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The Conference of the Italian Regional Science Association (AISRe), held in September 2023 in Naples, allowed scholars and policy makers to debate on the global issue of conflicts and transitions that are involving many regional economies worldwide, especially in the Euro-Mediterranean area. This book, collecting some contributions that were presented during the conference, aims at increasing the understanding of how regions are navigating and responding to the complex array of challenges they face in a rapidly changing world. The book considers a broad specification of conflicts that are closely related to the idea of exogenous shocks and consequent transitions interpreted as adaptation strategies to those shocks. The book is structured in two parts. The first part presents seven papers dealing with 'conflicts' of different nature such as regional disparities and cohesion, respect of law and social norms, occupational safety and health, urban congestion, gendered sectoral segregation, natural disasters. The second part of this book presents eight papers focuses on different types of 'transitions' related, for example, to climate change and environment, energy, digitalization and innovation. The book, even if does not cover all global conflicts and local responses comprehensively, however it provides useful insights to the debate on how regions are confronting the profound and often unexpected changes brought about by disruptive challenges.

FrancoAngeli
La passione per le conoscenze

ISBN 978-88-351-6653-5

Edizione fuori commercio

11390.8 M. MODICA, D. PIACENTINO (edited by) CONFLICT SCENARIOS AND TRANSITIONS

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Opportunities and Risks for Regions and Territories

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64 Scienze Regionali

Associazione italiana di scienze regionali

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Part 2 – Transitions

The Geography of Green Innovation in Italy

Adriana C. Pinate, Martina Dal Molin*, Maria Giovanna Brandano**

Abstract

This paper aims to analyse the specialization and geographical patterns of green innovation in Italy. The study utilises patent application data from 2019 to map green-related technologies by integrating three different approaches to identify green patents using their code classification: the IPC Green Inventory, the ENV-TECH and the Y02/Y04S Tagging scheme. Data is aggregated at the Local Labour Systems level and includes mapping green innovations along the urban gradient and examining spatial dependence using measures of global and local spatial autocorrelation. Results emphasize significant disparities in regional green innovation within Italy, in terms of the "North-South" divide and "urban non-urban" gradient.

1. Introduction[1]

According to the United Nations Environment Programme (UNEP) a "Green Economy" is one that significantly reduces environmental risks and ecological scarcity while improving human well-being. In green economy discourse, green innovation plays a central role to ensure environmental sustainability and economic growth (Galliano *et al*., 2023; Losacker *et al*., 2023a; Sheng, Ding, 2023; Wang *et al*., 2021; Mazzanti, 2018; Antonioli *et al*., 2016). At the more general level, green innovation (sometimes also referred as "eco-innovation") is defined as a new technological paradigm involving the creation of novel concepts, products, services, procedures, and managerial frameworks, while adhering to ecological principles and that prevents, eliminates, or mitigates environmental problems (Favot *et al.,* 2023; Galliano *et al*., 2023; Zhou *et al*., 2021; Antonioli *et al*., 2016; Kemp, 2010; Rennings, 2000).

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1. The work of Adriana Carolina Pinate has been funded by the European Union – NextGenerationEU under the Italian Ministry of University and Research (MUR) National Innovation Ecosystem grant ECS00000041 – Vitality – CUP D13C21000430001.

Green innovation, as a fundamental issue for green growth, has been studied from a variety of perspectives, such as, technology push and market pull factors (Montresor, Quatraro, 2020; Zhang *et al.*, 2019), path development (Trippl *et al*., 2020; Grillitsch, Hansen, 2019), their effect on both sustainability transition (Rohe, Chlebna, 2021) and firm performance (Marin-Vinuesa *et al*., 2020; Antonietti, Cainelli, 2011). However, the regional and local viewpoint has been only scantly addressed, even though regions are the key place in which green innovations are developed (Galliano *et al*., 2023; Losacker *et al.*, 2023a; 2023b), fostering, in turn, regional development (Sun *et al.*, 2020; Belik *et al*., 2019). Put simply, in Losacker *et al*. (2023) words "*the regional studies community lacks a critical overview of the importance of regions in the development and diffusion of environmental innovations*" (Losacker *et al*., 2023b, p. 293).

