AI, Spatial Methods and the Green-Digital Transformation of Official Statistics brings together a selection of original contributions that explore how artificial intelligence, spatial methodologies, and integrated data sources jointly enhance the production and interpretation of official statistics.

The volume stems from the scientific discussions developed during the international conference "*Measuring and Interpreting World Changes with Statistics, Data Science and AI*", held in Rome from 18 to 20 September 2024. The conference was jointly organised by the Association for Applied Statistics (ASA), the Department of Statistical Sciences of Sapienza University of Rome, and the Italian National Institute of Statistics (ISTAT), with the participation of several academic and institutional partners. The event provided a multidisciplinary forum for examining the contribution of statistics, data science, and artificial intelligence to the understanding of contemporary economic, environmental, and social transformations.

The Special Issue addresses both methodological and applied perspectives, focusing on the growing availability of complex, high-dimensional, and heterogeneous data generated by administrative systems, satellite infrastructures, business registers, and digital platforms. Particular attention is devoted to the integration of artificial intelligence within statistical production processes, the use of spatial and geostatistical models for territorial analysis, and the measurement of green and digital transitions in economic and governance systems.

The contributions collected in this volume investigate advanced methodological frameworks, empirical applications, and interdisciplinary approaches aimed at improving data-driven strategies in official statistics. By combining statistical rigour with advanced machine-learning techniques, the volume highlights both the opportunities and the challenges associated with the adoption of innovative tools, including issues related to interpretability, data quality, and the responsible use of algorithms.

Intended for researchers, practitioners, and policymakers, this Special Issue provides a rigorous and coherent overview of current developments at the intersection of artificial intelligence, spatial analysis, and sustainability measurement, contributing to the ongoing scientific debate on how official statistics can effectively support evidence-based decision-making in complex socio-economic contexts.

This volume is published within the TESI & TEMI editorial series, jointly promoted by Universitas Mercatorum and the Centro Studi delle Camere di Commercio G. Tagliacarne, and reflects their shared commitment—developed in cooperation with the Association for Applied Statistics—to fostering high-quality research and scientific dialogue in applied statistics and official data analysis.

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Special issue 2

AI, Spatial Methods and the Green-Digital Transformation of Official Statistics

Editors
Fabio Crescenzi, Luigi Fabbris, Andrea Mazzitelli, Alessandra Righi, Alessandro Rinaldi, Maurizio Vichi

Articles

40 ANNI 1986 2026
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EDITORIAL

Fabio Crescenzi[1], *Luigi Fabbris*[2], *Andrea Mazzitelli*[3], *Alessandra Righi*[4], *Alessandro Rinaldi*[5], *Maurizio Vichi*[6]

1. Introduction

Official statistics are undergoing a profound transformation. The rapid expansion of administrative archives, satellite imagery, business registers and digital infrastructures has reshaped the informational environment in which statistical institutes operate. At the same time, European policy agendas centred on climate neutrality, ESG accountability and Industry 5.0 strategies have intensified the demand for indicators capable of capturing environmental sustainability, organisational change and territorial dynamics.

This transformation is not merely technological. It raises fundamental methodological and institutional questions: how can artificial intelligence be embedded within transparent statistical frameworks? How can spatial interdependencies be modelled without compromising interpretability? How can new digital data streams be integrated while preserving quality standards and public trust? The contributions collected in this issue engage with these questions, illustrating how innovation can reinforce – rather than replace – the core principles of official statistics.

The reading pathway proposed in the following sections moves from artificial intelligence in statistical production to spatial intelligence and territorial modelling, and finally to governance and sustainability, highlighting the interconnected nature of the green-digital transition.

2. Artificial Intelligence within Official Statistical Frameworks

De Fausti and Tronti in “Leveraging Convolutional Neural Networks for Urban Vegetation Statistics from Satellite Imagery” develop a deep learning framework for extracting urban vegetation statistics from Sentinel-2 satellite imagery. Using semantic segmentation architectures such as U-Net and DeepLabv3+, the study moves beyond traditional NDVI threshold-based approaches by distinguishing trees from low vege-

1 Former Istat - Istituto Nazionale di Statistica, Rome, Italy - e-mail: fabio7826@gmail.com
2 University of Padua, Padua, Italy - e-mail: fabbris@stat.unipd.it
3 Universitas Mercatorum, Rome, Italy - e-mail: a.mazzitelli@unimercatorum.it
4 Istat - Istituto Nazionale di Statistica, Rome, Italy - e-mail: righi@istat.it
5 Centro Studi Tagliacarne, Rome, Italy - e-mail: alessandro.rinaldi@tagliacarne.it
6 Sapienza University of Rome, Rome, Italy- email: maurizio.vichi@uniroma1.it

tation with high classification accuracy. The methodological contribution lies in the construction of a labelled dataset aligned with official territorial boundaries and in the systematic evaluation of loss functions tailored to imbalanced classes.

