2}	2010	Nat. Veterinary Registry
	BOV	Bovines raised within the municipality	# km^{-2}	2010	Nat. Veterinary Registry
	OCF	Ovine and caprine breeding farms in the municipality	# km^{-2}	2010	Nat. Veterinary Registry
	SHEEPS	Sheeps raised within the municipality	# km^{-2}	2010	Nat. Veterinary Registry
	GOATS	Goats raised within the municipality	# km^{-2}	2010	Nat. Veterinary Registry
	SF	Suine farms in the municipality	# km^{-2}	2010	Nat. Veterinary Registry
	SUINE	Pigs raised within the municipality	# km^{-2}	2010	Nat. Veterinary Registry
	EF	Equine breeding farms in the municipality	# km^{-2}	2017	Nat. Veterinary Registry

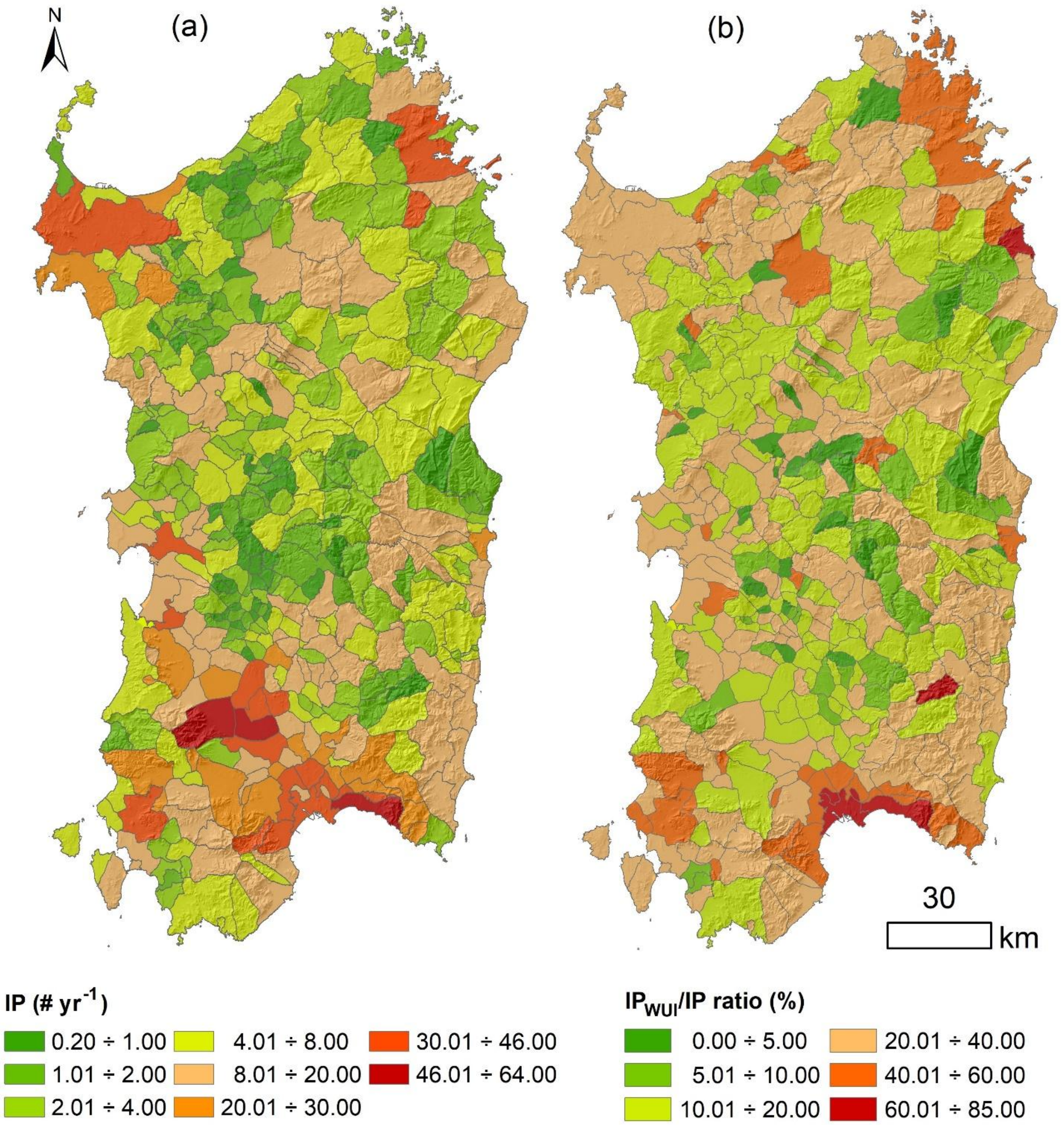
Suppl. Table S2. Description of the trained and evaluated models in this work (RF: Random Forest; SVM-L: Linear Support Vector Machine Kernel, SVM-R: Support Vector Machine Kernel with a radial basis kernel; LASSO: Least Absolute Shrinkage and Selection Operator; KNN: K-Nearest Neighbors: ENR: Elastic-net regression; BRR: Bayesian Ridge Regression; OLS: Ordinary least square linear regression).

