TeMA

Journal of
Land Use, Mobility and Environment

The Times They Are a-Changin' and cities have to face challenges which may not be further postponed. The three issues of the 13th volume will collect articles concerning the challenges that cities are going to face in the immediate future, providing readings and interpretations of these phenomena and, mostly, methods, tools, technics and innovative practices (climate proof cities, zero consumption cities, car free cities) oriented to gain and keep a new equilibrium between cities and new external agents.

TeMA is the Journal of Land Use, Mobility and Environment and offers papers with a unified approach to planning, mobility and environmental sustainability. With ANVUR resolution of April 2020, TeMA journal and the articles published from 2016 are included in the A category of scientific journals. From 2015, the articles published on TeMA are included in the Core Collection of Web of Science. It is included in Sparc Europe Seal of Open Access Journals, and the Directory of Open Access Journals.

THE CITY CHALLENGES AND EXTERNAL AGENTS. METHODS, TOOLS AND BEST PRACTICES

Vol.13 n.3 December 2020

print ISSN 1970-9889 e-ISSN 1970-9870
University of Naples Federico II

TeMA Journal of
Land Use, Mobility and Environment

THE CITY CHALLENGES AND EXTERNAL AGENTS. METHODS, TOOLS AND BEST PRACTICES

3 (2020)

Published by
Laboratory of Land Use Mobility and Environment
DICEA - Department of Civil, Architectural and Environmental Engineering
University of Naples "Federico II"

TeMA is realized by CAB - Center for Libraries at “Federico II” University of Naples using Open Journal System

Editor-in-chief: Rocco Papa
print ISSN 1970-9889 | on line ISSN 1970-9870
Licence: Cancelleria del Tribunale di Napoli, n° 6 of 29/01/2008

Editorial correspondence
Laboratory of Land Use Mobility and Environment
DICEA - Department of Civil, Architectural and Environmental Engineering
University of Naples "Federico II"
Piazzale Tecchio, 80
80125 Naples
web: www.tema.unina.it
e-mail: redazione.tema@unina.it

The cover image is a photo of the 1966 flood of the Arno in Florence (Italy).

TeMA. Journal of Land Use, Mobility and Environment offers researches, applications and contributions with a unified approach to planning and mobility and publishes original inter-disciplinary papers on the interaction of transport, land use and environment. Domains include: engineering, planning, modeling, behavior, economics, geography, regional science, sociology, architecture and design, network science and complex systems.

With ANVUR resolution of April 2020, TeMA Journal and the articles published from 2016 are included in A category of scientific journals. From 2015, the articles published on TeMA are included in the Core Collection of Web of Science. TeMA Journal has also received the *Sparc Europe Seal* for Open Access Journals released by *Scholarly Publishing and Academic Resources Coalition* (SPARC Europe) and the *Directory of Open Access Journals* (DOAJ). TeMA is published under a Creative Commons Attribution 4.0 License and is blind peer reviewed at least by two referees selected among high-profile scientists. TeMA has been published since 2007 and is indexed in the main bibliographical databases and it is present in the catalogues of hundreds of academic and research libraries worldwide.

EDITOR IN-CHIEF

Rocco Papa, University of Naples Federico II, Italy

EDITORIAL ADVISORY BOARD

Mir Ali, University of Illinois, USA
Luca Bertolini, University of Amsterdam, Netherlands
Luuk Boelens, Ghent University, Belgium
Dino Borri, Polytechnic University of Bari, Italy
Enrique Calderon, Polytechnic University of Madrid, Spain
Roberto Camagni, Polytechnic University of Milan, Italy
Pierluigi Coppola, Politecnico di Milano, Italy
Derrick De Kerckhove, University of Toronto, Canada
Mark Deakin, Edinburgh Napier University, Scotland
Carmela Gargiulo, University of Naples Federico II, Italy
Aharon Kellerman, University of Haifa, Israel
Nicos Komninos, Aristotle University of Thessaloniki, Greece
David Matthew Levinson, University of Minnesota, USA
Paolo Malanima, Magna Græcia University of Catanzaro, Italy
Agostino Nuzzolo, Tor Vergata University of Rome, Italy
Rocco Papa, University of Naples Federico II, Italy
Serge Salat, Urban Morphology and Complex Systems Institute, France
Mattheos Santamouris, National Kapodistrian University of Athens, Greece
Ali Soltani, Shiraz University, Iran

ASSOCIATE EDITORS

Rosaria Battarra, National Research Council, Institute of Mediterranean studies, Italy
Gerardo Carpentieri, University of Naples Federico II, Italy
Luigi dell'Olio, University of Cantabria, Spain
Isidoro Fasolino, University of Salerno,Italy
Romano Fistola, University of Sannio, Italy
Thomas Hartmann, Utrecht University, Netherlands
Markus Hesse, University of Luxemburg, Luxemburg
Seda Kundak, Technical University of Istanbul, Turkey
Rosa Anna La Rocca, University of Naples Federico II, Italy
Houshmand Ebrahimpour Masoumi, Technical University of Berlin, Germany
Giuseppe Mazzeo, National Research Council, Institute of Mediterranean studies, Italy
Nicola Morelli, Aalborg University, Denmark
Enrica Papa, University of Westminster, United Kingdom
Dorina Pojani, University of Queensland, Australia
Floriana Zucaro, University of Naples Federico II, Italy

EDITORIAL STAFF

Gennaro Angiello, Ph.D. at University of Naples Federico II, Italy
Stefano Franco, Ph.D. student at Luiss University Rome, Italy
Federica Gaglione, Ph.D. student at University of Naples Federico II, Italy
Carmen Guida, Ph.D. student at University of Naples Federico II, Italy

TeMA Journal of
Land Use, Mobility and Environment

THE CITY CHALLENGES AND EXTERNAL AGENTS. METHODS, TOOLS AND BEST PRACTICES

3 (2020)

Contents

FOCUS

LUME (Land Use, Mobility and Environment)

REVIEW NOTES

TeMA

Journal of
Land Use, Mobility and Environment

TeMA 3 (2020) 329-351
print ISSN 1970-9889, e-ISSN 1970-9870
DOI: 10.6092/1970-9870/7143
Received 2nd September 2020, Accepted 7th November 2020, Available online 31st December 2020

Land surface temperature and land cover dynamics. A study related to Sardinia, Italy

Sabrina Lai [a], Federica Leone [b]*, Corrado Zoppi [c]

[a] Department of Civil and Environmental Engineering and Architecture
University of Cagliari, Cagliari, Italy
e-mail: sabrinalai@unica.it
ORCID: https://orcid.org/0000-0002-4317-8007

[b] Department of Civil and Environmental Engineering and Architecture
University of Cagliari, Cagliari, Italy
e-mail: federicaleone@unica.it
ORCID: https://orcid.org/0000-0003-1071-2768
* Corresponding author

[c] Department of Civil and Environmental Engineering and Architecture
University of Cagliari, Cagliari, Italy
e-mail: zoppi@unica.it
ORCID: https://orcid.org/0000-0003-4114-5380

Abstract

This study aims at analyzing analogies and differences between the spatial relations regarding land surface temperature (LST) and land covers in May and August 2019. Land cover data are drawn from the most updated spatial datasets available from Copernicus, while LST is retrieved from Landsat 8 satellite images made available by the U.S. Geological Survey. The methodology couples GIS spatial analysis and regression analysis; the latter is used to implement spatial inferential analysis as regards LST. Moreover, on the basis of a "what if" assessment, the impact of future afforestation, as regards rural areas, is detected with respect to decrease in LST, building on the outcomes of the model which relates LST to land cover types. The Sardinian region is taken as case study because its climate homogeneity and its self-containment allow for a pretty straightforward identification of the regional boundaries. The correlation between the spatial distribution of LST and land cover reveals, in the two time periods, that urbanization and the spatial dynamics of heating phenomena are closely connected. The methodology can be easily implemented in other regional contexts, and comparison of analogies and differences are quite effective and useful in identifying stylized facts and policy implications.

Keywords

Land surface temperature; Land cover; Regulating ecosystem services.

How to cite item in APA format

Lai, S., Leone, F., & Zoppi, C. (2020). Land Surface Temperature and land cover dynamics. A study related to Sardinia, Italy. *Tema. Journal of Land Use, Mobility and Environment*, *13* (3), 329-351. http://dx.doi.org/10.6092/1970-9870/7143

1. Introduction

In the last decades, land cover transformations and transitions have been characterized by significant changes (Chadchan & Shankar, 2009; Nguyen et al., 2019) related to fast urbanization and progressive anthropization. Natural and semi-natural areas, such as forests and woodlands and shrubs, have changed into anthropized areas, which include not only urban areas, but also agricultural areas (Kim & Baik, 2005; Cui & Shi, 2012). According to the 2020 report on land take issued by the System for environmental protection of the Italian government, from 2018 to 2019 artificial areas increased by 57.5 square kilometers, which corresponds to a 16 hectares per day increasing trend (Munafò, 2020). Land-taking processes in coastal areas, plains and valley floors, and agricultural areas adjacent to urban zones show the most outstanding figures (Munafò, 2020). Moreover, the report highlights the tendency to convert natural zones into artificial areas within urban settlements (Munafò, 2020). The main problems connected to land-taking processes are identified by landscape fragmentation, urban heat island (UHT) and loss of ecosystem services. In terms of fragmentation, in 2019 around 35% of the Italian territory is classified as highly or very highly fragmented, whereas in relation to temperatures the difference between urban and suburban areas and rural zones is about 3.1°C in the Metropolitan City of Cagliari and 6.3°C in the Metropolitan City of Turin (Munafò, 2020). Moreover, according to the same source (Munafò, 2020), from 2012 to 2019 the national gross domestic product decreased by 69,956,781 Euros due to land-taking processes concerning agricultural land, which determined a huge loss in agricultural production, or, in the supply of an important provisioning ecosystem service (Millennium Ecosystem Assessment, 2003).

According to a number of studies (Weng et al., 2004; Feizizadeh et al., 2013; Pal & Ziaul, 2017) land cover changes influence the surface temperature due to the different heat capacity of soils associated to a given amount of solar radiation (Fonseka et al., 2019). From this perspective, the variation in land surface temperature (LST) represents a key variable to analyze the effects of land covers on local temperatures (Akinyemi et al., 2019; Zhang & Sun, 2019; Al Kafy et al., 2020).

According to Hulley et al. (2019), *Land Surface Temperature (LST) is a fundamental aspect of climate and biology, affecting organisms and ecosystems from local to global scales. LST measures the emission of thermal radiance from the land surface where the incoming solar energy interacts with and heats the ground, or the surface of the canopy in vegetated areas*. Moreover, according to the NASA Earth Observatory, LST is *how hot the 'surface' of the Earth would feel to the touch in a particular location. From a satellite's point of view, the "surface" is whatever it sees when it looks through the atmosphere to the ground. It could be snow and ice, the grass on a lawn, the roof of a building, or the leaves in the canopy of a forest. Thus, land surface temperature is not the same as the air temperature* [1]". From this point of view, the interaction between the spatial distribution of LST and land cover changes is an important parameter to assess the effects of land-taking processes on climate change (Alfraihat et al., 2016; Li et al., 2016). Al Kafy et al. (2020) analyze land cover changes and their influence on LST in relation to three years, 1999, 2009, and 2019, by means of Landsat TM/OLI satellite images in the area of Rajshahi City Corporation, Bangladesh. Gohain et al. (2020) investigate the relation between LST variation and land cover changes between 1990 and 2019 through remote sensing and GIS techniques in Pune city, India. Tran et al. (2017) study the impacts of land cover types on LST variation in the urban area of Hanoi through a methodology based on three phases: in the first phase, the authors investigate the relations between LST and vegetation, human induced features and agricultural areas by calculating normalized vegetation and built-up indices for each land cover class; next, the relations between land cover changes and urban heat islands are investigated by implementing hot spot analysis and urban landscape analysis; finally, a non-metric regression model is used to assess future urban climate scenarios. Akinyemi et al. (2019) focus on the relations between LST and vegetation changes between 2000

---

[1] This definition is available on the NASA Earth Observatory's website: https://earthobservatory.nasa.gov/global-maps/MOD_LSTAD_M (accessed on 31 August 2020).

and 2018 in the semi-arid areas of Caborone, Botswana’s Capital city, through MODIS daytime and night-time LST, and Normalized Difference Vegetation Index (NDVI).