Starting from this premise, the aim of this paper is twofold: *i*) to analyse the specialisation of the Italian regional green innovation and *ii*) to understand its geographical patterns of localization. To do that, we use local stocks of green-related patent applications based on the integration of the three different existing methodologies. Indeed, as suggested by Favot *et al.* (2023) the mutual integration of data identified by the World Intellectual Property Organization (WIPO), the Organisation for Economic Co-operation and Development (OECD), and European Patent Office (EPO), is recommended.

Patent application data come from the OECD-REGPAT database and refer to 2019. Given the significant impact of the pandemic on the Italian economy (Bruni *et al*., 2023; Cepparulo, Jump, 2022), and the correlation between innovation and economic growth (Fagerberg, Mowery, 2006), we decided to use the pre-COVID year to obtain a more realistic view of the geographical distribution of green innovations in Italy. The patent data are considered a good proxy for technological green innovation (Favot *et al*., 2023; Ghisetti, Quatraro, 2017). Data used provide information on the respective International Patent Classification (IPC) and Cooperative Patent Classification (CPC) codes and are linked to regions and the addresses of patents' applicants and inventors. The data are available at a NUTS-4 level and they were then aggregated at Local Labour Systems (LLSs). LLS represents a territorial grid whose boundaries are defined using the flows of daily home/work trips (commuting) detected during the general population and housing censuses. The adoption of this spatial unit is suitable for examining the geographical patterns of innovation as it relies on the social and economic connections within the territory, rather than on administrative boundaries. LLSs reflect, as closely as possible, local economies (O'Donoghue, Gleave, 2004). In fact, by working at this level ISTAT provides the level of urbanization, being possible to assess the urban dimension of LLSs.

From a methodological point of view, two steps of analysis are applied. First, we map green-related technologies across LLS's and thus detect differences along the urban gradient. Second, we focus on the spatial dependence to detect spatial autocorrelation between the co-location of green innovations and whether they occur in neighbouring LLS's. Two measures based on a spatial weight matrix that tracks contiguities between LLSs are used: the global Moran index, a general measure of association across the country, and the local indicators of spatial association (LISA).

This paper proceeds as follows. The extant literature is synthesized in section 2, data and methods are described in section 3; results are presented in section 4 and discussed in section 5.

2. Literature Review

Starting from the Rio+20 Conference on Sustainable Development in 2012, the concept of sustainable development and "green growth" gained momentum in policy discourses and international institutions. The OECD, the United Nations Environment Program and the World Bank have increasingly paid attention to the so-called "green growth", as an effective way to pursue a more "sustainable" development (Hickel, Kallis, 2019; Capasso *et al*., 2019; Guo *et al*., 2017; Bowen, Hepburn, 2014; Nielsen *et al*., 2014), i.e. a development that does not imply the over-exploitation of our planet with consequent depletion of natural resources (Song *et al*., 2020; Capasso *et al*., 2019; Shapira *et al*., 2014).

Studies on green growth are often linked with that on innovation, particularly eco- or green innovation (Favot *et al*., 2023; Galliano *et al*., 2023; Zhou *et al*., 2021; Castellacci, Lie, 2017), a concept usually referring to new products and/or new processes that increase business value while decreasing environmental impacts and ensuring efficient use of natural resources (Favot *et al*., 2023; Galliano *et al*., 2023; Rennings, 2000). When studying green innovations, the extant literature has mainly investigated the internal and external factors (i.e. technology push and market pull factors) facilitating the adoption of such innovation (Montresor, Quatraro, 2020; Zhang *et al.*, 2019; Horbach *et al*., 2013; Kesidou, Demirel, 2012; Rennings, 2000), the linkage between green innovation, often measured by green patents (e.g. Van Hoang *et al*., 2020; Acs *et al*., 2002) and firm performance (Marin-Vinuesa *et al*., 2020; Padilla-Perez, Gaudin, 2014; Antonietti, Cainelli, 2011; González-Benito, González-Benito, 2006).