Model	*Model acronym*	*Description*
Random Forest	RF	Random Forest is an ensemble machine learning algorithm used for classification research and regression analysis. It is a combination of tree predictors trained with the bagging method (Breiman and Cutler 2020); its principle is that it selects a random subset of variables at every node of every tree. Its high performance derives from a minimum correlation between trees and numerous resamples of the sets of data points (Jain et al. 2020). RF can select and estimate the importance of every single independent variable within a large dataset, examining the relationship between independent and dependent variables, and demonstrating high accuracy and tolerance to outliers (Su et al. 2018; Rihan et al. 2023).
Linear Support Vector Machine Kernel and Support Vector Machine Kernel with a radial basis kernel	SVM-L and SVM-R	The Support Vector Machine is a machine learning algorithm used to train models for classification or regression, that uses training and test feature vectors. It is useful for pattern recognition and function estimation (Cortes and Vapnik 1995). It classifies similar dataset features in the training model in the same category and different features in another category. It uses the kernel function to map data to high dimensional space and find the best hyperplane that divides the training samples of several classes or to divide data in space (D'Este et al. 2021; Gao et al. 2024). Differences between the SVM types depend on the type of the kernel function used (Wang et al. 2021): in linear SVM (SVM-L), data can be separated with a linear line, and classified with the help of a hyperplane, while for radial SVM (SVM-R), the kernel used in training and predicting is radial.
Least Absolute Shrinkage and Selection Operator	LASSO	The Least Absolute Shrinkage and Selection Operator is a shrinkage and variable selection method for regression models. It uses a penalty for training and to achieve a sparse solution (Friedman et al. 2010; Elshewey and Elsonbaty 2020). It identifies the neighborhood of each variable, namely the set of predictor variables corresponding to non-zero coefficients in a prediction model, by estimating the conditional independence separately for each variable (Ranstan and Cook 2018). It includes all the variables in the model, and a penalty factor is applied to the coefficients, limiting their magnitude. Variables that do not contribute or contribute very little to the response variables are excluded from the model (Keyser and Rodrigue 2023).
K-Nearest Neighbors	KNN	The K-Nearest Neighbors is a supervised machine learning algorithm that employs memorized data to classify new data points into the target class depending on the nearest available points (Sharma et al. 2022). In the training set, this algorithm finds the closest group of objects to the test object, and assigns a label based on the predominance of a particular class of the closest identified neighbors (Wu et al. 2008).
Elastic-net regression	ENR	The Elastic-net regression provides the advantages of both the ridge and lasso parameters in exploring the predictors and reducing bias, includes a generalized penalty term, and it is considered a convex combination of these two regressions (Minaravesh and Aydin 2023; Sloboda et al. 2023). It is valuable when there are significantly more predictors than observations, and can select groups of correlated variables and at the same time apply a variable selection and shrinkage (Zou and Hastie 2005; Friedman 2010).
Bayesian Ridge Regression	BRR	The Bayesian Ridge Regression is a linear regression model that estimates the model parameters using Bayesian inference (Tipping 2001). In the Bayesian approach, there is a preliminary, a likelihood, and a posteriori distribution. Its advantages are a good generalization performance, high data utilization, few training sample requirements, and the ability to prevent overfitting (Andari et al. 2023; Xiang et al. 2023), exhibiting the ability to incorporate previous parameters information and create good prior distributions (Michimae and Emura 2023).