The impacts of land cover changes on LST were analyzed in some studies focusing on Italian cases, mostly focusing on urban areas. In particular, Zullo at al. (2019) analyze the impacts of urbanized areas on LST in relation to the Po Valley with reference to the 2001-2011 time period. Guha et al. (2018) focus on Florence and Naples by investigating the relations between LST, NDVI, and normalized difference built-up index (NDBI). Scarano & Sobrino (2015) assess the impacts of landscape composition and urban morphology on LST in Bari. Moreover, Stroppiana et al. (2014) study the relations between LST, land cover changes, topography and solar radiation in four Italian contexts related to the Basilicata, Campania, Molise, and Apulia regions.

Moreover, it has to be highlighted that the Sardinian Regional Administration has recently approved the Regional Strategy for the adaptation to climate changes, which assumes heat islands and waves among the most relevant impacts generated by high temperatures. Adaptation and mitigation policies should address heat islands and waves in order to enhance the liveability of natural and urbanized environments, and eventually local societies’ quality of life (Regione Autonoma della Sardegna, 2019a). The Regional Strategy identifies several categories of extreme events as direct or indirect impacts of climate changes, such as sudden and disrupting floods, extended fires, droughts, heavy rains and, indeed, heat waves and heat islands in urban environments (Regione Autonoma della Sardegna, 2019b). From this standpoint, a clear-cut research gap in the Regional Strategy is represented by the lack of identified relations between the impacts of climate changes and spatial, social and economic covariates.

This study aims at filling a part of the gap by analyzing the connections between LST spatial distribution and land cover types and changes, and by doing so, at identifying narratives to explain heat waves and islands (Echevarria Icaza et al., 2016). The literature identifies two outstanding aspects to be further analyzed as regards the relations between LST and land cover changes. First, the regional dimension is under-researched and needs to be appropriately addressed (Ding & Shi, 2013). Secondly, spatial strategies grounded upon empirical evidence should be identified and recommended so as to be included in regional and local planning policies in order to decrease LST (Shirgir et al., 2019).

Under this perspective, the methodological approach proposed in this study aims at investigating the impacts of land cover changes on LST by combining GIS-based analysis with regression analysis, and at suggesting strategies and policies in order to decrease LST. The methodology is implemented in the regional context of Sardinia, Italy. In particular, this study investigates if, and to what extent, land cover transitions influence LST, on the basis of data related to the spring and summer periods.

The study is structured into five sections as follows. The second section provides a description of the study area, defines data and discusses the methodological approach used to assess the impacts of land cover changes on LST. The third section reports the results derived from the implementation of the methodological approach as regards the Sardinian region. The fourth section discusses the implications of the outcomes by comparison with analogous studies. Finally, the fifth section discusses the implications of the study in terms of strategies and policies to decrease LST and directions for future research.

2. Materials and Methods

2.1 Study area

Located in the western Mediterranean area (Fig.1), Sardinia is an Italian autonomous region with a size of around 24,000 km^2 and a population of 1,639,591 inhabitants[2].

---

[2] 2018 data, retrieved from SardegnaStatistiche—Popolazione e Famiglie—Popolazione (2007–2019). Available online: http://www.sardegnastatistiche.it/documenti/12_103_20191028124604.ods (accessed on 31 August 2020).

Sardinia was chosen as case study for this research because of its being an island, which makes it easier to explore environmental issues at the regional scale. Moreover, as far as the climate is concerned, the island shows great homogeneity: it has Mediterranean hot and dry summers, while in winter the temperature is mild and moderate rain occur (Canu et al., 2015). Sardinian landscapes are mostly hilly and wild; the island hosts only a few plains (the bigger of which is the Campidano plain, the light grey diagonal clearly visible in Fig.1, which stretches from the central-western part of the island to the south) that are significant for their agricultural uses; a number of small coastal valleys are also present, and their primary production potential is undermined by the pressure of coastal urbanization. Only some major groups of mountains, always lower than 2,000 m, mark the rugged landscape of the island (Pungetti et al., 2008).

As for land covers, the most significant traits of the island are its herbaceous vegetation associations, many of which endemic, and its scrubs: Mediterranean maquis and garrigue (Cardil et al., 2014). Agriculture and pastures, also comprising wooded grassland similar to Spanish *dehesas* (Seddaiu et al., 2013), i.e. multifunctional agro-sylvo-pastoral systems consisting of pastures with oaks and cork oaks, are also significant (Canu et al., 2015), while urbanized areas make up less than 3.8% of the region, which is a very low figure, if compared to the Italian average, recently assessed at 7.6% (Munafò, 2019).

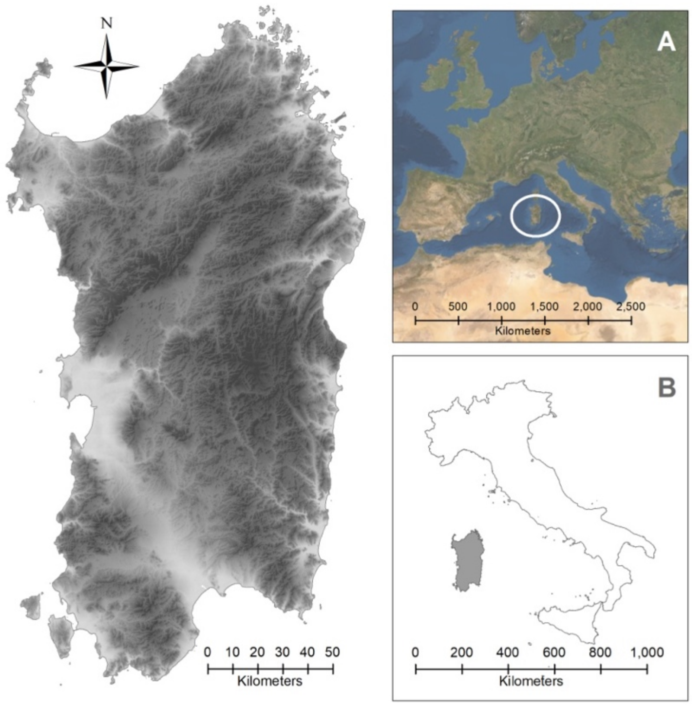

Fig.1 Topographic map of Sardinia and its location within Europe (A) and Italy (B)

2.2 Data

A number of satellite data are currently freely available; the most prominent are those distributed by the European Union's Earth Copernicus Observation Program[3] and by the USGS's Earth Resources Observation and Science[4]. The latter distributes, among many, Landsat 8 TIRS (Thermal Infrared Sensor) and OLI (Operational Land Imager) images, which were used in this study. Two searches were performed; the first concerns the mid-summer season (15 July - 30 August 2019), in which temperature peak in Sardinia, while the second concerns the mid-spring season (15 April - 31 May 2019), in which vegetation growth is at its highest, before the dry season and the annual crop harvesting. For each time period, five images were

---

[3] Copernicus. Europe's Eyes on Earth. Available online: https://www.copernicus.eu/en (accessed on 31 August 2020).

[4] USGS. Science for a Changing World—EarthExplorer. Available online: https://earthexplorer.usgs.gov/ accessed on 31 August 2020).

retrieved, two belonging to Landsat scene 192 (on May 16 for the spring search and August 20 for the summer search) and three to Landsat scene 193 (on May 23 for the spring search and August 11 for the summer search). Details for each image are provided in Tab.1, while Fig.2 provides the spatial layout of scenes 192 and 193, shown as dotted rectangles, and the images' footprints, shown as colorful squares inside the scenes. Land cover data in Europe are usually classed in a hierarchical structure, in accordance with the European program CORINE (COoRdination of INformation on the Environment) (Kosztra et al., 2019). The Land Monitoring Service of the European Union's Copernicus Earth Observation Program (CLC, 2018) makes freely available both raster and vector land cover datasets obtained through satellite image interpretation; such datasets have a minimum mapping unit (MMU) of 25 hectares and describe land covers at the third-level of the CORINE hierarchical taxonomy. As for temporal resolution, datasets are available for the years 1990, 2000, 2006, 2012, and 2018; for this study, the latter, and most recent, dataset was used.

The third input data for this study is a regional Digital Terrain Model (DTM) produced by the Regional Administration of Sardinia in 2011, freely available from its geoportal[5], and having a spatial resolution of 10 meters.

Image code	Scene	Cell size	Date	Season
LC08_L1TP_192032_20190516_20190521_01_T2	192	30 m	May 16, 2019	Spring
LC08_L1TP_192033_20190516_20190521_01_T1	192	30 m	May 16, 2019	
LC08_L1TP_193031_20190523_20190604_01_T2	193	30 m	May 23, 2019	
LC08_L1TP_193032_20190523_20190604_01_T1	193	30 m	May 23, 2019	
LC08_L1TP_193033_20190523_20190604_01_T1	193	30 m	May 23, 2019	
LC08_L1TP_193031_20190811_20190820_01_T1	193	30 m	August 11, 2019	Summer
LC08_L1TP_193032_20190811_20190820_01_T1	193	30 m	August 11, 2019	
LC08_L1TP_193033_20190811_20190820_01_T1	193	30 m	August 11, 2019	
LC08_L1TP_192032_20190820_20190903_01_T1	192	30 m	August 20, 2019	
LC08_L1TP_192033_20190820_20190903_01_T1	192	30 m	August 20, 2019	

Tab.1 Selected Landsat 8 images

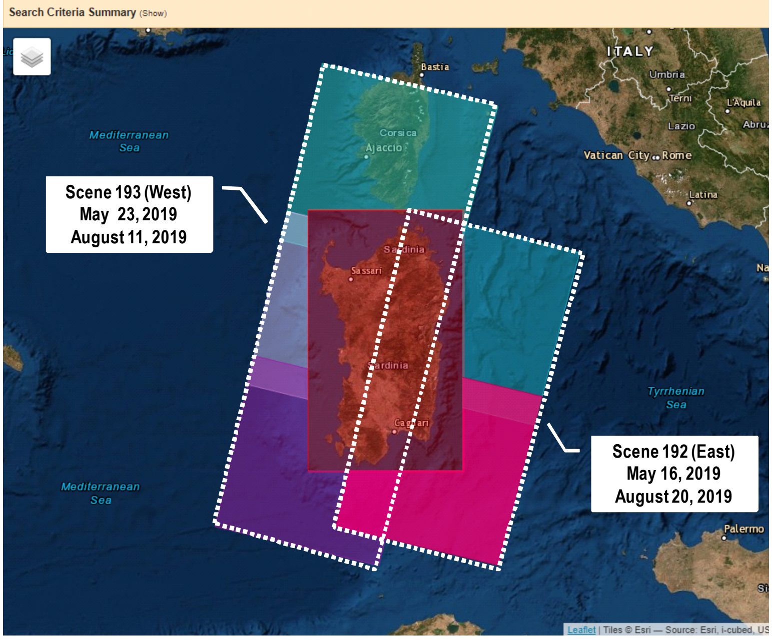

Fig.2 Spatial layout of the ten Landsat 8 OLI-TIRS images selected for this study

---

[5] DTM passo 10 metri [DTM Sampling Rate 10]. Available online: http://webgis2.regione.sardegna.it/catalogodati/card.jsp?uuid=R_SARDEG:JDCBN (accessed on 31 August 2020).

2.3 Methodological framework

The methodology implemented in this study is based on two steps, as follows. The LST spatial taxonomy is derived through the procedure described in subsection LST Extraction and Spatial Layout; data related to elevation and land covers are next processed (subsection Land Cover Types and Elevation) in order to set up a spatial database that integrates the three items (subsubsection Land Cover Types and Elevation). Finally, a linear regression model is implemented to identify the relations between LST and land cover types (subsection Linear regression model), on the basis of the spatial database described in subsection Land Cover Types and Elevation. A graphical summary of the methodology adopted in this study is provided in Fig.3. The outcomes of the regression model implemented with reference to summer 2019 are then compared with the results of an analogous model concerning spring time 2019, in order to identify seasonal analogies and differences related to the impacts of different land covers on LST.