Bernardini, Chieppa, Cibella and Solari in "Integrazione di modelli expert-based e data-driven a supporto della produzione dei risultati censuari" propose a hybrid classification framework for resident population estimation in the Italian Permanent Census. By integrating expert-defined deterministic rules with data-driven models such as decision trees and adaptive Mixture of Experts approaches, the paper demonstrates how interpretability and predictive performance can be reconciled within register-based population estimation.

Distefano, Bosso, Di Paolo and Papa in "Leveraging Industry 5.0 for Official Business Statistics Innovation" examine the implications of digitalisation paradigms for business statistics, assessing firms' digital maturity and outlining machine-to-machine transmission models integrated within ERP systems. The contribution situates digital infrastructures as strategic assets for modernising statistical production.

3. Spatial Intelligence and Territorial Dynamics

Digrandi and Cimmino in "Geostatistical and spatial applications for optimizing olive grove management within the European carbon emission reduction strategy" integrate Copernicus data, geostatistical techniques and official micro-territorial units to construct a composite indicator of bioenergetic potential, illustrating how spatial intelligence supports climate policy evaluation.

Vurro, Bumbea, Giuffrida, Mazzitelli and Espa in "Business Alliances and Spatial Network Backbones: A National-Scale Analysis of Formal Collaborations" apply network modelling and backbone extraction techniques to formal collaboration agreements, revealing spatial clusters and sectoral specialisation patterns relevant for regional development.

Bruno, Castellano and Punzo in "Le aziende vicine sono sempre più verdi? L'effetto domino delle performance ambientali in Europa" investigate spatial spillover effects in ESG environmental performance, showing how sustainability behaviours may diffuse through proximity-based mechanisms.

4. Governance, Human Capital and Sustainable Competitiveness

Di Manno, Nicosia and Trinca in "La governance delle imprese e le strategie di formazione: spunti di riflessione dalla statistica ufficiale" analyse the relationship between governance typologies and vocational training strategies, highlighting structural differences between multinational and domestic firms and reinforcing the importance of governance variables in official business statistics.

5. Concluding reflections: towards an integrated statistical paradigm

Taken together, the seven contributions portray a statistical system evolving towards deeper integration between artificial intelligence, spatial intelligence and sustainability measurement. The common thread linking these works is not simply technological innovation, but the search for methodological coherence and institutional responsibility in an increasingly complex data environment.

The green-digital transformation of official statistics emerges as a structural evolution of statistical science. Artificial intelligence enhances analytical capacity; spatial modelling enriches territorial understanding; governance analysis connects microeconomic behaviour with broader policy objectives. When embedded within robust quality frameworks, these elements collectively strengthen the role of official statistics as a cornerstone of democratic accountability and evidence-based decision making.

LEVERAGING CONVOLUTIONAL NEURAL NETWORKS FOR URBAN VEGETATION STATISTICS FROM SATELLITE IMAGERY: A STUDY OVER MAJOR ITALIAN CITIES

Fabrizio De Fausti[1], *Michelangelo Tronti*[2]

Sommario

Questo articolo tratta dell'elaborazione dei dati di telerilevamento, in particolare le immagini satellitari, per misurare le aree verdi urbane utilizzando modelli di Deep Learning. Durante questo studio sono state sviluppate metodologie per l'estrazione di statistiche relative alle aree verdi urbane nelle principali città italiane. Sono state implementate tecniche di segmentazione semantica per identificare con precisione alberi e zone di vegetazione bassa, utilizzando dati della missione Sentinel-2 dell'Agenzia Spaziale Europea, con una risoluzione di 10 metri e con quattro bande di frequenza. È stato creato un dataset personalizzato e sono state testate architetture di modelli come U-Net e DeepLabv3+ per ottimizzare la precisione della segmentazione. I risultati hanno mostrato che entrambi i modelli hanno raggiunto oltre l'80% di accuratezza, con la U-Net allenata con la Focal Tversky Loss che ha raggiunto un'accuratezza del 90,11% sul set di test del nostro dataset etichettato personalizzato. Questa ricerca evidenzia il potenziale delle reti neurali convoluzionali nel migliorare l'analisi della vegetazione urbana per le statistiche ufficiali.