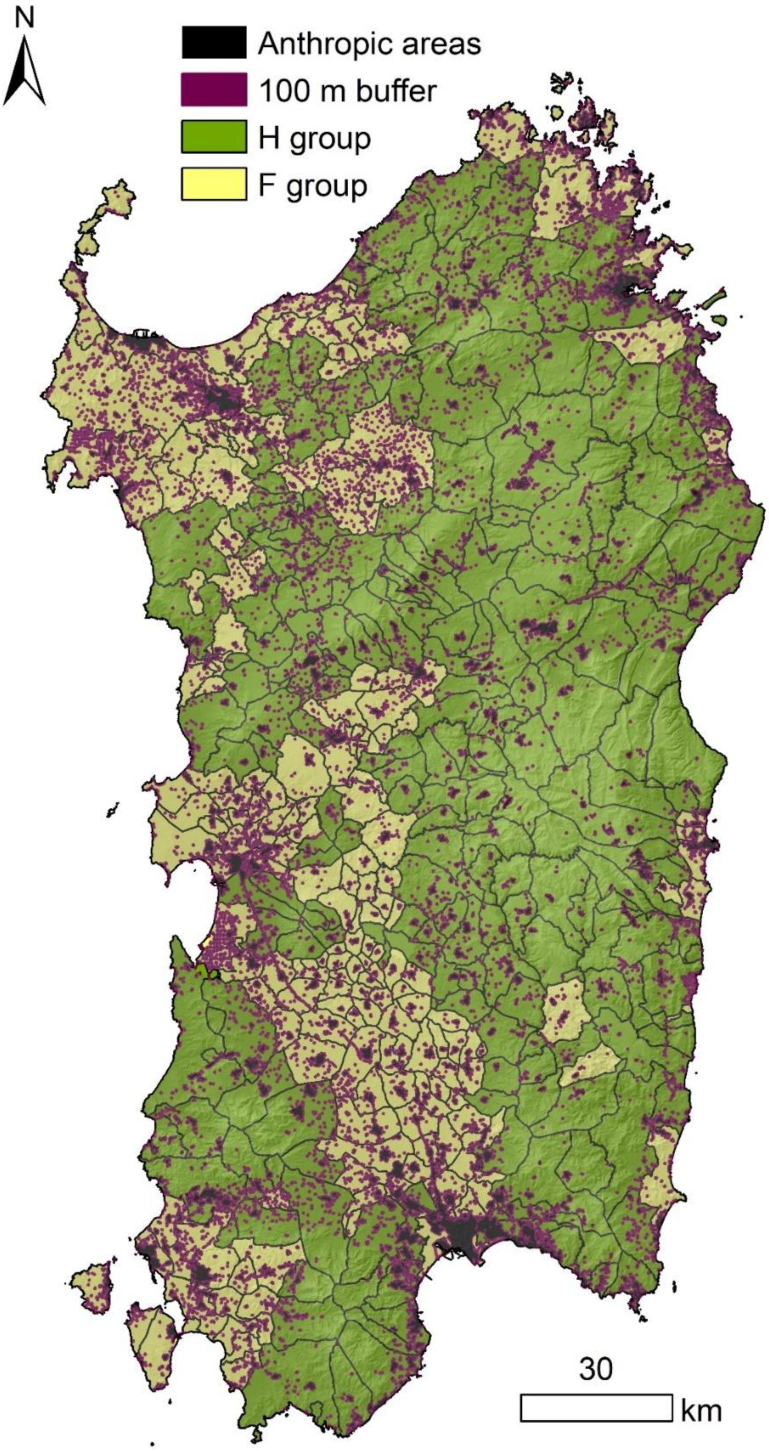
Ordinary least square linear regression	OLS	The Ordinary least square linear regression models the relationships between the target variable and one or several predicting variables that can be continuous or categorical. The target variable is modeled as a function of a constant term, coefficients on each predictor variable, and an error term (Acito 2023). This technique minimizes the sum of squared errors between the observed and predicted target values. OLS assumptions are the independent samples, error variance constancy, normality of model error term among others (Yahya et al. 2014); moreover, OLS assumes that the explanatory variables are measured without errors, and that errors are limited to the dependent variable (Leng et al. 2007).



Suppl. Fig. S1. (a) Average annual area burned at the municipal level, and (b) ratio between annual area burned at WUI and annual area burned at the municipal level. Both maps refer to observed data and to the study period 2005-2019



Suppl. Fig. S2. (a) Average annual wildfire ignitions at the municipal level, and (b) ratio between annual wildfire ignitions at WUI and annual wildfire ignitions at the municipal level. Both maps refer to observed data and to the study period 2005-2019



Suppl. Fig. S3. Map of the two groups of Sardinian municipalities based on the average municipal altitude and the elevation range, as described in the text. H = hilly and mountainous municipalities (mean altitude ≥350 m a.s.l. and elevation range ≥600 m); F = flat municipalities (mean altitude <350 m a.s.l. and elevation range <600 m). Black: anthropic land cover areas; purple: 100-meter buffer area around the anthropic layer

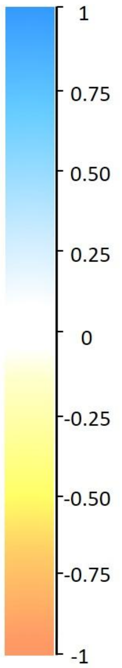
	MASCUL	POPURB	COMM	ILLITER	POPINC	TMAX	PREC	WS	SRAD	RAIL	ROADS	NAT	BF	BOV	OCF	SHEEPS	GOATS	SF	SUINE	EF	HERB	FOR	SHR
MASCUL	1.00	-0.19	-0.18	-0.09	-0.19	0.09	-0.08	-0.03	-0.04	-0.09	-0.10	-0.12	-0.04	-0.02	-0.01	-0.14	-0.04	-0.01	-0.01	-0.06	-0.09	-0.02	-0.02