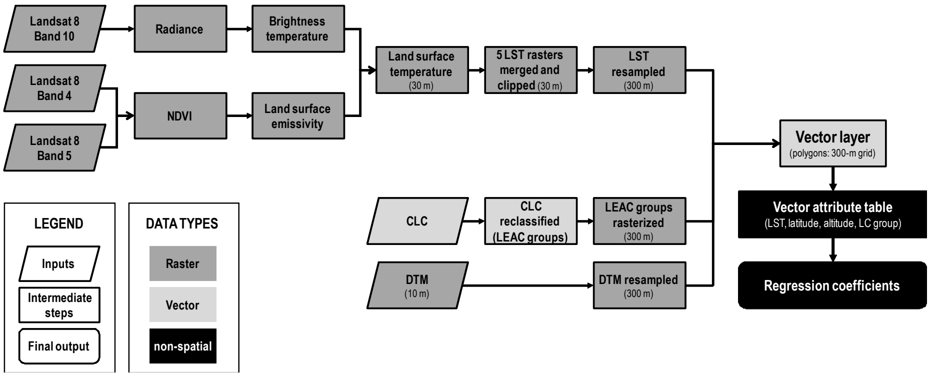

Fig.3 Overview of the methodology

LST Extraction and Spatial Layout

The ten images listed in Tab. 1 were separately processed through Ndossi and Avdan's QGIS plugin (Ndossi & Avdan, 2016), which has been used in a number of studies (for instance, Alves, 2016; Barbierato et al., 2019; Dhar et al., 2019; Lai et al., 2020) to retrieve LST from Landsat satellite images. This retrieval process comprises five steps, of which the first is the calculation of the top-of-atmosphere spectral radiance (ToA) for each pixel, based on pixel values of Landsat 8 band 10 as per equation (1):

$$ToA = (M \cdot Q) + A \tag{1}$$

where[6] M and A are two rescaling factors (respectively, multiplicative and additive) provided in the image's metadata, and Q is band 10 pixel value quantized and calibrated.

Next, the top-of-atmosphere brightness temperature (BT, measured in Kelvin) is calculated through equation (2):

$$BT = \frac{C_2}{\ln\left(\frac{C_1}{ToA} + 1\right)} \tag{2}$$

where[5] C1 and C2 are two thermal conversion constants that can be retrieved from the image's metadata.

Subsequently, the plugin calculates the normalized difference vegetation index (NDVI) based on Landsat 8's bands 4 and 5 pixel values following equation (3) (Townshend et al., 1985):

---

[6] Using the USGS Landsat Level-1 Data Product. Available online: https://www.usgs.gov/land-resources/nli/landsat/using-usgs-landsat-level-1-data-product (accessed on 31 August 2020).

$$NDVI = \frac{N - R}{N + R} \tag{3}$$

where N is the near-infrared band and R is the visible red band, i.e., for Landsat 8 images, band 5 and band 4 respectively.

In the final two steps, where Land Surface Emissivity (LSE) and LST are calculated, the user can choose among various available algorithms. In this study, for LSE the algorithm by Zhang et al.'s (2006), which assesses LSE based on NDVI values, was chosen since it has been considered as the most reliable one (Ndossi & Avdan, 2016), while for LST the Planck function was used, because it does not require atmospheric variables and is therefore regarded as easier to use (Ndossi & Avdan, 2016). The Plank function is provided in equation (4):

$$LST = \frac{BT}{1 + \left(\lambda \cdot \frac{\mathrm{BT}}{\alpha}\right) \cdot \ln(\mathrm{LSE})} \tag{4}$$

where λ is the wavelength of the emitted radiance (equaling 1.0895·10-5 m for Landsat 8 TIRS (Zhao et al., 2018), and α = h·c/σ (where h is Planck's constant; c is the velocity of light; σ is Boltzmann's constant), equaling 1.438·10-2 mK (Avdan & Jovanovska, 2016). LST and BT are both measured in Kelvin.

By implementing the steps in the plugin, ten LST raster maps were retrieved. Each of these maps, having cell size 30 meters, corresponds to one Landsat image listed in Tab. 1. The five spring images were next merged, as well as the five summer images; in this way, two LST regional maps were obtained, one for the time period 16-23 May, 2019 and one for the time period 11-20 August, 2019. Since in both cases the images pertaining to scene 192 overlap the ones pertaining to scene 193 (as shown in Fig.2), and since in both cases the maximum values always correspond to pixels belonging to scene 193, for overlapping pixels the value associated to images in scene 193 was consistently retained. Finally, the two regional LST maps were resampled, and the final resolution was set at 300m, so as to lower computational time and efforts in the following steps.

Land Cover Types and Elevation

The 2018 CORINE Land Cover (CLC) vector dataset was retrieved from the Copernicus program website and processed so as to extract only polygons concerning Sardinia. These were subsequently reclassified, meaning that land covers were grouped on the basis of the Land and Ecosystem Accounting (LEAC) taxonomy established by the European Environment Agency (EEA, 2006, p. 98) for environmental accounting purposes. As shown in Tab.2, the 44 third-level classes of the CLC nomenclature are grouped into seven LEAC groups.

	Land and Ecosystem Accounting (LEAC) groups	**CORINE Land Cover Classes**			
ART	Artificial surfaces	1.*			
INTAG	Intensive agriculture (permanent crops and arable land)	2.1.*	2.2.*	2.4.1	
EXTAG	Extensive agriculture (pastures and mosaic farmland)	2.3.*	2.4.2	2.4.3	2.4.4
FWS	Forests, woodlands, and shrubs	3.1.*	3.2.4		
SHNG	Sclerophyllous vegetation, heathland, and natural grasslands	3.2.1	3.2.2	3.2.3	
OPEN	Open spaces with little or no vegetation	3.3.*			
WATER	Water bodies and wetlands	4.*	5.* (except 523-sea)		

The asterisk (*) marks any sub-classes of a given class, or any sub-sub-classes of a given sub-class. (CORINE: Coordination of Information on the Environment).

Tab.2 CORINE land cover classes and LEAC groups

From the CLC vector dataset, a second vector layer providing the spatial distribution of the LEAC groups for the study area was thus obtained and next converted into a raster map having the same grid as the resampled

LST and, therefore, a spatial resolution of 300 meters. Values for each cell in this raster map corresponded to the prevailing LEAC group in that cell.

As regards altitude, the DTM retrieved from the regional geoportal was resampled so as to obtain a new raster file matching both the LST and LEAC group raster maps as far as both the grid and the spatial resolution (300 meters) are concerned. Linear interpolation was performed to resample the DTM because this technique is deemed to best suit continuous data[7], as elevation.

Land Cover Types and Elevation

To begin with, a vector layer was created, whose polygons coincide with pixels in the three raster maps (LST, LEAC groups, elevation) derived as per the previous subsubsections. This vector layer is therefore, from a spatial perspective, a squared grid where every polygon is a 300m by 300m square in the projected reference system WGS 84 / UTM zone 32N (code EPSG 32632[8]), the same as that of the three above mentioned raster maps.

A "spring" vector dataset was then created by assigning to each polygon (square) the values of the three raster maps as attributes. Hence, the attribute table of the vector datasets brings together, for each polygon, the May LST value, the prevailing land cover group, and the altitude. To these, two further attributes were added: first, the latitude of the polygon's centroid, because the temperature is likely to depend upon the latitude; second, a field taking the value 1 or 0 depending on whether the polygon is contained in scene 193 (that is, the western one in Fig.2), or in scene 192 (that is, the eastern one in Fig.2). Polygons comprised in both scenes were considered as belonging to scene 193, which is consistent with the fact that the maximum LST value, which always corresponded to images in scene 193, was retained when building the regional LST map.

A "summer" vector dataset was also created, which only differs from the spring one as regards the LST values, which were retrieved from the August Landsat images.

Linear regression model

The polygons described in the previous subsection are identified as the spatial units to estimate a multiple linear regression which takes the following form:

$$\mathrm{LST} = \alpha_0 + \alpha_1\,\mathrm{ART} + \alpha_2\,\mathrm{INTAG} + \alpha_3\,\mathrm{EXTAG} + \alpha_4\,\mathrm{FWS} + \alpha_5\,\mathrm{SHNG} + \alpha_6\,\mathrm{OPEN} + \alpha_7\,\mathrm{HEIGH} + \alpha_8\,\mathrm{LATIT} + \alpha_9\,\mathrm{WEST} \tag{5}$$

where:

- independent variables from ART through OPEN identify the LEAC groups of land covers; these variables are Boolean, each of them taking either value 1 or value 0, depending on the prevailing size of the area of a LEAC group in a cell compared to the other LEAC groups sizes; consequently, if the area of the ART group is the largest in a cell, the variable ART is equal to 1, if not, it is equal to 0; if the area of the INTAG group is the largest in a cell, the variable INTAG is equal to 1, if not, it is equal to 0, etc.; each estimated coefficient of regression model (5), α_i, i = 1, …, 6, shows the LST variation of a cell whose largest area corresponds to the covariate identified by α_i (namely, ART, INTAG, and so on) compared to the reference condition represented by the largest area of the cell being identified by the covariate WATER (Wetlands and water bodies);

---

[7] ArcGis Help. Resample. Available online: https://pro.arcgis.com/en/pro-app/tool-reference/data-management/resample.htm (accessed on 31 August 2020).

[8] EPSG 32632. Available online: https://epsg.io/32632 (accessed on 31 August 2020).

- "HEIGH" is the elevation, in meters, associated to the polygon, computed as shown in subsubsection Land Cover Types and Elevation;
- "LATIT" is the latitude, in meters, associated to the centroid of the polygon, as described in subsubsection Land Cover Types and Elevation;
- "WEST" is a Boolean covariate, which equals either 0 or 1 as per subsection Land Cover Types and Elevation.

The estimated coefficients of regression model (5), α_i, i = 1, …, 6, class the zone types on the basis of the marginal effects on LST identified by the values of α_i.

This study compares the outcomes of regression model (5) implemented as regards two times of the year 2019. Namely, the values of LST were detected in May and in August, in order to assess analogies and differences between the spatial relations regarding LST and land covers. Moreover, on the basis of a "what if" assessment, the impact of future afforestation, as regards rural areas, is detected with respect to decrease in LST, building on the outcomes of the model which relates LST to land cover types.

The covariates HEIGH and LATIT are included in the model to control the effects of a cell's elevation and latitude on LST; therefore, if the estimated coefficients α_7 and α_8 were significant in terms of their p-values, this would imply that the elevation and latitude have impacts on LST, which are expected to be negative, since a higher elevation and a greater latitude are expected to be related to a lower LST, ceteris paribus. Lastly, the covariate WEST controls the effect of the timing of the Landsat 8 images, which are likely to exhibit a systematic difference with reference to the two May's and August's days the Landsat 8 images were taken. In both cases, May and August, the images related to Western Sardinia (Scene 193 of the Landsat 8 images) were taken on sunny and clear days, whereas the other cells, located more to the Eastern side of Sardinia, were taken in partly cloudy days. That being so, the cells belonging to Scene 193 should exhibit higher LSTs, ceteris paribus, and the expected sign of WEST is positive.

3. Findings

The findings coming from the implementation of the methodology described in the previous section are shown as follows. First, the spatial distribution of LST is presented, on the basis of steps (1) through (4). Secondly, model (5) is operationalized with reference to August 2019 and the impacts of LEAC groups on LST are described, which define a taxonomy of the LEAC groups, from water bodies and wetlands (lowest level) up to intensive and extensive agricultural land (upper levels). Moreover, differences and analogies between the spatial relations regarding LST and land covers as regards May and August 2019 are presented as well. Finally, the effects of changes in selected LEAC groups, namely afforestation, as regards rural areas are described on the basis of a "what if" assessment.

3.1 The LST Spatial Layout

Fig. 4 provides all of the maps obtained from the Landsat satellite images concerning the spring season by following the procedure explained in subsection LST Extraction and Spatial Layout. As clearly visible in Fig.4, spring images are affected by the presence of clouds, which in turns locally affected both NDVI and LST values. For this reason, cloudy pixels (amounting to approximately 25,000, less than 9.4% of the total number of cells, equaling 266,818) were removed for the spring images only, since this issue does not affect summer images. Fig. 5 provides a full picture of the spatial dataset that were used to build the attribute table next used as input data for the regression: LST (minus the cloudy cells for the spring dataset only), LEAC groups, and finally elevation.