Among these studies, the geographical and regional perspectives have received scant, but increasing, relevance. This growing attention is justified due to the relevant role regions might have in fostering the development and adoption of green innovation (Galliano *et al.* 2023; Losacker *et al*., 2023a; Montresor, Quatraro, 2020; Antonioli *et al*. 2016). Moreover, the geographical perspective is much more relevant among European countries, where small-medium enterprises (SMEs) and regional and local industrial districts play a central role in the development and diffusion of innovation (Antonioli *et al.*, 2016).

The relevance of space to understand the diffusion of green innovation and technologies found its justification in the different sources of knowledge creation for firms, i.e., internal sources and external collaborations, where the spatial proximity of different firms creates the conditions for knowledge diffusion and new idea generation (Scott, Storper, 2007). Moreover, previous innovation studies pointed that the diffusion of specific technologies occurs faster within the same and similar geographical clusters (Lengyel *et al*., 2020), due to the geographical proximity to the innovator (Losacker *et al.*, 2023a).

Extant studies generally found an important role in the geographical dimension also for the specific case of green technologies. Antonioli *et al*., (2016) in a study of the Emilia-Romagna region in Italy found that local conditions and agglomeration economies play a fundamental role in supporting the development and adoption of green technologies. Montresor and Quatraro (2020), focusing on smart specialization strategy and green technologies, found that the acquisition of such technologies follows a process of regional branching and that regions innovate incrementally and according to a path-dependent approach. More recently, Losacker *et al.* (2023a), focusing on green innovation in China, provide evidence that geographical proximity to the inventor matters and is associated with a faster time to adoption. Moreover, regions where a pre-existing green specialisation already exists favour the faster adoption of green innovation also in the neighbouring regions. Similarly, Galliano *et al.* (2023), focusing on France, found that spatial externalities played an important role in shaping innovative behavior at the firm level and this may depend on their locations.

Starting from these premises, this study focuses on both the specialisation of regional green innovation and its geographical patterns of localization in Italy, where growing attention to green innovation has been devoted by national and regional policy makers.

3. Data and Methodological Approach

To examine the geographical distribution of sustainable innovations in Italy we retrieved green-related patents through three code classification methodologies available: 1) the "IPC Green Inventory" concerning Environmentally Sound Technologies (ESTs) developed by WIPO; 2) the "ENV-TECH" concerning Environmental Technologies developed by the OECD; and 3) the "Y02/Y04S Tagging scheme" concerning Climate Change Mitigation Technologies (CCMTs) developed by EPO. The use of classification codes is the most common approach being based on detailed knowledge of patent examiners and it is necessary when a large dataset is available, as for our analysis. Indeed, the three methodologies are considered a good proxy of eco-innovation and have been used by several scholars to measure inventions in green-related technologies (Durán-Romero and Urraca-Ruiz, 2015; Cvijanović *et al.*, 2021; Cohen *et al.*, 2021; Bellucci *et al.*, 2023). Moreover, to get the broadest possible coverage and to ensure the findings are not influenced by the selected classification method, we follow authors such as Favot *et al.* (2023) and Ghisetti and Quatraro (2017), who recommended integrating them.

To classify patents dealing with green-related technologies WIPO, OECD and EPO use an alphanumeric code[2]. The WIPO methodology is based on the IPC and is distributed into seven macro areas. The OECD uses both the IPC and CPC codes and is also divided into seven macro areas. The EPO methodology is based on the CPC coding scheme and is composed into two classes (see Table 1 for a detailed description of these classifications).

Table 1 – WIPO, OECD and EPO Green Classification

	WIPO IPC Green Inventory		*OECD ENV-TECH*		*EPO Y02/Y04S Tagging scheme*
1	Alternative Energy Production	1	Environmental management	1	Y02 Climate Change Mitigation Tecnologies
2	Transportation	2	Water-related adaptation technologies	2	Y04s Smart Grid
3	Energy conservation	3	Biodiversity protection and ecosystem health		
4	Waste management	4	Climate Change Mitigation related to Energy generation, transmission of distribution		
5	Agriculture / Forestry	5	Capture, storage, sequestration or disposal of greenhouse gases		
6	Administrative, regulatory or design aspects	6	Climate Change Mitigation related to Transportation		
7	Nuclear power generation	7	Climate Change Mitigation related to Buildings		

Source: Authors' elaborations

2. For full OECD code classification see WP "Measuring environmental innovation using patent data" OECD (2015). For full WIPO classification see: https://www.wipo.int/classifications/ipc/green-inventory/home. For full EPO classification see: https://www.epo.org/en/news-events/in-focus/classification/classification/updatesYO2andY04S.