POPURB	-0.19	1.00	0.99	0.46	0.99	0.15	0.38	0.26	0.18	0.14	0.31	-0.05	-0.14	-0.08	-0.21	-0.07	-0.05	-0.09	-0.01	0.12	0.59	0.23	0.32
COMM	-0.18	0.99	1.00	0.44	0.98	0.15	0.40	0.26	0.17	0.14	0.30	-0.01	-0.13	-0.04	-0.21	-0.07	-0.05	-0.09	-0.01	0.13	0.64	0.25	0.35
ILLITER	-0.09	0.46	0.44	1.00	0.43	0.34	-0.13	0.26	0.25	0.44	0.65	-0.07	-0.16	-0.05	-0.10	-0.09	-0.05	-0.06	-0.01	0.37	-0.08	-0.11	-0.01
POPINC	-0.19	0.99	0.98	0.43	1.00	0.13	0.34	0.23	0.16	0.14	0.31	-0.01	-0.12	-0.04	-0.19	-0.06	-0.05	-0.08	-0.01	-0.10	0.57	0.20	0.30
TMAX	0.09	0.15	0.15	0.34	0.13	1.00	-0.37	0.28	0.54	-0.06	0.43	-0.18	-0.33	-0.16	-0.05	-0.05	-0.04	-0.07	-0.06	0.22	0.18	-0.31	-0.01
PREC	-0.08	0.38	0.40	-0.13	0.34	-0.37	1.00	0.15	-0.10	-0.07	-0.38	0.18	0.08	0.11	-0.32	-0.10	-0.02	-0.15	-0.04	-0.18	0.60	0.69	0.45
WS	-0.03	0.26	0.26	0.26	0.23	0.28	0.15	1.00	0.30	0.04	0.08	-0.08	-0.24	-0.04	-0.49	-0.27	0.09	-0.34	-0.07	-0.14	0.23	0.11	0.43
SRAD	-0.04	0.18	0.17	0.24	0.16	0.54	-0.10	0.30	1.00	-0.04	0.14	0.17	-0.31	-0.08	-0.07	-0.13	-0.13	-0.03	-0.01	0.09	0.13	-0.17	-0.03
RAIL	-0.09	0.14	0.14	0.44	0.14	0.06	-0.07	0.04	0.01	1.00	0.34	-0.08	-0.13	-0.05	-0.04	-0.01	-0.04	-0.05	0.07	0.20	-0.01	-0.05	-0.03
ROADS	-0.10	0.31	0.30	0.65	0.31	0.43	-0.38	0.08	0.14	0.34	1.00	-0.17	-0.19	-0.10	0.13	0.06	-0.07	0.01	0.01	0.38	-0.03	-0.25	-0.05
NAT	-0.12	0.05	-0.04	-0.07	-0.04	-0.18	0.18	-0.06	0.17	-0.08	-0.17	1.00	0.01	0.01	-0.08	-0.04	0.01	-0.13	-0.03	-0.15	0.01	0.01	0.01
BF	-0.04	-0.14	-0.13	-0.16	-0.12	-0.33	0.08	-0.24	-0.31	-0.13	-0.19	0.01	1.00	0.49	0.39	0.20	-0.01	0.19	-0.06	0.13	-0.05	0.19	0.01
BOV	-0.01	-0.05	-0.04	-0.09	-0.04	-0.16	0.11	-0.04	-0.08	-0.05	-0.10	0.01	0.49	1.00	0.01	-0.04	-0.04	0.07	-0.02	-0.01	0.12	0.21	-0.02
OCF	-0.03	-0.21	-0.21	-0.10	-0.19	-0.05	-0.32	-0.49	-0.07	-0.04	0.13	-0.09	0.39	-0.01	1.00	0.33	-0.01	0.37	-0.01	0.33	-0.16	-0.25	-0.29
SHEEPS	-0.14	-0.07	-0.07	-0.09	-0.06	-0.05	-0.10	-0.27	-0.13	0.01	-0.06	-0.04	0.20	-0.04	0.33	1.00	-0.04	0.28	-0.05	0.18	-0.05	-0.07	-0.11