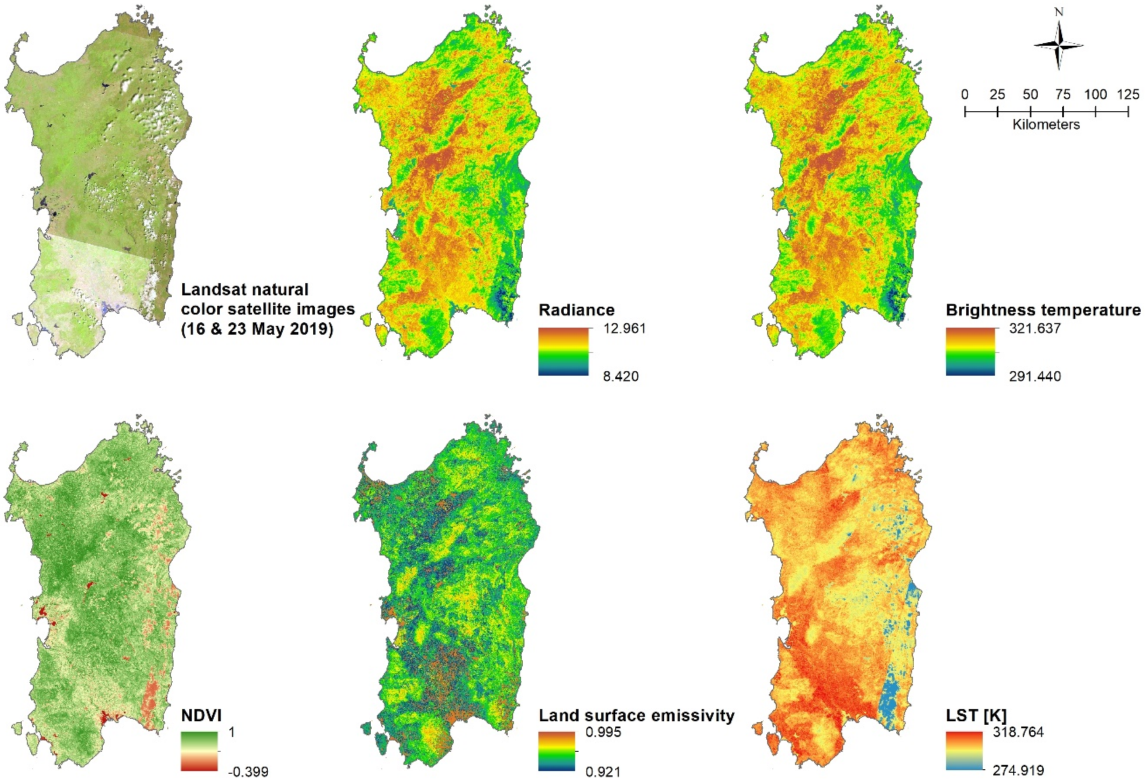

Fig.4 From Landsat images to LST: all of the maps extracted as per Subsection LST Extraction and Spatial Layout

3.2 The Implementation of the Regression Model

The estimated coefficients of the regression model show the impacts of the six LEAC groups of land covers on LST. The estimates of the dichotomous covariates identify the differential impact of each covariate with respect to the LEAC group "Water bodies and wetlands," whose impact on LST is the least relevant.

Tab. 3 reports the regression estimates and statistics for the summer dataset.

Moreover, Tab.4 shows the differences between the estimates of the coefficients reported in Tab.3, concerning two days of August 2019 (August 11 and August 20), and the estimated coefficients of regression model (equation 5) applied to the LST spatial distribution related to two days of May 2019 (May 23 and May 16). These represent the differential impacts of the LEAC groups on LST as regards the selected summer and spring periods. If the difference is negative, the summer impact is lower than the spring impact and the other way around.

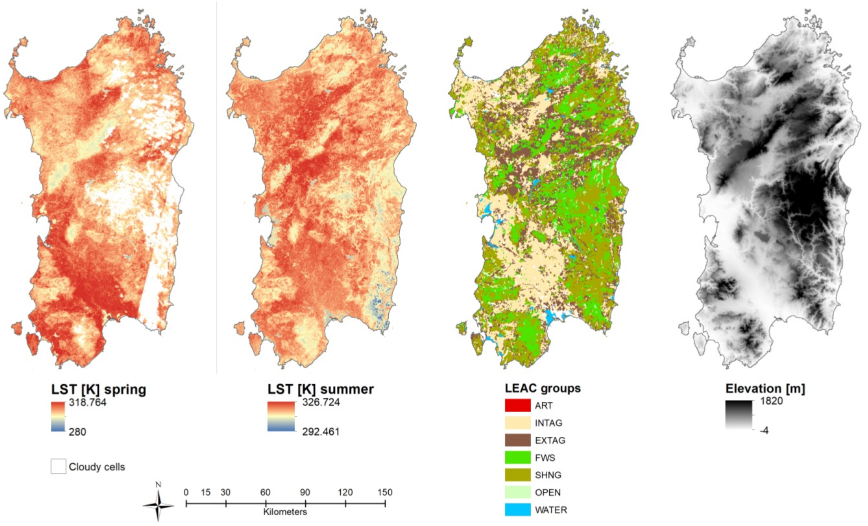

Fig.5 Spatial distribution of LST in May and August 2019, of LEAC groups, and of elevation

Independent Variable	Coefficient	Standard Deviation	t-statistic	p-value	Mean of the Independent Variable
ART	8.297	0.0685	121.039	0.000	0.0295
INTAG	11.576	0.0595	194.578	0.000	0.247
EXTAG	10.491	0.0601	174.673	0.000	0.218
FWS	4.584	0.0611	74.955	0.000	0.175
SHNG	7.365	0.0598	123.113	0.000	0.302
OPEN	7.312	0.0756	96.792	0.000	0.0178
HEIGH	−0.000117	0.0000260	−4.481	0.000	339.347
LATIT	−0.000000643	0.0000000991	−6.484	0.000	4437093.555
WEST	5.004	0.0249	201.055	0.000	0.926
Dependent variable: LST: 313.751 K; Standard deviation: 4.453; Adjusted R-squared: 0.476.					

Tab.3 Regression results for the summer dataset (August 11 and 20, 2019)

The estimated coefficients of latitude and height show significant p-values and the expected signs. That being so, consistently with expectations, higher altitudes and larger latitudes correspond to lower LST. As regards altitude, an increase of 100 meters will entail a decrease of 0.0117 K in LST, while a 10 km increase in LATIT will imply a 0.0006 K decrease in LST. The estimated coefficient of variable WEST is significant and shows the expected sign as well. This entails that, on average, a cell whose LST was identified by the satellite images on August 11 shows an LST 5 K higher than a cell whose LST was taken on August 20, everything else being equal.

Independent Variable	Difference
ART	-0.62
INTAG	3.06
EXTAG	3.08
FWS	−0.20
SHNG	1.09
OPEN	−0.04
HEIGH	0.0063
LATIT	0.000015
WEST	0.69

Tab.4 Differences in the estimated coefficients between summer and spring days (K)

Moreover, as reported in Tab.4, the differences between the regression models implemented with reference to the summer and to the spring periods are negligible, so the results related to latitude and height can be considered quite robust across year 2019. That being so, the estimated coefficients of the three control variables are consistent with expectations and statistically significant, which makes pretty consequential and reliable the identification of the impacts on LST related to the six LEAC groups associated to the Boolean variables from ART to OPEN.

The estimates of the coefficients of the six covariates are significant with reference to a standard p-values test and imply the following outcomes, under the condition that everything else remains the same.

Intensive and extensive agriculture show the highest impacts on LST. The estimates of the coefficients entail that the cells characterized either by arable land and permanent crops or by mosaic farmland and pastures show a temperature higher by: 11.6 or 10.5 K than cells belonging to the water bodies and wetland LEAC group; 3.2 or 2.1 K than cells belonging to the ART LEAC group; 4.2 or 3.1 K higher than cells belonging to the SHNG and OPEN LEAC group; 7.0 or 5.9 K higher than cells belonging to the FWS LEAC group.

Secondly, intensive and extensive agriculture have much higher impacts on LST in the summer period than in spring, as shown in Tab.4. The summer differential impacts of INTAG and EXTAG are more than 3 K higher than in the spring period, which makes intensive and extensive agriculture effects on LST even higher than the impact of urbanized land LEAC group, which shows the highest effect as regards the spring period.

Another relevant finding is that land covers characterized either by sparse or rare vegetation (OPEN) or by grassland and heathland (SHNG) have lower effects on LST, even though the latter LEAC group shows a higher impact than in the spring period, that is more than a 1 K increase, as reported in Tab.4.

Finally, the FWS LEAC macroclass, that is forests, woodlands and shrubs, shows the most relevant impact on temperature mitigation, with almost complete consistency between the summer and spring periods, as reported in Tab.4.

3.3 The Impact of the Covariates Change on LST Based on a "What If" Assessment

The outcomes of the regression analysis shown in Tab.3 make it possible to develop "what if" scenarios and spatially represent them.

A possible scenario is one in which afforestation measures are implemented in rural areas to mitigate LST. Such measures would be unlikely to target INTAG, because these represent the most profitable agricultural areas and harsh conflicts would inevitably arise; rather, they would target EXTAG, where conflicts would be milder because some farming activities, such as sheep or goat grazing, quite significant in the island, could still take place, and might even be mitigated through incentives that can be allocated to land-owners under the current European financial schemes concerning agriculture and rural development. The "what if" assessment is therefore based on the hypothesis that all of the EXTAG cells in rural areas are targeted by afforestation measures and, therefore, are turned into FWS. This is, of course, only a hypothetical and extreme scenario, which could further be refined by assuming that only a certain percentage of the cells that meet some predefined selection criteria (for instance based on elevation, slope, distances from already afforested areas) can effectively be turned into FWS.

Under this working hypothesis, cells having EXTAG as LEAC type were selected; this returned 58,220 cells out of the 266,818 total cells comprising both the summer and the spring datasets. Out of the 58,220 EXTAG cells, 3,211 are included within either the "inhabited centers" or the "inhabited nucleuses" as defined by the National Institute of Statistics[9], while the remaining are located within rural areas. The latter 55,009 cells can therefore be targeted by afforestation policies, taking for instance the form of incentives under the European Agriculture Fund for rural Development.

As regards the summer seasons, if an EXTAG cell were turned into an FWS cell, then its LST would decrease by 5.904 K, which equals the difference between the corresponding coefficients in Tab. 4. Some visual examples of how this change in the LEAC types would affect the spatial distribution of the LST at the local level are shown in Fig. 6: panels A1, B1, and C1 provide details of the LST map retrieved from the Landsat images (i.e., of the map shown at the bottom in Fig.5), while panels A2, B2, and C2, relating to the same areas as A1, B1, and C1 respectively, show how the LST would change as a result of afforestation policies targeting rural EXTAG areas only.

As for the spring seasons, if an EXTAG cell were turned into an FWS cell, then its LST would decrease by 2.627 K, which equals the difference between the corresponding coefficients from the regression analysis concerning the spring dataset (i.e., 7.413 and 4.786, respectively, for EXTAG and FWS (Lai et al., 2020)). Some visual examples of how this change in the LEAC types would affect the spatial distribution of the LST at the local level are shown in Fig.7: panels A1, B1, and C1 provide local details of the LST map retrieved from the Landsat images (i.e., of the map shown in Fig.5), while panels A2, B2, and C2, relating to the same areas as A1, B1, and C1 respectively, show how the LST would change as a result of afforestation policies targeting rural EXTAG

---

[9] Basi territoriali e variabili censuarie [Territorial units and census variables]. Available online: https://www.istat.it/it/archivio/104317 (accessed on 31 August 2020).

areas only. Spring cells, quite diffuse in panels B1 and B2, were removed from the map, since the LST retrieval process is deeply affected by the presence of clouds.