Abstract

This paper investigates the processing of Remote Sensing Data, specifically satellite imagery, to assess urban green areas through Deep Learning models. The study developed methodologies for urban green statistics extraction across major Italian cities. Semantic segmentation techniques were implemented to accurately identify trees and low vegetation zones using four bands Sentinel-2 mission data from the European Space Agency with a resolution of 10 meters. A custom dataset was created, and model architectures such as U-Net and DeepLabv3+ were tested to optimize segmentation accuracy. Results indicated that both models achieved over 80% accuracy, with U-Net, specifically when trained with Focal Tversky Loss, reaching an accuracy of 90.11% on the test set of our custom labeled dataset. This research highlights the potential of convolutional neural networks in enhancing urban vegetation analysis for official statistics.

1 Istat - Italian National Statistical Institute, Rome, Italy - e-mail: defausti@istat.it.

2 University of Rome Tor Vergata, Department of Biomedicine and Prevention, Rome, Italy - e-mail: michelangelo.tronti@uniroma2.it

Parole chiave: Telerilevamento, Deep Learning, Verde Urbano, Convolutional Neural Networks, Immagini Satellitari.
Keywords: Remote Sensing, Deep Learning, Urban Vegetation, Convolutional Neural Networks, Satellite Imagery.

1. Introduction[3]

Remote sensing technologies have revolutionized the collection and analysis of Earth observation data, particularly in monitoring vegetation, land use, and urban development. Openly accessible satellite imagery provides extensive coverage but often lacks the resolution needed for detailed analysis, when compared to proprietary data sources. Conversely, aerial orthophotos offer finer details, making it essential for understanding urban environments, but often the licenses to use them are expensive to acquire. Traditional methods, such as the Normalized Difference Vegetation Index (NDVI) (Rouse *et al.*, 1973), have been widely used to evaluate vegetation health but suffer from limitations like saturation in dense vegetation and susceptibility to environmental noise and bad weather conditions (Redowan *et al.*, 2012).

Binary masks created by identifying an NDVI threshold value to distinguish between vegetated areas and built-up zones in urban context from aerial orthophotos are capable of finding green zones (Mugnoli *et al.*, 2024), but lack the ability to distinguish different vegetation types.

This study explores the effectiveness of modern deep learning techniques, specifically Convolutional Neural Networks (CNNs), for semantic segmentation of urban green areas in Italy's 14 most populated municipalities. The aim was to enhance existing NDVI-based methodologies by finding a methodology capable of accurately classifying vegetation types, specifically trees and low vegetation.

The introduction of deep learning methods, such as the one proposed in this study, could enhance official statistics in different ways. Indeed, these innovative methods could enable the production of objective information, updateable with high frequency, and replicable across the entire national territory, at lower costs than traditional surveys or extensive photo-interpretation. Some applications that could be ideal use cases for a model capable of quantifying high and low vegetation are the estimation of indicators related to the quality of urban life, such as the contribution of urban green spaces to CO_2 absorption, the mitigation of urban heat islands or the availability of natural spaces for the public. Moreover, the estimates produced via deep learning methods can be used to build indicators of green space accessibility by cross-referencing ISTAT's informational

[3] The introduction is attributed to De Fausti, while the remaining sections of the article are authored by Tronti.

assets, such as the population residing in census tracts. In perspective, this approach could extend to other areas of official statistics, such as classifying agricultural crops or forests. In this way, deep learning becomes an operational tool to support statistical production, strengthening national statistical institutes' capacity to rapidly describe complex phenomena.

2. Methodology

The project began with the collection of satellite imagery using the Sentinel-2 mission, which provides high-resolution images suitable for vegetation studies. The WorldCover[4] dataset served as the foundation for creating a custom labeled semantic segmentation dataset, containing satellite images and corresponding masks. The segmentation masks were adapted to classify three primary categories: background, trees, and low vegetation.

The semantic segmentation models evaluated were U-Net (Ronnerberg *et al*., 2015) and DeepLabv3+ (Chen *et al*., 2018). The models were implemented using the PyTorch Lightning library, and various loss functions, tailored specifically to train semantic segmentation models on unbalanced datasets, were tested, including Cross Entropy Loss, Weighted Cross Entropy Loss, Dice Loss, and Focal Tversky Loss. The U-Net architecture, known for its symmetric encoder-decoder structure and skip connections, is particularly effective in retaining spatial information, while DeepLabv3+ utilizes atrous convolution for multi-scale feature extraction.