For our analysis, we use a database from the OECD-REGPAT for Italian patents in 2019. The record contains over 2,234 patent applications, each accompanied by the corresponding CPC/IPC codes and the addresses of the applicants. Given that the data is available at a NUTS-4 level, we combine[3] the three methodologies and we spatially aggregated them at the Local Labour Systems level (LLSs). In particular, the NUTS4 data has been matched with the respective LLS-2011 by using the correspondence national matching tables developed by the Italian National Institute of Statistics (ISTAT). Local labour systems, also known as Labour market areas (LMAs) or Sistemi locali del lavoro (SLL) in Italy, refer to sub-regional geographical areas where most of the workforce resides and works. Since each local system is the place where the population resides and works and where therefore exercises most of the social and economic relations, the home/work trips are used as a proxy of the existing relations on the territory. The adoption of this spatial unit, compounded by 611 district areas, is suitable for analysing the geographical patterns of innovation since it is based on the social and economic connections within the region, rather than on administrative boundaries, useful to accurately depict local economies (O'Donoghue, Gleave, 2004). Furthermore, we can identify urban and inner polycentric structures of LLSs since ISTAT provides the level of urbanization, divided into three typologies: main urban reality "Core" (21 units); medium-sized city "Medium" (86 units); and Other LLSs (the remaining 504 units). To the best of our knowledge, spatial analyses of green innovations in Italian regions, or any other EU country, have not been conducted yet (an example can be found instead for China, for instance, see Zhou *et al.*, 2021).

3.1. Geographical Patterns

To identify the geographical distribution of green innovation two steps of analysis are used. First, we map green-related technologies across LLS's and thus detect differences along the urban gradient. Second, we focus on the spatial dependence to detect spatial autocorrelation between the co-location of green innovations and whether they occur in neighbouring LLS's. Two measures based on a spatial weight matrix are used: the global Moran index, a general measure of association across the country, and the Local Indicators of Spatial Association (LISA)[4]. The neighbouring structure across LLSs is measured by a spatial queen contiguity weights matrix. Due to the skewed distribution of the data (skewness above 1), with most

3. Based on Favot *et al.* (2023), the three techniques were merged by creating a list of non-duplicated green codes inside the same LLSs. We have found that approximately 17.7% of the total filings can be attributed to eco-inventions.

4. Geoda (Anselin *et al.*, 2006) are used to perform the spatial analyses.

regions exhibiting low performance levels, particularly in the South as depicted in Figure 1, we have adopted the square root transformation methodology employed by the European Commission Innovation Scoreboard (2023).

3.2. Local and Global Spatial Correlation

Following Zhou *et al.* (2021), who examined the regional patterns of green innovation in China, we utilise the global Moran's *I* index and the local Moran's *I* LISA. The former index quantifies the extent to which the entire region exhibits correlation at the spatial level, expressed by Equation 1 (Wrigley *et al.,* 1982):

$$I = \frac{n}{\Sigma_i^n \Sigma_j^n w_{ij}} \frac{\Sigma_i^n \Sigma_j^n w_{ij} \left(y_i - \underline{y}\right)\left(y_j - \underline{y}\right)}{\Sigma_i^n \left(y_i - \underline{y}\right)^2} \qquad [1]$$

where n represents the number of spatial units, which are referred to LLSs, w_{ij} is the weight between locations i and j, y represents the variable of interest – in this study, the number of green-related patent applications – and $\underline{y}$ represents the average value over all locations of the variable (i.e., the mean of y). The range of values is between +1 and -1. A number close to +/-1 suggests a high positive/ negative spatial autocorrelation, whereas a value of 0 shows a random spatial pattern.