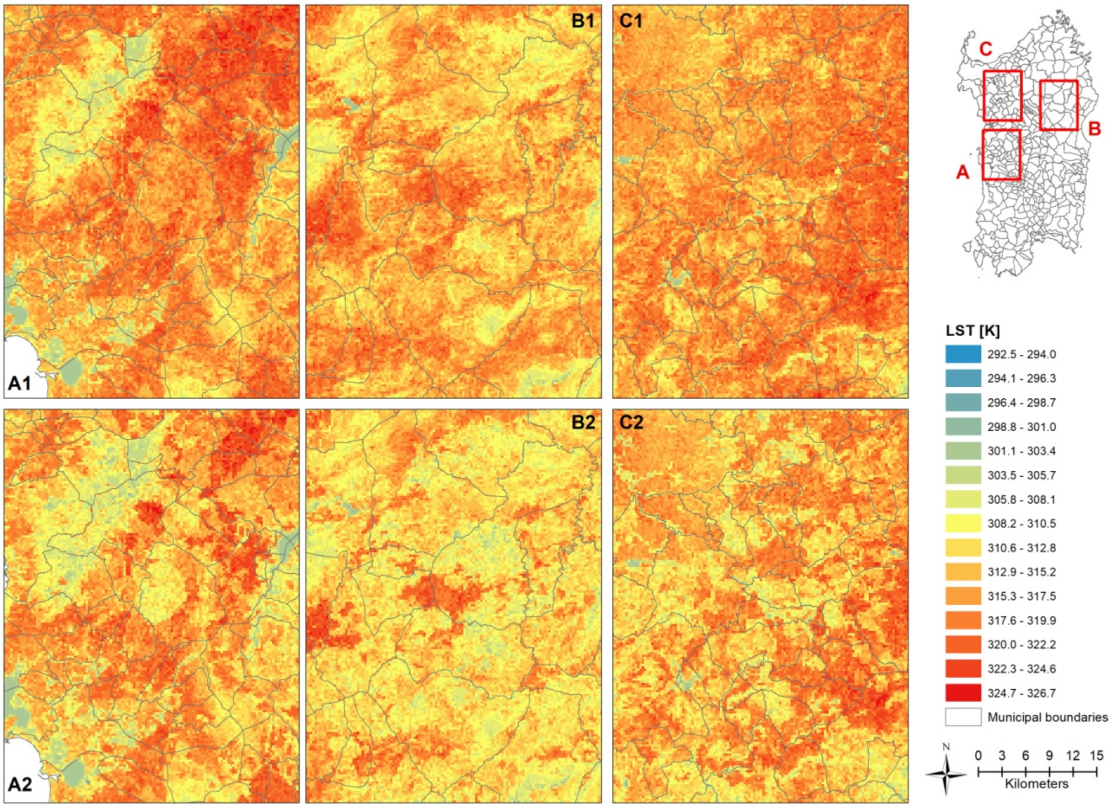

Fig.6 "What if" assessment: actual (A1, B1, C1) and simulated (A2, B2, C2) LST summer maps

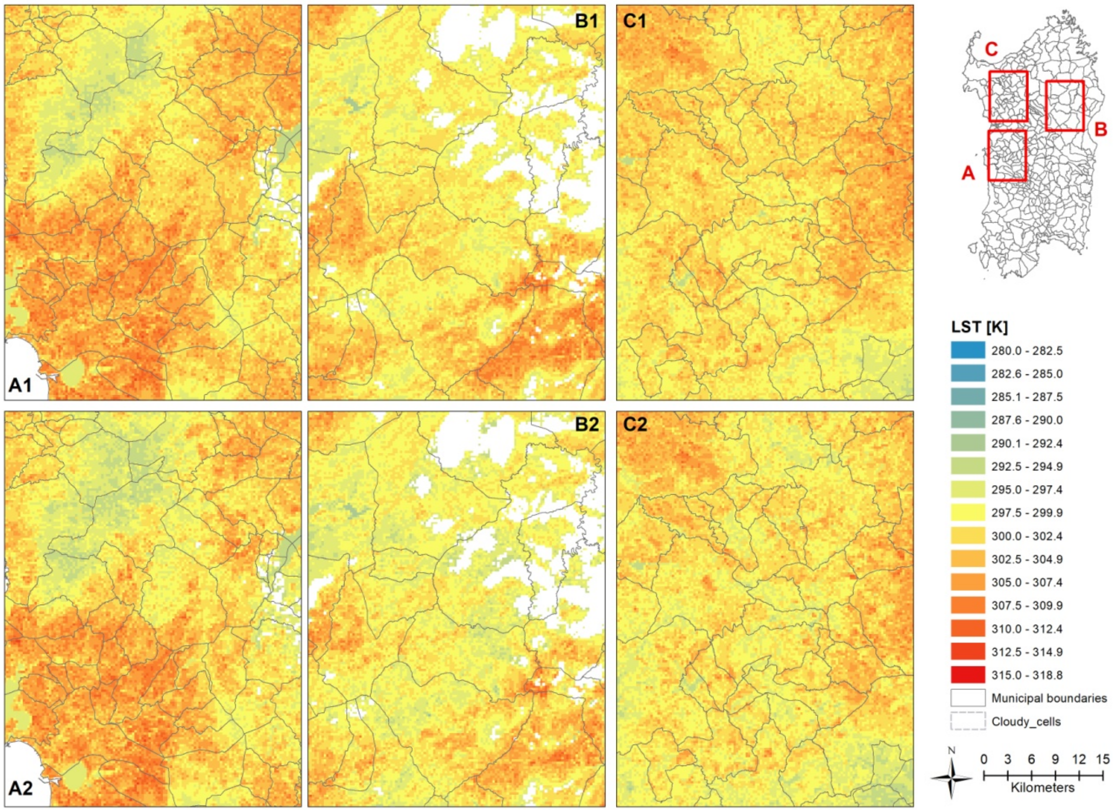

Fig.7 "What if" assessment: actual (A1, B1, C1) and simulated (A2, B2, C2) LST spring maps

4. Discussion

The regression model presented in section 3.2., which investigates the impacts on LST of land cover changes, classified according to the LEAC groups, provides findings consistent with the literature. With reference to the model estimates related to the summer period, arable land and permanent crops (INTAG), and mosaic farmland and pastures (EXTAG) show the most relevant impacts on LST increase, that is around 11.6 and 10.5 K higher than cells belonging to the water bodies and wetland LEAC group (WATER). This result differs from the outcomes related to the spring period, where artificial areas (ART) show the most relevant impact on LST increase (8.9 K) and the effect of intensive farming (INTAG) is slightly lower than that of artificial areas (8.5 K) (ART) (Lai et al., 2020). Both these findings are consistent to the results of analogous studies. As for the spring outcomes, the higher values related to the ART LEAC group are connected with sealed soils that either prevent or reduce air circulation, and with downwind cooling (Oke, 1988). Indeed, on the one hand, vegetation, which positively influences the thermal comfort in urban areas, is absent or scarce (Skelhorn et al., 2014; Zucaro & Morosini, 2018; Geneletti et al., 2019), and, on the other hand, artificial surfaces prevent evapotranspiration (Demuzere et al., 2014) and generate high radiant temperature (Ding & Shi, 2013). Moreover, according to Fonseka et al. (2019), an increase in LST may be correlated to the higher heat discharge generated by human activities entailed by the growing population that characterizes urbanized areas. All these factors cause higher LST in urban contexts than in non-artificial areas. From this perspective, increasing vegetated areas through green roofs, rooftop gardens, and urban forestry is likely to mitigate heat-island phenomena in urban areas (Fischer & Schär, 2010).

INTAG and ART LEAC groups are characterized by similar conditions in terms of downwind cooling, air circulation, thermal comfort, and evapotranspiration. Indeed, intensive farming areas are characterized by dense low-growing vegetation with little or no trees (Irmak, 2012; Launeau et al., 2018). The situation is made even worse by transitions from natural areas to arable and permanent crops due to the change of climate-related variables, such as soil moisture, surface roughness of vegetation and leaf conductance. In addition, the continuous supply of water needed by intensive farming increases physical evaporation and evapotranspiration; however, it also entails a decrease in sensible heat flux that cools the land surface. As a consequence, rainfalls are affected by the latent heat produced by the moisture flux in the atmosphere (Ge, 2010). Higher LST values in rural areas correlated to higher values of the ART LEAC group are reported in other studies as well (Munafò, 2020). The already-quoted Italian report on land take (Munafò, 2020) presents the results of a study on the difference in average daytime LST between urban and rural areas in relation to fourteen Italian metropolitan cities during the 2018 and 2019 summer periods. The findings show negative differences, which implies higher LST values in rural areas, within the metropolitan cities of Bari and Palermo, both located in Southern Italy. This outcome is related to the particular climate conditions of Southern Italy, where large agricultural areas with poor vegetation cover generate an increase in LST during summer (Munafò, 2020). The same results are reported in a study by Gohain et al. (2020), according to which the measured difference between LST in the city center and in a 5 kilometer-buffer rural zone around the consolidated urban tissue was -1.4 Celsius degree, as a consequence of the formation of an urban cool island. According to Mendonca (2009), some soil features, such as mineral composition, compactness and color, affect thermal variation; in particular, naked and dry soils show low albedo. These conditions, combined with direct sun flow, entail lower values of thermal inertia in agricultural areas with respect to green urban areas. As a consequence, rural areas may show a higher LST than urban areas. The urban cool island phenomenon is common across urban contexts characterized by semi-arid climate (Mohammad et al., 2019; Peng et al., 2012; Rasul et al., 2015; Rasul et al., 2016).

Furthermore, according to the results of a study by Walawender et al. (2014), in relation to the city of Krakow, Poland, the INTAG and EXTAG LEAC groups change their behaviors in terms of LST during the year. In the early vegetative period (i.e., in Poland, April and May), the higher values of LST in intensively farmed areas are related to the absence of vegetation, which entails that such agricultural areas show the same thermal properties as bare soils. As regards extensively farmed areas, at the beginning of the vegetative period the thermal property is different to that of arable land. In addition, rainfalls affect the capacity of regenerating living biomass by preventing continuous forage production during the vegetative period (Feldhake et al., 1996). Moreover, the decrease in LST within rural areas implies important advantages in terms of water shortage mitigation, and economic and social issues (Mokhtari et al., 2011). Indeed, the negative correlation between vegetation density and LST reported in a study by Sruthi & Aslam (2015) is relevant during drought periods, when scarce rainfalls and soil humidity entail a decline in productivity, which is likely to generate economic and social unrest (Dodo, 2014; Kaniewski et al., 2020). This outcome is particularly significant in relation to regional contexts characterized by the massive presence of rural areas, such as Sardinia, where agricultural areas cover around 50% (11,500 km^2) of the regional territory and 7.5% (41,000 people) of the work force employed in the agricultural sector (Centro Studi di Confagricoltura, 2015).

Heathland, natural grasslands and sclerophylous vegetation (SHNG) and Open spaces with sparse or absent vegetation (OPEN) show lower values of LST than the other LEAC groups with the exception of Forests, shrubs and woodlands (FWS), during both the summer and the spring periods. The presence of vegetation delivers evapotranspiration that reduces the heat stored in soils (Youneszadeh et al., 2015). Moreover, the vegetation shade generates air movement and heat exchange, by preventing or decreasing the solar radiation absorbed by the land surface (Geneletti et al., 2019). However, seasons affect the influence of vegetation on LST. Indeed, findings from a study by Zhou et al. (2014) show that the tree canopy is responsible for about 69% of LST decrease during the spring period, whereas, during the summer period, the evapotranspiration is limited due to leaf fall, and the positive effect of the tree canopy is almost totally prevented. This study shows that in the spring and summer periods, Forests, shrubs and woodlands (FSW) show positive effects on LST mitigation. This result is consistent with Walawender et al.'s work (2014), implemented as regards the city of Krakow, Poland. Moreover, the study focuses on the seasonality that characterizes different land covers in terms of LST mitigation. In fact, in March, before the flowering period, LST of waters is significantly lower than forests' figures. During the beginning of the vegetative period (May, in Poland), the difference between the LST of the two LEAC groups (WATER and FSW) becomes negligible. At the end of the vegetative period (between June and August, in Poland), the difference becomes close to zero. The main factor that affects the behavior of the two LEAC groups during the year, according to the research concerning Krakow, is evapotranspiration, that peaks during the vegetative period.

The findings of this study entail a number of policy implications.

As regards the consolidated urban tissues of small villages, towns and cities, where heat island and wave phenomena are likely to take place as a consequence of high LSTs, the implementation of micro-scale measures, such as planting new green areas or enlarging existing ones, or plantation of trees, can be very effective (Geneletti et al., 2019; Ustaoglu & Aydinoglu, 2019).

Important urban micro-scale policies are based on green wall and facades and blue and green grids as well. A relevant example of these measures is the London Green Grid (Mayor of London, 2006). This study tackles a 3 K temperature increase in the metropolitan area of London, which will cause important negative effects on the local living quality, community health, production of water, vermin and insect outbreak, drought, public parks and green areas. The London Green Grid conceptual framework was implemented through the East London Green Grid, which implies a fabric of blue and green infrastructures which implements an urban landscape which integrates the built environment, featured by people living and working there and characterized by sealed soils, commuting centers, and the Green Belt that envelopes the Thames and London (Pötz et al., 2016).