GOATS	-0.04	-0.05	-0.05	-0.05	-0.05	-0.04	-0.02	0.09	-0.13	-0.04	-0.07	-0.01	-0.01	-0.04	-0.02	-0.04	1.00	-0.05	-0.05	-0.07	-0.02	-0.02	-0.01
SF	0.01	-0.09	-0.09	-0.09	-0.08	-0.07	-0.15	-0.34	-0.03	-0.05	-0.01	-0.13	0.19	-0.07	0.37	0.28	-0.05	1.00	0.11	0.30	0.01	-0.09	-0.17
SUINE	0.01	0.01	0.01	0.01	0.01	0.06	-0.01	-0.07	-0.01	-0.07	-0.03	-0.03	-0.06	-0.02	-0.01	0.05	0.05	0.11	1.00	0.08	-0.02	-0.03	-0.05
EF	-0.06	0.12	0.13	0.37	0.10	0.22	-0.18	-0.14	0.09	0.20	0.38	-0.14	0.13	0.01	0.33	0.18	-0.07	0.30	0.08	1.00	0.09	-0.14	-0.16
HERB	-0.09	0.59	0.64	0.08	0.56	0.18	0.60	0.23	0.13	0.03	0.01	0.01	-0.05	0.12	-0.16	-0.05	-0.02	-0.02	0.02	0.09	1.00	0.43	0.44
FOR	-0.02	0.23	0.25	-0.11	0.20	-0.31	0.69	0.11	-0.17	-0.05	-0.25	0.10	0.19	0.21	-0.25	-0.07	-0.02	-0.09	-0.03	-0.14	0.43	1.00	0.40
SHR	-0.02	0.32	0.35	-0.01	0.30	-0.01	0.45	0.43	-0.03	-0.03	-0.05	-0.02	-0.02	-0.02	-0.29	-0.11	-0.01	-0.17	-0.05	-0.16	0.44	0.40	1.00

Suppl. Fig. S4. Correlation matrix of the independent variables used in this study (regional scale)

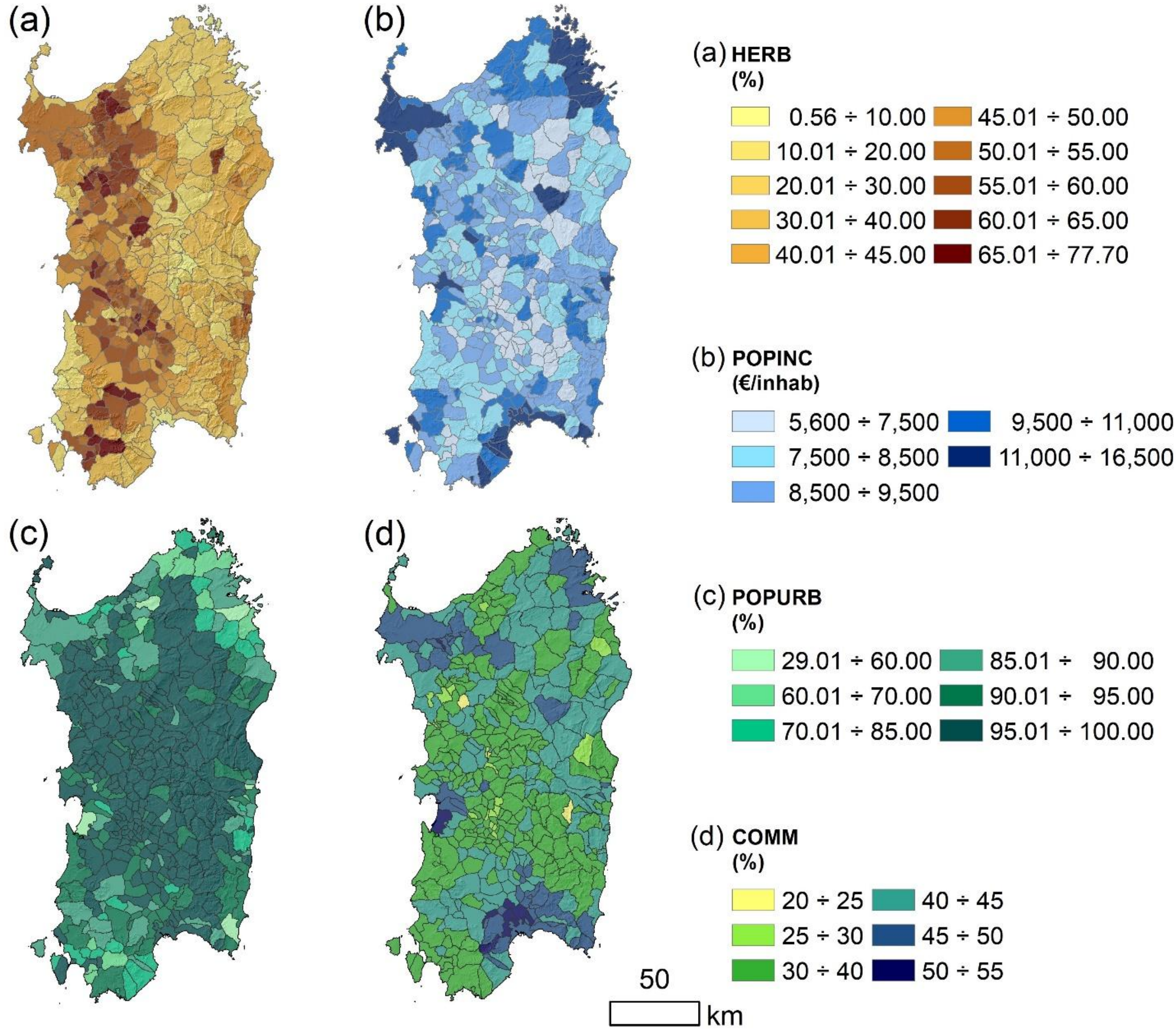
	MASCUL	POPURB	COMM	ILLITER	POPINC	TMAX	PREC	WS	SRAD	RAIL	ROADS	NAT	BF	BOV	OCF	SHEEPS	GOATS	SF	SUINE	EF	HERB	FOR	SHR
MASCUL	1.00	-0.23	-0.22	-0.12	-0.23	0.14	-0.11	-0.05	-0.04	-0.09	-0.10	-0.12	-0.04	-0.03	-0.02	-0.23	0.12	0.08	-0.01	-0.02	-0.11	-0.08	-0.02
POPURB	-0.23	1.00	0.99	0.43	0.99	0.13	0.54	0.25	0.17	0.20	0.31	0.07	-0.12	-0.03	-0.24	-0.09	-0.06	-0.09	-0.03	0.10	0.57	0.30	0.23
COMM	-0.22	0.99	1.00	0.41	0.99	0.13	0.59	0.25	0.16	0.20	0.30	-0.05	-0.12	-0.02	-0.24	-0.09	-0.06	-0.08	-0.02	0.11	0.63	0.33	0.25
ILLITER	-0.12	0.43	0.41	1.00	0.40	0.32	-0.04	0.27	0.18	0.56	0.66	-0.06	-0.14	-0.07	-0.16	-0.13	-0.06	-0.10	-0.01	0.40	-0.02	-0.07	-0.03
POPINC	-0.23	0.99	0.99	0.40	1.00	0.11	0.51	0.23	0.15	0.19	0.31	0.07	-0.11	-0.03	-0.22	-0.08	-0.05	-0.08	-0.01	0.07	0.53	0.28	0.23
TMAX	0.14	0.13	0.13	0.32	0.11	1.00	-0.14	0.19	0.49	0.12	0.25	-0.08	-0.36	-0.05	-0.09	-0.20	-0.01	-0.24	0.15	0.20	-0.04	-0.21	-0.15
PREC	-0.11	0.54	0.59	-0.04	0.51	-0.14	1.00	0.12	-0.04	-0.02	-0.21	0.07	0.07	0.09	-0.18	-0.07	-0.03	-0.01	-0.02	-0.03	0.92	0.75	0.47