At the local level the spatial correlation has been computed through a local Moran Index LISA (Anselin, 1995; Crociata *et al*., 2022). LISA enables us to precisely evaluate the level of spatial autocorrelation at each individual site, specifically in our investigation at LLSs level, by applying a contiguity criterion, which is the same criterion used in the global Moran I index (Brandano *et al*., 2023). The local version of the Moran in spatial entity i, I_i is defined in Equation 2 (Anselin, 1995):

$$I_i = \frac{n\left(y_i - \underline{y}\right)}{\sum_i^n \left(y_i - \underline{y}\right)^2} \sum_j^n w_{ij} \left(y_j - \underline{y}\right) \qquad [2]$$

The result of the LISA quantifies the connections between spatial units and their neighbouring units, and maps out statistically significant clusters of the analysed phenomenon (Cerqua *et al.,* 2021). The LISA maps can reveal positive spatial autocorrelation, indicated by the clustering of high values surrounded by high values (High-High, HH) or low values surrounded by low values (Low-Low, LL); or negative spatial autocorrelation observed when low values surround high values (High-Low, HL) or vice versa (Low-High, LH). To assess the significance of the coefficient I, we adopted the methodology used by Frigerio *et al.* (2018) and Cerqua *et al.* (2021) and implemented a randomised simulation using 999 permutations.

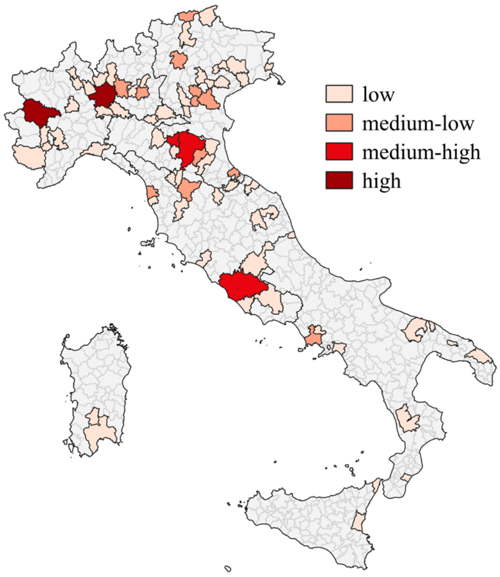
4. Results

Figure 1 shows the geographical distribution of green patent applications in the Italian LLSs in 2019. In general, we can see that the majority of green patents are located in the northern part of Italy (82%). A minor percentage is present in the Centre (14%) and very few examples can be found in the South and Islands (4%). Moreover, if we look at the number of these patents, we can conclude that the North is the part of the country with the highest concentration of LLS hosting the most applications, in fact, the urban centres of Turin and Milan account for 38% of the national total (see Table 2). The only exception in the Centre is given by Rome and Pisa with a medium-high and medium-low number of applications (see Figure 1). In the South and Islands, the level of patents is very low and also spatially limited in core urban centres.

4.1. Local and Global Spatial Correlation Results

The global Moran's I shows a value of 0.088 that is positive and significant, indicating that spatial autocorrelation is present in the distribution of green patents. This means that LLSs with a similar number of green patents tend to cluster, namely, to be located next to each other. However, it is important to note that the value of the index is very low, signalling that the concentration is small. Indeed, it is very spread out in space having a small degree of spatial clustering. As a confirmation of that, Figure 2 (panel a) identifies LLSs that are similar in their values of green patents at a 95% significance level of spatial concentration. More specifically, positive spatial autocorrelation is observed in 20 LLSs labelled high-high (HH), while no LLSs labelled low-low are found. The two most important clusters of specialization in green patents are concentrated around Milan and Bologna. This means that these two core cities generate positive spillover effects in their neighbour LLSs. Another relevant finding pertains to the North of the country and corresponds to the case of Turin and Padua. These two main urban realities appear surrounded by LLSs with lower degrees of green patenting in proximity to those with higher levels. It is worth noting that in the Central region of the country spatial dependency is weak, despite the presence of medium-high and high levels of patent applications (Figure 1). Take the case of Rome, a main urban city that exhibits a higher volume of applications but does not seem to produce any spillover effects. This trend becomes much more evident when we shift to the Southern region of the country, where the major urban areas exhibit negative spatial correlations, resulting in isolation and a lack of spillover effects. Cheeking for the distribution of these clusters according to the degree of urbanization, we find that in 48% of core LLSs shows significant spatial autocorrelation (see Panel b, Figure 2). This percentage decreases to 8% in peripheral areas.