The increase in the provision of ecosystem services aimed at regulating LST implies relevant positive impacts on the urban living quality (Gómez-Baggethun & Barton, 2013). These policies integrate different types of planning measures which are likely to encourage best practice-oriented behaviors by the local societies, residents' organizations, building firms, and public bodies (Mazzeo et al., 2019). A relevant question is related to the strict connection between urban land prices and the allowed building volume, be it for housing or for services. As a consequence, newly-planted vegetated areas or the extension of existing green ones, which entails a relevant decrease in the value of these areas due to the loss in permitted building cubage, should imply the adoption of integrated planning policies which should take account of landowners' interests and of urban sustainability-oriented goals. First, sound building regulations should establish that new developments, and existing settlements as well, should have an adequate endowment of green areas, which may possibly consist of green facades and roofs or of the implementation of green or blue grids into part of the newly-developed land, as it has occurred in the case of East London (Mathey et al., 2011; Jenning et al., 2016). Secondly, since financial support is important as well, a framework of incentives should be implemented in order to develop vegetated roofs and facades, and blue and green grids in newly-planned and existing settlements, so as to make them attractive to investors (Webster, 2005; Bramley & Watkins, 2014). Financial support can be based on impact fee decrease, property tax and VAT reductions, incentives granted to developers to improve the landscape quality through greening operations, etc. (Buijs et al., 2019; Slätmo et al., 2019). Finally, greening operations, based on grids, infrastructure and so on, is a matter of visibility concerning the public administration's commitment towards the implementation of planning measures and policies, which can be made explicit through public purchase offers regarding areas where new green and blue grids are planned (Fors et al., 2015; Pérez-Urrestarazu et al., 2015).

The other side of the coin is represented by the impacts on LST generated by the non-artificial LEAC groups. The most effective LEAC land cover group in reducing LST is FWS (forests, woodlands and shrubs), while the impacts generated by OPEN (open space with sparse or rare vegetation) and SHNG (sclerophyllous vegetation, grassland and heathland) are similar to the negative effects of urbanized land (ART). Even more negative are the impacts coming from the intensive and extensive agriculture LEAC groups (INTAG and EXTAG), which are likely to occur for the reasons discussed in Section 4. This outcome implies that the LEAC FWS macroclass should be identified as a point of reference to target land cover transitions with the aim of reducing LST and mitigating the related phenomena, such as heat islands and waves.

That being so, afforestation is the most relevant reference for planning policies designed to decrease LST as regards non-urbanized areas, such as rural zones[10]. A thorough analysis of the issue of land cover change from croplands to forests is developed in an article concerning economic and social determinants of afforestation coming from agricultural land, which gives particular attention to public decision-making processes thereof (Ryan & O'Donoghue, 2016). Under this perspective, perceived non-market benefits from agricultural activities are relevant hurdles related to the implementation of afforestation (Howley et al., 2015). These points in favor of farming are mainly connected to the flexibility of agricultural practices (Duesberg et al., 2014), and to the reluctance on behalf of farmers to lose their abiding traditional know-how, which is often much more relevant than the predicted income increase generated by afforestation (Ryan & O'Donoghue, 2016). Furthermore, afforestation from intensive agriculture-related land cover (INTAG) and from extensive agriculture-related land cover (EXTAG) are quite different from each other (Kumm & Hessle, 2020). In the first case, a land cover change is quite difficult, while it is much more viable in the second case, since, on average, the expected rent from forests is higher than the rent generated by extensive agriculture, whereas intensive agriculture, which takes place in arable land through permanent crops, provides comparatively higher rents than forest farming (Kumm & Hessle, 2020). Furthermore, the regional land cover shares of the regional land of INTAG and EXTAG are close to each other (about 25% and 22%, respectively), as shown in the sixth column

---

[10] Small-scale forestry conference proceedings. Small-scale forestry and rural development - The intersection of ecosystems, economics and society - Proceedings of IUFRO 3.08 Conference hosted by Galway-Mayo Institute of Technology, Galway, Ireland, 3-6 July 2006. Available online: http://www.coford.ie/publications/reports/small-scaleforestryconferenceproceedings/ (accessed on 31 August 2020).

of Tab.4, and their spatial distribution is fairly homogeneous with respect to the whole Sardinian region. Planning policies aimed at decreasing LST should target both, INTAG and EXTAG, on the basis of the following approach. Afforestation should be promoted by means of incentives granted to farmers who earn low rents from agriculture, in order to become forest farmers. The incentives are likely to be very effective as regards rural areas whose land cover is classified as pastures and mosaic croplands according to the LEAC taxonomy (labeled EXTAG in this study), while it is not probable that farmers of arable land and permanent crops (INTAG land cover) be tempted by these incentive schemes (Hyytiainen et al., 2008). On the other hand, the afforestation expansion across rural areas characterized by high-rent agriculture should be a matter of careful evaluation on behalf of public planning bodies, since the financial resources needed to make the incentives attractive would probably be unaffordable, and the resulting weakening of the traditional agricultural structure may generate an unwanted decay of the social, economic and environmental situation of rural areas (Behan et al., 2006). From this point of view, the different levels of the public administration, local, regional, national, have an important task since they have to optimize the degree of afforestation with the size of the affordable investment needed to support the land-cover changes, mainly from extensive agriculture (Zavalloni et al., 2019).

The perception, on behalf of the local societies, of a sound commitment by the involved public administrations is a fundamental factor for a successful implementation of policies aimed at decreasing LST based on afforestation. Measures such as public purchase of low-rent agricultural land, pastures or open space characterized by rare or sparse vegetation are very effective in building community awareness and consensus (Brouwer et al., 2015).

5. Conclusions

This study proposes and develops a methodology to estimate, in quantitative terms, the effects of planning measures aimed at decreasing LST effects in Sardinian urban and rural areas. The findings not only imply that planning measures should be based on endowing new and existing buildings and urbanized land with green roofs and facades and urban areas with green and blue grids, or on implementing land cover transitions towards forests in rural areas, but also provide estimates of the quantitative size of the effects on LST caused by such measures. This knowledge is relevant to set up public investment aimed at addressing the LST decrease question taking account of the budget constraints which feature the public administrations' policy-making processes. Furthermore, the methodological approach implemented in this study is easy to export since the LST spatial layout can be straightforwardly identified through images from satellite, and the LEAC classification, based on CORINE land cover, is freely accessible for all the countries of the European Union. Moreover, the implementation of the methodological approach into the Sardinian regional spatial context helps explaining the correlations between one of the most outstanding negative impacts of climate changes identified by the Regional Strategy, that is heat waves and islands (Regione Autonoma della Sardegna, 2019a), and the spatial distribution of land cover types and transformations.

This study shows two main limitations concerning results validation and the complete implementation of policy recommendation proposed in this work. First, validation should be pursued through direct observations of LST values by following, for example, the methodology proposed by Nguyen et al. (2019). Secondly, Sardinian local administrations, such as both the regional administration and local municipalities, do not take into account measures for mitigating LST values, and, by doing so, public commitment and financial investments are lacking. In this situation, implementing this kind of measure into planning practice in the short run seems a utopia.

With reference to the results of this study, two recommendations for further research concerning the identification of planning measures and policies should be highlighted. First, a local network of data points to detect LST on-site would be very important to validate the spatial distribution of LST, which would make possible to implement experiments based on policy measures used to decrease LST. The only way to develop experiments aimed at measuring the impacts on LST generated by green roofs and facades, green and blue grids, and so on, is to set up a data point network that can provide LST observations before and after the implementation of these policies, on the basis of an impact analysis approach (Gutiérrez Rodríguez et al., 2015; Gutiérrez Rodríguez et al., 2016). Secondly, testing the implementation of afforestation and blue and green urban grids policies would entail thorough participation of the local administrations and communities of urban and rural areas. Researchers and practitioners involved in action-research experiments aimed at implementing policies to decrease LST, and local urban and rural administrations and communities, should work together in order to attract public and private investments from national and international agencies and bodies to develop experimental projects to mitigate the negative impacts of heat islands and waves on the local communities' quality of life.

Acknowledgments

Author Contributions: Sabrina Lai (S.L), Federica Leone (F.L.), and Corrado Zoppi (C.Z.) collaboratively designed this study. Individual contributions are as follows: F.L. wrote Sections 1 and 4; S.L. wrote Sections 2.1, 2.2, 3.1 and 3.3 and Subsections LST Extraction and Spatial Layout, Land Cover Types and Elevation; C.Z. wrote Sections 3.2 and 5 and Subsection Linear regression model.

The study was implemented within the Research Program "Paesaggi rurali della Sardegna: pianificazione di infrastrutture verdi e blu e di reti territoriali complesse" [Rural landscapes of Sardinia: Planning policies for green and blue infrastructure and spatial complex networks], funded by the Autonomous Region of Sardinia for the period 2019–2021, under the provisions of the call for the presentation of "Projects related to fundamental or basic research" of the year 2017, implemented at the Department of Civil and Environmental Engineering and Architecture (DICAAR) of the University of Cagliari, Italy.

Authors Contribution

Author Contributions: Sabrina Lai (S.L), Federica Leone (F.L.), and Corrado Zoppi (C.Z.) collaboratively designed this study. Individual contributions are as follows: F.L. wrote Sections 1 and 4; S.L. wrote Sections 2.1, 2.2, 3.1 and 3.3 and Subsections LST Extraction and Spatial Layout, Land Cover Types and Elevation; C.Z. wrote Sections 3.2 and 5 and Subsection Linear regression model. Conflicts of Interest: The authors declare no conflict of interest.

References

Akinyemi, F.O, Ikanyeng, M., & Muro, J. (2019). Land cover change effects on land surface temperature trends in an African urbanizing dryland region. *City and Environment Interactions, 4* (100029). https://doi.org/10.1016/j.cacint.2020.100029

Al Kafy, A., Rahman, Md. S., Al- Faisal, A., Hasan, M.M., & Islam, M. (2020). Modelling future land use land cover changes and their impacts on land surface temperatures in Rajshahi, Bangladesh. *Remote Sensing Applications: Society and Environment*, *18 (*100314), 18 pp. https://doi.org/10.1016/j.rsase.2020.100314

Alfraihat, R., Mulugeta, G., & Gala, T. (2016). Ecological evaluation of urban heat island in Chicago City, USA. *Journal of Atmospheric Pollution*, *4* (1), 23–29. https://doi.org/10.12691/jap-4-1-3

Alves, E.D.L. (2016). Seasonal and spatial variation of surface urban heat island intensity in a small urban agglomerate in Brazil. *Climate*, *4* (4, 61), 11 pp. https://doi.org/10.3390/cli4040061

Avdan, U., & Jovanovska, G. (2016). Algorithm for automated mapping of land surface temperature using Landsat 8 satellite data. *Journal of Sensors*, 1480307, 8 pp. https://doi.org/10.1155/2016/1480307

Barbierato, E., Bernetti, I., Capecchi, I., & Saragosa, C. (2019). Quantifying the impact of trees on land surface temperature: A downscaling algorithm at city-scale. *European Journal of Remote Sensing*, *52* (4), 74–83. https://doi.org/10.1080/22797254.2019.1646104

Behan, J., McQuinn, K.& Roche, M.J. (2006). Rural land use: Traditional agriculture or forestry? *Land Economics*, *82* (1), 112–123. https://doi.org/10.3368/le.82.1.112

Bramley, G., & Watkins, D.G. (2014). 'Measure twice, cut once'—Revisiting the strength and impact of local planning regulation of housing development in England. *Environment and Planning B*, *41* (5), 863–884. https://doi.org/10.1068/b39131

Brouwer, R., Lienhoop, N., & Oosterhuis, F. (2015). Incentivizing afforestation agreements: Institutional-economic conditions and motivational drivers. *Journal of Forest Economics*, *21* (4), 205–222. https://doi.org/10.1016/j.jfe.2015.09.003

Buijs, A., Hansen, R., Van der Jagt, S., Ambrose-Oji, B., Elands, B., Lorance Rall, E., Mattijssen, T., Pauleit, S., Runhaar, H., Stahl Olafsson, A., & Steen Møller, M. (2019). Mosaic governance for urban green infrastructure: Upscaling active citizenship from a local government perspective. *Urban Foresting & Urban Greening*, 40, 53–62. https://doi.org/10.1016/j.ufug.2018.06.011

Canu, S., Rosati, L., Fiori, M., Motroni, A., Filigheddu, R., & Farris, E. (2015). Bioclimate map of Sardinia (Italy). *Journal of Maps*, *11* (5), 711–718. https://doi.org/10.1080/17445647.2014.988187

Cardil, A., Salis, M., Spano, D., Delogu, G., & Molina Terrén, D. (2014). Large wildland fires and extreme temperatures in Sardinia (Italy). *iForest – Biogeosciences and Forestry*, *7* (3), 162–169. https://doi.org/10.3832/ifor1090-007