WS	-0.05	0.25	0.25	0.27	0.23	0.19	0.12	1.00	0.35	0.25	0.10	-0.02	-0.23	-0.04	-0.51	-0.32	-0.02	-0.18	-0.03	-0.04	0.16	0.10	0.43
SRAD	-0.04	0.17	0.16	0.18	0.15	0.49	-0.04	0.35	1.00	-0.05	-0.03	0.20	-0.21	-0.02	-0.17	-0.21	-0.03	-0.16	-0.01	-0.02	0.07	-0.04	-0.06
RAIL	-0.09	0.20	0.20	0.56	0.19	0.12	-0.20	0.25	0.05	1.00	0.40	-0.10	-0.15	-0.06	-0.14	-0.06	-0.11	0.07	-0.01	0.22	-0.03	-0.01	-0.01
ROADS	-0.10	0.31	0.30	0.66	0.31	0.25	-0.21	0.10	-0.03	0.40	1.00	-0.14	-0.14	-0.06	-0.02	-0.02	-0.06	-0.13	-0.02	-0.34	-0.06	-0.17	-0.08
NAT	-0.12	-0.07	-0.05	-0.06	0.07	-0.08	0.07	-0.02	0.20	-0.10	-0.14	1.00	0.06	-0.01	-0.01	-0.06	-0.01	-0.14	-0.02	-0.17	-0.01	0.07	-0.01
BF	-0.04	-0.12	-0.12	-0.14	-0.11	-0.36	0.07	-0.23	-0.21	-0.15	-0.14	0.06	1.00	0.46	0.43	0.28	0.01	0.13	-0.07	0.15	-0.01	0.24	-0.01
BOV	-0.01	-0.04	-0.02	-0.07	-0.03	-0.05	0.09	0.04	-0.02	-0.06	-0.06	-0.01	0.46	1.00	-0.05	-0.01	0.08	0.06	-0.03	-0.02	0.18	0.36	-0.01
OCF	0.01	-0.24	-0.24	-0.16	-0.22	-0.09	-0.18	-0.51	-0.17	-0.14	-0.01	-0.03	0.43	-0.05	1.00	0.39	0.03	0.18	0.01	0.20	-0.18	-0.13	-0.31
SHEEPS	-0.23	-0.09	-0.09	-0.13	-0.08	-0.20	-0.07	-0.32	-0.21	-0.06	-0.02	-0.06	0.28	-0.02	0.39	1.00	0.12	0.14	0.05	0.11	-0.06	-0.02	-0.13
GOATS	0.12	-0.06	-0.06	-0.06	-0.05	-0.01	-0.01	-0.02	-0.09	-0.11	-0.06	-0.01	-0.02	-0.08	0.08	0.12	1.00	0.05	-0.01	-0.05	-0.01	-0.01	-0.03
SF	0.08	-0.03	-0.08	-0.10	-0.08	-0.24	-0.01	-0.18	-0.16	-0.07	-0.13	-0.14	0.13	0.06	0.18	0.14	0.05	1.00	0.08	0.11	0.04	0.08	-0.14
SUINE	-0.01	-0.01	-0.01	-0.01	-0.01	0.15	-0.02	-0.03	-0.01	-0.01	-0.02	-0.04	-0.07	-0.03	-0.02	-0.05	-0.02	0.08	1.00	-0.06	-0.04	-0.02	-0.06
EF	-0.02	0.10	0.11	0.40	0.07	0.20	-0.03	-0.04	-0.02	0.22	0.34	-0.17	0.15	-0.02	0.20	0.11	-0.05	0.11	-0.06	1.00	0.07	-0.02	-0.14
HERB	-0.11	0.57	0.63	-0.02	0.53	0.04	0.92	0.16	0.07	0.02	-0.06	0.01	0.01	0.18	-0.18	-0.06	0.01	0.01	0.01	0.07	1.00	0.72	0.37
FOR	-0.08	0.30	0.33	-0.07	0.28	-0.21	0.75	0.10	-0.04	-0.01	-0.17	0.07	0.24	0.36	-0.13	0.01	0.01	0.08	0.02	0.02	0.72	1.00	0.38