To identify the territory of the different municipalities, the official shapefiles available on the ISTAT website[5] were used.

Dataset Creation

To ensure robust model training, the dataset was expanded to include the 136 largest cities in Italy, representing diverse urban landscapes. Moreover, the dataset featured images from the same areas recorded in 2022, 2021 and 2019 to cover years with significantly different precipitation levels. These images, were then divided in 256x256 pixel tiles, resulting in approximately 15,000 smaller tiles, which were split into fixed train, test and validation sets. The segmentation masks were processed to feature only the three relevant classes – low vegetation, trees and background – out of the original 11 classes for the WorldCover datset. In particular, the original WorldCover dataset classes representing shrubland, grassland, cropland, bare / sparse vegetation, herbaceous wetland and moss and lichen were mapped to the new low vegetation class, the tree cover class remained the same, and the remaining ones were mapped to the areas without ve-

4 https://esa-worldcover.org/en
5 https://www.istat.it/notizia/basi-territoriali-e-variabili-censuarie/

getation. An independent validation assessment has estimated that the overall accuracy of the WorldCover dataset labels is 76.7%[6], but the accuracy is higher for some of the classes corresponding to vegetation. Although the satellite images used were captured in different years, the WorldCover dataset presents a land cover classification only for 2021. Unfortunately, this led to noisy labels due to the lack of additional data. Different data augmentations transformations were applied to the tiles during the training of the models, such as random gaussian blur, random gaussian noise and random affine transformations.

Model Training and Evaluation

Models were trained in environments equipped with an Nvidia T4 GPU, and hyperparameter tuning was conducted to optimize learning rates and batch sizes, that resulted in the choice of a learning rate of 5x10^–5 and of batches of 32 for the U-Net and 64 for the DeepLabV3+. The U-Net architecture outperformed the DeepLabV3+ model, achieving a notable accuracy of 90.11% on the test set when trained to minimize the Focal Tversky Loss. The performance of both models was assessed through various metrics, including the mean accuracy and F1 score on all the three classes, to ensure a comprehensive evaluation of model performance.

3. Results

The results show that the U-Net and DeepLabV3+ models can accurately segment urban vegetation, with accuracies exceeding 80 %. The U-Net, in particular, excelled in identifying vegetation zones, highlighting the potential for deep learning models to provide detailed insights into urban greenery. Furthermore, the analysis revealed that the models could discern classes beyond what traditional NDVI methods based on finding adequate threshold values for the different vegetation types (Hashim *et al*., 2019) could achieve, managing to perform this task with very high accuracy levels.

[6] https://esa-worldcover.s3.eu-central-1.amazonaws.com/v200/2021/docs/WorldCover_PVR_V2.0.pdf

Table 1. Test Set Accuracy of U-Net and DeepLabv3+ Models Trained with the Different Loss Functions

Loss Function	U-Net Accuracy (%)	DeepLabV3+ Accuracy (%)
Cross Entropy	89.93	88.77
Weighted Cross Entropy	88.34	87.93
Focal Loss	88.91	83.43
Dice Loss	90.09	88.30
Focal Tversky Loss	90.11	88.41

Source: our elaboration on Sentinel 2 data

A qualitative analysis of the results from the U-Net and NDVI-based binary vegetation masks indicated a significant advantage of the new methodology, since the deep learning approach not only identified green areas but also provided insights into the distribution of different vegetation types, a crucial aspect for urban planning and environmental policy-making.

Table 2. City Area and Vegetation Surfaces Computed by the U-Net

City	**City Surface (km^2)**	**Vegetation Surface (km^2)**	**Vegetation Surface (%)**
Milano	146.78	53.27	36.29
Messina	36.65	12.14	33.13
Venezia	53.32	15.38	28.84
Reggio Calabria	48.08	24.47	50.89
Bari	56.75	17.95	31.64
Torino	112.02	40.99	36.60
Firenze	60.61	27.01	44.57
Catania	44.53	12.85	28.87
Bologna	76.02	36.73	48.31
Cagliari	27.54	6.55	23.78
Napoli	105.53	35.15	33.31
Palermo	86.66	33.34	38.47
Genova	79.21	33.88	42.77
Roma	423.51	205.74	48.58

Source: our elaboration on Sentinel 2 data

Table 2 presents the vegetated surfaces of the cities computed with the U-Net, while Table 3 shows the distribution of vegetation types in the *città metropolitane* according to the classification made by the same model. Using the previous methodology, only the first table could have been built.

The new method provides researchers with access to crucial information necessary for developing indicators related to urban life quality and sustainable city development.