Centro Studi di Confagricoltura [Study Center of the Italian Confederation of Agriculture] (2015). L'agricoltura nelle Regioni d'Italia—2015—Sardegna [Agriculture in the Italian Regions—2015—Sardinia] – Retrieved from: http://confagricoltura.sardegna.it/download.php?id_file=GqIekCx7cV27DW8GoUH73cZ4gPKTXO%2Fki0dq2QPbe%2B3LUFQiyWPz7Wy4tFm8rrZ7ABsSHpzPqXrjFRIhP3wRm6GjEKxM51bWNKHOdwbA%2BAL6KOUmwu6HCW6Xh2Wd4yc0ahtc0d%2BVVgEhIERk6kmKRuRLxBu1ffAsQpkecln4RFg%3D

Chadchan, J., & Shankar, R. (2009). Emerging urban development issues in the context of globalization. *Institute of Town Planners, India Journal*, *6* (2), 78–85 – Retrieved from: http://www.itpi.org.in/pdfs/apr6_09.pdf

CLC (Corine Land Cover) (2018). Retrieved from: https://land.copernicus.eu/pan-european/corine-land-cover/clc2018

Cui, L., & Shi, J. (2012). Urbanization and its environmental effects in Shanghai, China. *Urban Climate*, 2, 1–15. https://doi.org/10.1016/j.uclim.2012.10.008

Demuzere, M., Orru, K., Heidrich, O., Olazabal, E., Geneletti, D., Orru, H., Bhave, A.G., Mittal, N., Feliu, E., & Faehnle, M. (2014). Mitigating and adapting to climate change: Multi-functional and multi-scale assessment of green urban infrastructure. *Journal of Environmental Management*, 146, 107–115. https://doi.org/10.1016/j.jenvman.2014.07.025

Dhar, R.B., Chakraborty, S., Chattopadhyay, R., & Sikdar, P.K. (2019). Impact of land-use/land-cover change on land surface temperature using satellite data: A case study of Rajarhat Block, North 24-Parganas District, West Bengal. *Journal of the Indian Society of Remote Sensing*, 47, 331–348. https://doi.org/10.1007/s12524-019-00939-1

Ding, H., & Shi, W. (2013). Land-use/land-cover change and its influence on surface temperature: A case study in Beijing City. *International Journal of Remote Sensing*, *34* (15), 5503–5517. https://doi.org/10.1080/01431161.2013.792966

Dodo, M.K. (2014). Examining the potential impacts of climate change on international security: EU-Africa partnership on climate change. *SpringerPlus*, *3* (194), 18 pp. https://doi.org/10.1186/2193-1801-3-194

Duesberg, S., Ní Dhubháin, A., & O'Connor, D. (2014). Assessing policy tools for encouraging farm afforestation in Ireland. *Land Use Policy*, 38, 194–203. https://doi.org/10.1016/j.landusepol.2013.11.001

EEA (European Environment Agency) (2006). *Land Accounts for Europe 1990–2000: Towards Integrated Land and Ecosystem Accounting*, Report no. 11. Luxembourg: Office for Official Publications of the European Communities.

Echevarria Icaza, L., Van der Hoeven, F., & Van den Dobbelsteen, A. (2016), Surface thermal analysis of North Brabant cities and neighbourhoods during heat waves, *TeMA – Journal of Land Use, Mobility and Environment*, *9* (1), 63-87. https://doi.org/10.6092/1970-9870/3741

Feizizadeh, B., Blaschke, T., Nazmfar, H., Akbari, E., & Kohbanani, H.R. (2013). Monitoring land surface temperature relationship to land use/land cover from satellite imagery in Maraqeh County. *Journal of Environmental Planning and Management*, *56* (9), 1290–1315. https://doi.org/10.1080/09640568.2012.717888

Feldhake, C.M., Glenn, D.M., & Peterson, D.L. (1996). Pasture soil surface temperature response to drought. *Agronomy Journal*, *88* (4), 652–656. https://doi.org/10.2134/agronj1996.00021962008800040025x

Fischer, E.M., & Schär, C. (2010). Consistent geographical patterns of changes in high-impact European heatwaves. *Nature Geoscience*, 3, 398–403. https://doi.org/10.1038/ngeo866

Fonseka, H.P.U., Zhang, H., Sun, Y., Su, H., Lin, H., & Lin, Y. (2019). Urbanization and its impacts on land surface temperature in Colombo metropolitan area, Sri Lanka, from 1988 to 2016. *Remote Sensing*, 11 (8, 957), 18 pp. https://doi.org/10.3390/rs11080957

Fors, H., Frøik Molin, J., Murphy, M.A., & Konijnendijk van den Boschab, C. (2015). User participation in urban green spaces—For the people or the parks? *Urban Foresting & Urban Greening*, *14* (3), 722–734. https://doi.org/10.1016/j.ufug.2015.05.007

Ge, J. (2010). MODIS observed impacts of intensive agriculture on surface temperature in the southern Great Plains. *International Journal of Climatology*, *30* (13), 1994–2003. https://doi.org/10.1002/joc.2093

Geneletti, D., Cortinovis, C., Zardo, L., & Adem Esmail, B. (2019). *Planning for Ecosystem Services in Cities*. Dordrecht, Germany: Springer. https://doi.org/10.1007/978-3-030-20024-4

Gohain, K.J., Mohammad, P., & Goswami, A. (2020). Assessing the impact of land use land cover changes on land surface temperature over Pune city, India. *Quarternary International*, in press. https://doi.org/10.1016/j.quaint.2020.04.052

Gómez-Baggethun, E., & Barton, D.N. (2013). Classifying and valuing ecosystem services for urban planning. *Ecological Economics*, 86, 235–245, https://doi.org/10.1016/j.ecolecon.2012.08.019

Guha, S., Govil, H., Dey, A., & Gill, N. (2018). Analytical study of land surface temperature with NDVI and NDBI using Landsat 8 OLI and TIRS data in Florence and Naples city, Italy. *European Journal of Remote Sensing*, *51* (1), 667–678. https://doi.org/10.1080/22797254.2018.1474494

Gutiérrez Rodríguez, L., Hogarth, N., Zhou, W., Xie, C., Zhang, K., & Putzel, L. (2015). Socioeconomic and environmental effects of China's conversion of cropland to forest program after 15 years: A systematic review protocol. *Environmental Evidence*, *4* (6), 11 pp. https://doi.org/10.1186/s13750-015-0033-8

Gutiérrez Rodríguez, L., Hogarth, N., Zhou, W., Putzel, L., Xie, C., & Zhang, K. (2016). China's conversion of cropland to forest program: A systematic review of the environmental and socioeconomic effects. *Environmental Evidence*, *5* (21), 22 pp. https://doi.org/10.1186/s13750-016-0071-x

Howley, P., Buckley, C., O'Donoghue, C., & Ryan, M. (2015). Explaining the economic 'irrationality' of farmers' land use behaviour: The role of productivist attitudes and non-pecuniary benefits. *Ecological Economics*, 109, 186–193. https://doi.org/10.1016/j.ecolecon.2014.11.015

Hulley, G.C., Ghent, D., Göttsche, F.M., Guillevic, P.C., Mildrexler, D.J., Coll, & C. Land (2019). Surface temperature. In Hulley, G.C., & Ghent, D. (Eds.). *Taking the Temperature of the Earth Steps Towards Integrated Understanding of Variability and Change*, pp. 57-127, Amsterdam, The Netherlands: Elsevier. https://doi.org/10.1016/B978-0-12-814458-9.00003-4

Hyytiainen, K., Leppanen, J., & Pahkasalo, T. (2008). Economic analysis of field afforestation and forest clearance for cultivation in Finland. In *Proceedings of the International Congress of European Association of Agricultural Economists, Ghent, Belgium, 26–29 August 2008*. https://doi.org/10.22004/ag.econ.44178

Irmak, A. (Ed.) (2012). *Remote Sensing and Modeling*. London, United Kingdom: IntechOpen. https://doi.org/10.5772/725

Jenning, V., Larson, L., & Yun, J. (2016). Advancing sustainability through urban green space: Cultural ecosystem services, equity, and social determinants of health. *International Journal of Environmental Research and Public Health*, *13* (2, 196), 15 pp. https://doi.org/10.3390/ijerph13020196

Kaniewski, D., Marriner, N., Cheddadi, R., Fischer, P.M., Otto, T., Luce, F., & Van Campo, E. (2020). Climate change and social unrest: A 6,000-year chronicle from the eastern Mediterranean. *Geophysical Research Letters*, *47* (7). https://doi.org/10.1029/2020GL0 87496

Kim, Y.-H., & Baik, J.-J. (2005). Spatial and temporal structure of the urban heat island in Seoul. *Journal of Applied Meteorology*, *44* (5), 591–605. https://doi.org/10.1175/JAM2226.1

Kosztra, B., Büttner, G., Hazeu, G., & Arnold, S. (2019). *Updated CLC Illustrated Nomenclature Guidelines*. Vienna, Austria: Environment Agency Austria. Retrieved from: https://land.copernicus.eu/user-corner/technical-library/corine-land-cover-nomenclature-guidelines/docs/pdf/CLC2018_Nomenclature_illustrated_guide_20190510.pdf

Kumm, K.-I., & Hessle, A. (2020). Economic comparison between pasture-based beef production and afforestation of abandoned land in Swedish forest districts. *Land*, *9* (2, 42), 20 pp. https://doi.org/10.1016/10.3390/land9020042

Lai, S., Leone, F., & Zoppi, C. (2020). Spatial distribution of surface temperature and land cover: A study concerning Sardinia, Italy. *Sustainability*, *12* (8, 3186), 20 pp. https://doi.org/10.3390/su12083186

Launeau, P., Giraud, M., Ba, A., Moussaoui, S., Robin, M., Debaine F., Lague, D., & Le Menn, E. (2018). Full-waveform LiDAR pixel analysis for low-growing vegetation mapping of coastal foredunes in Western France. *Remote Sensing*, *10* (5, 669), 14 pp. https://doi.org/10.3390/rs10050669

Li, X.-X., Koh, T.-Y., Panda, J., & Norford, L.K. (2016). Impact of urbanization patterns on the local climate of a tropical city, Singapore: An ensemble study. *Journal of Geophysical Research Atmospheres*, *121* (9), 4386–4403. https://doi.org/10.1002/2015JD024452

Mathey, J., Rößler, S., Lehmann, I., & Bräuer, A. (2011). Urban green spaces: Potentials and constraints for urban adaptation to climate change. In Otto-Zimmermann, K. (Ed.). *Resilient Cities. Cities and Adaptation to Climate Change. Proceedings of the Global Forum 2010, Munich, Germany, 19–20 May 2010*, *Volume 1*, Dordrecht, Germany: Springer, pp. 479–485. https://doi.org/10.1080/01426397.2016.117365

Mayor of London (2006). *London's Urban Heat Island: A Summary for Decision Makers*. Greater London, United Kingdom: London Authority, City Hall.