SHR	-0.02	0.23	0.25	-0.08	0.23	-0.15	-0.47	-0.43	-0.06	-0.01	-0.08	0.01	-0.01	-0.01	-0.31	-0.13	-0.01	-0.14	-0.06	-0.14	0.37	0.38	1.00

Suppl. Fig. S5. Correlation matrix of the independent variables used in this study (F municipal group)

	MASCUL	POPURB	COMM	ILLITER	POPINC	TMAX	PREC	WS	SRAD	RAIL	ROADS	NAT	BF	BOV	OCF	SHEEPS	GOATS	SF	SUINE	EF	HERB	FOR	SHR
MASCUL	1.00	-0.12	-0.11	-0.01	-0.12	0.18	-0.11	0.12	-0.01	-0.08	-0.03	-0.15	-0.06	-0.16	-0.05	-0.08	-0.01	-0.03	-0.01	-0.15	-0.06	-0.01	-0.03
POPURB	-0.12	1.00	1.00	0.71	0.99	0.23	0.35	0.32	0.19	-0.05	0.32	-0.07	-0.16	-0.10	-0.20	-0.06	-0.05	-0.13	-0.01	0.15	0.69	0.31	0.55
COMM	-0.11	1.00	1.00	0.71	1.00	0.24	0.34	0.33	0.18	-0.04	0.34	-0.06	-0.16	-0.11	-0.21	-0.06	-0.05	-0.12	-0.01	0.15	0.71	0.30	0.59
ILLITER	-0.01	0.71	0.71	1.00	0.69	0.42	-0.11	0.34	0.32	-0.06	0.50	-0.04	-0.20	-0.19	-0.08	-0.06	-0.01	-0.01	-0.01	0.30	0.38	-0.05	0.12
POPINC	-0.12	0.99	1.00	0.69	1.00	0.23	0.33	0.31	0.17	-0.04	0.34	-0.05	-0.15	-0.10	-0.20	-0.06	-0.05	-0.12	-0.01	0.02	0.69	0.30	0.59
TMAX	0.18	0.23	0.24	0.42	0.23	1.00	-0.19	0.42	0.49	-0.13	0.28	-0.10	-0.26	-0.36	-0.01	-0.01	-0.01	-0.01	-0.01	0.12	0.43	-0.16	0.17
PREC	-0.11	0.35	0.35	-0.11	0.33	-0.19	1.00	0.23	-0.01	-0.06	-0.42	0.17	-0.01	0.13	-0.40	-0.13	-0.07	-0.30	-0.08	-0.21	0.46	0.60	0.45
WS	0.12	0.32	0.33	0.34	0.31	0.42	0.23	1.00	0.25	-0.26	-0.01	0.14	-0.24	-0.25	-0.49	-0.23	0.17	-0.46	-0.09	-0.27	0.42	0.14	0.43
SRAD	-0.01	0.19	0.18	0.32	0.17	0.49	-0.01	0.25	1.00	-0.06	0.09	0.24	-0.35	-0.27	-0.05	-0.08	-0.13	0.08	0.04	0.11	0.22	-0.12	-0.04
RAIL	-0.08	-0.05	-0.04	-0.06	-0.04	-0.13	-0.06	-0.26	-0.06	1.00	0.14	-0.02	-0.06	-0.04	0.08	0.07	0.06	0.20	0.13	0.13	-0.01	-0.06	-0.08
ROADS	-0.08	0.32	0.34	0.50	0.34	0.28	-0.42	-0.01	0.03	0.14	1.00	-0.10	-0.12	-0.15	0.21	0.18	-0.01	0.26	0.12	0.40	0.22	-0.19	0.11
NAT	-0.15	-0.07	-0.06	-0.04	-0.05	-0.10	0.17	0.14	0.26	-0.02	-0.10	1.00	-0.08	-0.01	-0.09	-0.11	-0.01	-0.13	-0.08	-0.08	-0.05	-0.09	-0.04