Figure 1 – Green Patents, LLSs in Italy (2019)



	Core	*Medium*	*Other*	*Total*
North	8	14	25	47
	73%	44%	14%	21%
Centre	2	8	6	16
	100%	32%	8%	15%
South	5	4	5	14
	63%	14%	2%	5%
Total	15	26	36	77
Total LLS	21	86	504	611
	71%	30%	7%	13%

Note: The map displays the distribution of green patents 'natural break'. The table displays the total number -and percentage- of LLSs with at least one green patent application per macro-area and level of urbanization.

Source: Authors' elaborations

Table 2 – Top-10 LLSs with the Highest Green Patent Applications

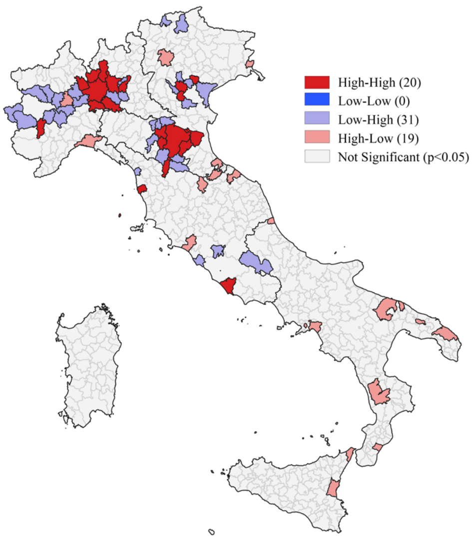
LLSs	*Macro-area*	*Level of Urbanization*	*Green Patents*
Milan	north	Core	92
Turin	north	Core	59
Modena	north	Medium	37
Bologna	north	Core	31
Rome	centre	Core	28
Padua	north	Core	13
Vicenza	north	Medium	10
Vipiteno	north	Other	9
Pisa	centre	Medium	8
Imola	north	Other	8

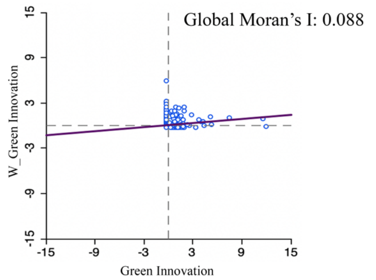
Note: Total number of green patent applications per macro-area and level of urbanization.

Source: Authors' elaborations

Figure 2 – LISA, Local and Global Indicator of Spatial Association, LLS in Italy (2019)

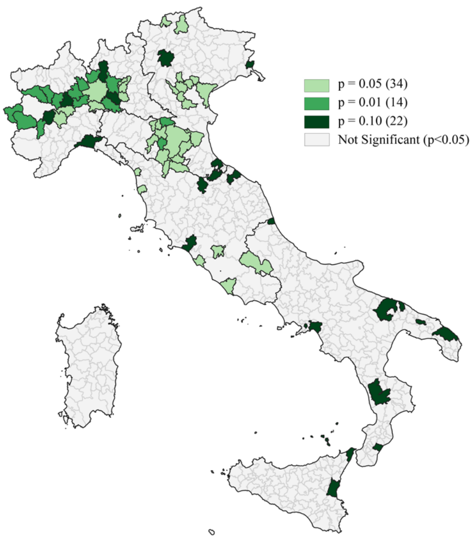
Panel a) Cluster LISA Map





		Core	*Medium*	*Other*	*Total*
North	HH	5	4	8	17
	LH	1	4	20	25
	HL	1	3	1	5
Centre	HH		3		3
	LH		1	4	5
	HL		1	3	4
South	HH				
	LH			1	1
	HL	3	3	4	10
Total		10	19	41	70
Total LLS		21	86	504	611
		48%	22%	8%	11%

Panel b) Cluster LISA Significance



		Core	*Medium*	*Other*	*Total*
North	p=0.05	3	5	17	25
	p=0.01	3	2	9	14
	p=0.10	1	4	3	8
Centre	p=0.05		4	4	8
	p=0.01				
	p=0.10		1	3	4
South	p=0.05			1	1
	p=0.01				
	p=0.10	3	3	4	10
Total		10	19	41	70
Total LLS		21	86	504	611
		48%	22%	8%	11%

Note: The abbreviations refer to: low-low (LL), low-high (LH), high-low (HL), high-high (HH). The tables display the number of LLS per macro-area and level of urbanization. Spatial association is calculated at squared root.