Mazzeo, G., Zucaro, F., & Morosini, R. (2019). Green is the colour. Standards, equipment and public spaces as paradigm for the Italian sustainable city. *TeMA – Journal of Land Use, Mobility and Environment*, *12* (1), 31-52. https://doi.org/10.6092/1970-9870/5836

Mendonca, F. (2009). Urban heat and urban cool islands: influences of vegetation and soil surface in some cities, southern Brazil. Paper presented at the Seventh International Conference on Urban Climate, 29 June – 3 July 2009, Yokohama, Japan. Retrieved from: http://www.ide.titech.ac.jp/~icuc7/extended_abstracts/pdf/381053-1-090514071731-004.pdf

Millennium Ecosystem Assessment (2003). *Ecosystems and Human Well-Being: A Framework for Assessment*. Washington, DC, United States: Island Press. Retrieved form: http://pdf.wri.org/ecosystems_human_wellbeing.pdf

Mohammad, P., Goswami, A., & Bonafoni, S. (2019). The impact of the land cover dynamics on surface urban heat island variations in semi-arid cities: a case study in Ahmedabad City, India, using multi-sensor/source data. *Sensors*, *19* (17, 3701), 21 pp. https://doi.org/10.3390/s19173701

Mokhtari, A., Mansor, S.B., Mahmud, A.R., & Helmi, Z.M. (2011). Monitoring the impacts of drought on land use/cover: A developed object-based algorithm for NOAA AVHRR time series data. *Journal of Applied Sciences*, *11* (17), 3089–3103. https://doi.org/10.3923/jas.2011.3089.3103

Munafò, M. (Ed.) (2019). *Consumo di Suolo, Dinamiche Territoriali e Servizi Ecosistemici. Edizione 2019 [Land Take, Territorial Dynamics and Ecosystem Services. 2019 Edition]*, Report no. 8. Rome, Italy: Sistema Nazionale per la Protezione dell'Ambiente (SNPA). Retrieved from: https://www.snpambiente.it/wp-content/uploads/2019/09/Rapporto_consumo_di_suolo_20190917-1.pdf

Munafò, M. (Ed.) (2020). *Consumo di Suolo, Dinamiche Territoriali e Servizi Ecosistemici. Edizione 2020 [Land Take, Territorial Dynamics and Ecosystem Services. 2020 Edition]*, Report no. 15. Rome, Italy: Sistema Nazionale per la Protezione dell'Ambiente (SNPA). Retrieved from: https://www.snpambiente.it/wp-content/uploads/2020/07/Rapporto_consumo_di_suolo_2020.pdf

Ndossi, M.I., & Avdan, U. (2016). Application of open source coding technologies in the production of Land Surface Temperature (LST) maps from Landsat: A PyQGIS Plugin. *Remote Sensing*, *8* (5, 413), 31 pp. https://doi.org/10.3390/rs8050413

Nguyen, T.M., Lin, T.-H., & Chan, H.-P. (2019). The environmental effects of urban development in Hanoi, Vietnam from satellite and meteorological observations from 1999–2016. *Sustainability*, *11* (6, 1768), 24 pp. https://doi.org/10.3390/su11061768

Oke, T.R. (1988). The urban energy balance. *Progress in Physical Geography: Earth and Environment*, *12* (4), 471–508. https://doi.org/10.1177/030913338801200401

Pal, S., & Ziaul, S. (2017). Detection of land use and land cover change and land surface temperature in English Bazar urban centre. *Egyptian Journal of Remote Sensing and Space Science*, *20* (1), 125–145. https://doi.org/10.1016/j.ejrs.2016.11.003

Peng, S., Piao, S, Ciais, P., Friedlingstein, P., Ottle, C., Bréon, F.M., Nan, H., Zhou, L., & Myneni, R.B. (2012). Surface urban heat island across 419 global big cities. *Environmental Science & Technology*, *46* (2), 696–703. https://doi.org/10.1021/es2030438

Pérez-Urrestarazu, L., Fernández-Cañero, R., Franco-Salas, A., & Egea, G. (2015). Vertical greening systems and sustainable cities. *Journal of Urban Technology*, *22* (4), 65–85. https://doi.org/10.1080/10630732.2015.1073900

Pötz, H., Sjauw En Wa-Windhorst, A., & van Someren, H. (2016). *Urban Green-Blue Grids Manual for Resilient Cities*. Delft, The Netherlands: Atelier Groenblauw.

Pungetti, G., Marini, A., & Vogiatzakis, I. (2008). Sardinia. In Vogiatzakis, I., Pungetti, G., & Mannion, A.M. (Eds). *Mediterranean Island Landscapes*, Landscape Series, Vol. 9, Dordrecht, Germany: Springer, 143–169. https://doi.org/10.1007/978-1-4020-5064-0_8

Rasul, A., Balzter, H., & Smith, C. (2015). Urban climate spatial variation of the daytime surface urban cool island during the dry season in Erbil, Iraqi Kurdistan, from Landsat 8. *Urban Climate*, *14* (2), 176–186. https://doi.org/10.1016/j.uclim.2015.09.001

Rasul, A., Balzter, H., & Smith, C. (2016). Diurnal and seasonal variation of surface urban cool and heat islands in the semi-arid city of Erbil, Iraq. *Climate*, *4* (3, 42), 16 pp. https://doi.org/10.3390/cli4030042

Regione Autonoma della Sardegna [Autonomous Region of Sardinia] (2019°). Strategia regionale di adattamento ai cambiamenti climatici [Regional Strategy for the adaptation to climate changes]. Retrieved from: http://delibere.regione.sardegna.it/protected/45523/0/def/ref/DBR45368/

Regione Autonoma della Sardegna [Autonomous Region of Sardinia] (2019b). Strategia regionale di adattamento ai cambiamenti climatici. Allegato 1. Metodi e strumenti per la Strategia regionale di adattamento ai cambiamenti climatici [Regional Strategy for the adaptation to climate changes. Annex 1. Methods and tools for the Regional Strategy for the adaptation to climate changes.]. Retrieved from: http://delibere.regione.sardegna.it/protected/45525/0/def/ref/DBR45368/

Ryan, M., & O'Donoghue, C. (2016). Socio-economic drivers of farm afforestation decision-making. *Irish Forestry Journal*, *73* (1-2), 96–121. Retrieved from: https://journal.societyofirishforesters.ie/index.php/forestry/article/view/10847

Scarano, M., & Sobrino, J.A. (2015). On the relationship between the sky view factor and the land surface temperature derived by Landsat-8 images in Bari, Italy. *International Journal of Remote Sensing*, *36* (19-20), 4820–4835. https://doi.org/10.1080/01431161.2015.1070325

Seddaiu, G., Porcu, G., Ledda, L., Roggero, P.P., Agnelli, A, & Corti, C. (2013). Soil organic matter content and composition as influenced by soil management in a semi-arid Mediterranean agro-silvo-pastoral system. *Agriculture, Ecosystems & Environment*, *167*(1), 1–11. https://doi.org/10.1016/j.agee.2013.01.002

Shirgir, E., Kheyroddin, R., & Behzadfar, M. (2019). Defining urban green infrastructure role in analysis of climate resiliency in cities based on landscape ecology theories. *TeMA – Journal of Land Use, Mobility and Environment*, *12*(3), 227-247. https://doi.org/10.6092/1970-9870/6250

Skelhorn, C., Lindley, S., & Levermore, G. (2014). The impact of vegetation types on air and surface temperatures in a temperate city: A fine scale assessment in Manchester, UK. *Landscape and Urban Planning*, 121, 129–140. https://doi.org/10.1016/j.landurbplan.2013.09.012

Slätmo, E., Nilsson, K., & Turunen, E. (2019). Implementing green infrastructure in spatial planning in Europe. *Land*, *8* (4, 62), 21 pp. https://doi.org/10.3390/land8040062

Sruthi, S., & Aslam, M.A.M. (2015). Agricultural drought analysis using the NDVI and land surface temperature data: A case study of Raichur District. *Aquatic Procedia*, 4, 1258–1264. https://doi.org/10.1016/j.aqpro.2015.02.164

Stroppiana, D., Antoninetti, M., & Brivio, P.A. (2014). Seasonality of MODIS LST over Southern Italy and correlation with land cover, topography and solar radiation. *European Journal of Remote Sensing*, *47*(1), 133–152. https://doi.org/10.5721/EuJRS20144709

Townshend, J.R.G., Goff, T.E., & Tucker, C.J. (1985). Multitemporal dimensionality of images of normalized difference vegetation index at continental scales. *IEEE Transactions on Geoscience and Remote Sensing*, GE-23 (6), 888–895. https://doi.org/10.1109/TGRS.1985.289474

Tran, D.X., Pla, F., Latorre-Carmona, P., Myint, S.W., Caetano, M., & Kieu, H.V. (2017). Characterizing the relationship between land use land cover change and land surface temperature. *ISPRS Journal of Photogrammetry and Remote Sensing*, 124, 119–132. Doi: https://doi.org/10.1016/j.isprsjprs.2017.01.001

Ustaoglu, E., & Aydınoglu, A. (2019). Land suitability assessment of green infrastructure development. A case study of Pendik District (Turkey). *TeMA – Journal of Land Use, Mobility and Environment*, *12*(2), 165-178. https://doi.org/10.6092/1970-9870/6118

Walawender, J.P., Szymanowski, M., Hajto, M.J., & Bokwa, A. (2014). Land surface temperature patterns in the urban agglomeration of Krakow (Poland) derived from Landsat-7/ETM+ Data. *Pure and Applied Geophysics*, 171, 913–940. https://doi.org/10.1007/s00024-013-0685-7

Webster, C. (2005). The new institutional economics and the evolution of modern urban planning: Insights, issues and lessons. *Town Planning Review*, *76*(4), 455–484. https://doi.org/10.3828/tpr.76.4.5

Weng, Q., Lu, D., & Schubring, J. (2004). Estimation of land surface temperature–vegetation abundance relationship for urban heat island studies. *Remote Sensing of Environment*, *89*(4), 467-483. https://doi.org/10.1016/j.rse.2003.11.005

Youneszadeh, S., Amiri, N., & Pilesjo, P. (2015). The effect of land use change on land surface temperature in the Netherlands. In *Proceedings of the International Conference on Sensors & Models in Remote Sensing & Photogrammetry, Kish Island, Iran, 23–25 November 2015*, Volume 41, 745–748. https://doi.org/10.5194/isprsarchives-XL-1-W5-745-2015.

Zavalloni, M., D'Alberto, R., Raggi, M., & Viaggi, D. (2019). Farmland abandonment, public goods and the CAP in a marginal area of Italy. *Land Use Policy*, in press. 10. https://doi.org/10.1016/j.landusepol.2019.104365

Zhang, J., Wang, Y., & Li, Y. (2006). A C++ Program for retrieving land surface temperature from the data of Landsat TM/ETM+ band6. *Computers & Geosciences*, *32*(10), 1796–1805. https://doi.org/10.1016/j.cageo.2006.05.001

Zhang, Y., & Sun, L. (2019). Spatial-temporal impacts of urban land use land cover on land surface temperature: Case studies of two Canadian urban areas. *International Journal of Applied Earth Observation and Geoinformation*, 75, 171–181. https://doi.org/10.1016/j.jag.2018.10.005

Zhao, C., Jensen, J., Weng, Q., & Weaver, R. (2018). A geographically weighted regression analysis of the underlying factors related to the surface urban heat island phenomenon. *Remote Sensing*, *10*(9, 1428), 18 pp. https://doi.org/10.3390/rs10091428

Zhou, W., Qian, Y., Li, X., Li, W., & Han, L. (2014). Relationships between land cover and the surface urban heat island: Seasonal variability and effects of spatial and thematic resolution of land cover data on predicting land. *Landscape Ecology*, 29, 153–167. https://doi.org/10.1007/s10980-013-9950-5

Zucaro, F., & Morosini, R. (2018). Sustainable land use and climate adaptation: A review of European local plans. *TeMA – Journal of Land Use, Mobility and Environment*, *11*(1), 7-26. https://doi.org/10.6092/1970-9870/5343

Zullo, F., Fazio, G., Romano, B., Marucci, A., & Fiorini, L. (2019). Effects of urban growth spatial pattern (UGSP) on the land surface temperature (LST): A study in the Po Valley (Italy). *Science of the Total Environment*, 650 (2), 1740–1751. https://doi.org/10.1016/j.scitotenv.2018.09.331

Image Sources

Fig.1: Authors’ elaboration;

Fig.2: https://earthexplorer.usgs.gov/;

Fig.3: Authors’ elaboration;

Fig.4: Authors’ elaboration;

Fig.5: Authors’ elaboration;

Fig.6: Authors’ elaboration;

Fig.7: Authors’ elaboration.

Authors’ profile

Sabrina Lai

She is a civil engineer, a Doctor of Research in Land Engineering (Italy, 2009), and an MSc in International Planning and Development (UK, 2008). She is an Assistant Professor at the University of Cagliari (Sector ICAR/20 – Spatial planning), where she is presently teaching at the Department of Civil and Environmental Engineering and Architecture of the University of Cagliari in the Graduate Program in Environmental and Territorial Engineering (module leader for the Strategic Planning course).

Federica Leone

She is a building engineer, a Doctor of Research in Land Engineering (Italy, 2013), and an MSc in International Planning and Development (UK, 2012). She is currently a research fellow at the Department of Civil and Environmental Engineering and Architecture of the University of Cagliari.

Corrado Zoppi

He is a civil engineer, a Doctor of Philosophy in Economics (USA, 1997), a Doctor of Research in Territorial Planning (Italy, 1992), and an MSc in Economic Policy and Planning (USA, 1990). He is a Professor at the University of Cagliari (Sector ICAR/20 – Spatial planning). He is presently teaching at the Department of Civil and Environmental Engineering and Architecture of the University of Cagliari in the Undergraduate and Graduate Programs in Environmental and Territorial Engineering and in Sustainable Tourism Management and Monitoring (Regional and Urban Planning, Strategic Planning and Environmental planning).