BF	-0.06	-0.16	-0.16	-0.20	-0.14	-0.26	-0.02	-0.24	-0.35	-0.06	-0.12	-0.08	1.00	0.69	0.41	0.15	-0.06	0.24	-0.06	0.19	-0.15	0.09	-0.07
BOV	-0.16	-0.10	-0.11	-0.19	-0.10	-0.36	0.13	-0.25	-0.27	-0.01	-0.15	-0.01	0.69	1.00	0.19	0.14	-0.03	0.11	-0.02	0.18	-0.13	-0.06	-0.09
OCF	-0.05	-0.20	-0.21	-0.08	-0.20	-0.01	-0.40	-0.49	-0.05	0.08	0.21	-0.09	0.41	0.19	1.00	0.28	-0.08	0.54	-0.05	0.46	-0.19	-0.31	-0.27
SHEEPS	-0.08	-0.06	-0.06	-0.06	-0.06	-0.01	-0.13	-0.23	-0.03	0.07	0.18	-0.11	0.15	0.14	0.28	1.00	-0.01	0.36	-0.05	0.24	-0.06	-0.09	-0.10
GOATS	-0.01	-0.05	-0.05	-0.01	-0.05	-0.01	-0.07	0.17	-0.13	0.06	0.00	-0.01	-0.06	-0.06	-0.08	-0.01	1.00	-0.10	0.08	-0.07	-0.05	-0.06	-0.01
SF	-0.01	-0.13	-0.12	-0.01	-0.12	-0.01	-0.30	-0.46	0.08	0.20	0.26	-0.13	0.24	0.11	0.54	0.36	-0.10	1.00	0.13	0.49	-0.11	-0.19	-0.19
SUINE	-0.01	-0.01	-0.01	-0.01	-0.01	-0.03	-0.08	-0.09	-0.01	0.13	0.12	-0.08	-0.06	-0.01	-0.01	0.05	0.08	0.13	1.00	0.09	-0.01	-0.01	-0.04
EF	-0.15	0.15	0.15	0.30	0.15	0.12	-0.21	-0.27	0.11	0.13	0.40	-0.08	0.19	0.18	0.46	0.24	-0.07	0.49	0.09	1.00	0.10	-0.16	-0.15
HERB	-0.06	0.69	0.71	0.38	0.69	0.43	0.46	0.42	0.22	-0.01	0.22	-0.05	-0.15	-0.13	-0.19	-0.06	-0.05	-0.11	-0.01	0.10	1.00	0.35	0.69
FOR	-0.01	0.31	0.30	-0.05	0.30	-0.16	0.61	0.14	-0.12	-0.06	-0.19	-0.05	0.09	-0.06	-0.33	-0.09	-0.06	-0.19	-0.04	-0.16	0.35	1.00	0.41
SHR	0.01	0.55	0.59	0.12	0.59	0.17	0.45	0.43	-0.04	-0.08	0.11	-0.04	-0.07	-0.09	-0.27	-0.10	-0.01	-0.19	-0.04	-0.15	0.69	0.41	1.00



Suppl. Fig. S6. Correlation matrix of the independent variables used in this study (H municipal group)



Suppl. Fig. S7. (**a**) Percent area covered by herbaceous vegetation inside Sardinian WUIs; (**b**) average annual net taxable income of resident population (€/inhabitant); (**c**) resident population living inside urban areas, as percentage of the total municipal population; (**d**) number of commuters in the municipality (ratio between commuters from other municipalities and resident population living inside a given municipality)

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