Source: Authors' elaborations

5. Conclusions and Policy Implications

Attention to green innovation is growing not only among scholars but also outside academic boundaries, especially among national policy makers, since its role in fostering green growth is widely recognized. As a result, literature on this topic has grown fast in recent years, leading to relevant results in different disciplines. However, in this growing literature the regional and local dimensions have been scantly addressed and this is a relevant gap to be addressed, since regions and local conditions play a fundamental role in green innovation development and diffusion (Galliano *et al.* 2023; Losacker *et al.,* 2023a; 2023b).

Starting from this premise, this paper wants to address this gap by investigating both the specialisation of regional green innovation and its geographical patterns of localization in Italy, where growing attention to green innovations has been devoted to by national and regional policy makers. Moreover, since green innovation plays a central role in ensuring environmental sustainability and economic growth (Galliano *et al*., 2023; Losacker *et al*., 2023a; Sheng, Ding, 2023), Italy represents an interesting case study given the well-known North-South divide (Iammarino, Marinelli, 2015; Fratesi, Percoco, 2014).

The use of high spatial resolution as LLSs has enabled a more accurate identification of the patterns of green innovation. The findings of our study align with the recent existing body of research (Losacker *et al*., 2023a; Schwab, 2023) which emphasises the significance of spatial factors. Our research demonstrates significant disparities in regional green innovation within Italy, characterised by the presence of both the "North-South" divide and the "urban non-urban" gradient. The country's dualism division is evident, with a greater concentration of green innovation in the wealthier Northern region, which also appears to be able to generate spillover effects from major urban areas 'core' to medium-sized neighbouring cities. In contrast, the Southern regions have a much lower capacity to generate eco-innovation. This is primarily limited to the main core cities, which do not have the ability to generate spillovers. These cities appear isolated and negatively spatially correlated.

Furthermore, employing high spatial resolution, such as LLSs, to map and detect spatial patterns offers empirical information that is valuable for public authorities and policy makers. In fact, understanding which regions can contribute to the greening of the country is of paramount relevance for policy makers (Schwab, 2023), as well as to design and implement evidence-based "green" policy to foster green innovation in the lagging Italian regions. Considering the significant disparity observed among regions and urban gradients in our findings, it is crucial to develop policies that take into account the specific characteristics of each region. There are several policy instruments to support green innovation also in the South of the country. First, as already highlighted by Schwab (2023) in their European study on twin transition, interregional cooperation plays a fundamental role in supporting the development of the lagging regions (Pontikakis *et al.* 2022). Moreover, "complementarities" in interregional cooperation is fundamental, i.e. searching "*for capabilities in other regions that are absent at home*" (Schwab, 2023, p. 30). Third, it is crucial to prioritize human capital and promote the growth of green skills and competencies. This is because skilled human capital plays a vital role in driving green innovation, specifically in facilitating the development and the adoption of products and processes innovation (Montresor, Quatraro, 2020).

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Sommario

La geografia dell'innovazione green in Italia

Il presente lavoro si propone di analizzare il grado di specializzazione e la distribuzione geografica dell'innovazione green in Italia. A tal fine, vengono utilizzati i dati brevettuali relativi al 2019 per mappare le tecnologie green, integrando tre diversi approcci: l'IPC Green Inventory, l'ENV-TECH e lo schema di tagging Y02/Y04S. I dati sono aggregati a livello di Sistemi Locali del Lavoro e comprendono la mappatura delle innovazioni green in base alla classificazione urbano – non urbano e l'esame della dipendenza spaziale utilizzando misure di autocorrelazione globale e locale. I risultati sottolineano le significative disparità nell'innovazione green regionale in Italia, in termini di divario Nord-Sud e classificazione urbano-periferia.