Analyzing the table reveals that urban green spaces account for between 20% and 50% of the surface of largest Italian municipalities. Reggio Calabria has the highest proportion of green areas, followed by Roma, while Cagliari has the least. It is also noteworthy that urban areas typically exhibit a significant dominance of tree cover over low vegetation. For instance, over 90% of the urban vegetation of Genoa consists of trees, while in other cities, trees generally make up between 60% and 70% of the urban greenery. In Venice, Bari, and Cagliari, this trend is inverted, with low vegetation predominating over tree areas, contributing between 60% and 70% to the total vegetation of those cities.

Table 3. Distribution of the Different Types of Vegetation Built with the U-Net

City	Tree (%)	Low Vegetation (%)
Milano	70.80	29.20
Messina	69.73	30.27
Venezia	39.90	60.10
Reggio Calabria	73.89	26.11
Bari	30.57	69.43
Torino	79.10	20.90
Firenze	83.41	16.59
Catania	64.88	35.12
Bologna	64.90	35.10
Cagliari	36.03	63.97
Napoli	79.81	20.19
Palermo	78.66	21.34
Genova	96.60	3.40
Roma	64.50	35.50

Source: our elaboration on Sentinel 2 data

4. Discussion

The use of Convolutional Neural Networks to process satellite images in urban vegetation analysis presents both opportunities and challenges. While this study successfully demonstrated the capability of deep learning models to enhance vegetation classification, certain limitations remain. For instance, applying the methodology to smaller municipalities could be challenging, as the 10-meter spatial resolution of Sentinel-2 imagery may not be sufficient to accurately represent detailed urban vegetation patterns. The introduction of high-resolution aerial imagery, such as orthophotos, could effectively address this limitation by providing a much higher level of spatial detail. However the use of Sentinel-2 imagery compared with high-resolution orthophotos presents a set of trade-offs that affect both the quality of the estimates and their operational applicability. Sentinel-2 provides complete national coverage, is freely available, and is updated at least annually, enabling the regular production of time series and methodological repeatability across the entire territory. Its main limitation is the spatial resolution, which in complex urban environments may be insufficient to precisely distinguish fine-scale elements of urban vegetation. High-resolution orthophotos, such as those provided by AGEA and used in ISTAT's experimental statistics[7], offer a much finer geometric detail (20 cm, 4-band RGB+I), allowing a significantly more accurate representation of vegetation in urban areas. However, these data are not temporally homogeneous and follow a three-year update cycle that is staggered across regions (some updated at t+1, others at t+2 or t+3). This heterogeneity complicates the construction of indicators that are comparable across territories and over time. In summary, Sentinel-2 maximizes coverage, cost-free availability, and update frequency, whereas AGEA orthophotos maximize informational detail at the cost of reduced timeliness, lower temporal uniformity, and stronger usage constraints. Finally, the lack of a great labeled dataset based on othophotos of Italian territory built for this task, represents a limit to the use of this kind of datasource. Annotating such a dataset relative to a specific year manually would need a great amount of labour, and the training of a robust model would need data from more than just one year, due to the seasonal differences of the vegetation.

Currently, quality has been measured just using the test set of our custom dataset, obtained from splitting the labeled samples adapted from the WorldCover dataset. No additional sampling points for external validation have been identified. Future analyses can be conducted to refine the accuracy assessment, for example through photointerpretation exercises on orthophotos. This approach, however, is complex if limited to the resolution of Sentinel-2 images, which does not allow a sufficient level of detail to easily distinguish between different types of vegetation cover. Moreover the masks built with the models could not be confronted to ISTAT's report on urban green space[8], since the two sources describe different phenomena. The report relates to the formal availability of green areas, as reported by the Municipalities, while the masks reflect the actual presence of vegetation (trees and low vegetation) observable from satellite imagery. Therefore, a direct comparison could potentially lead to misleading interpretations.

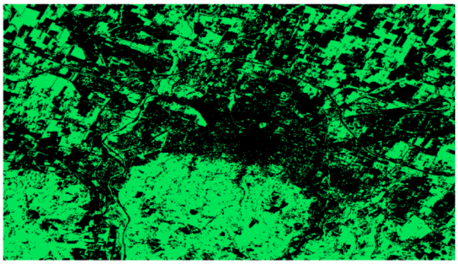
[7] https://www.istat.it/statistica-sperimentale/quantificazione-delle-aree-verdi/

[8] https://www.istat.it/wp-content/uploads/2024/05/REPORT-ambiente-2022.pdf

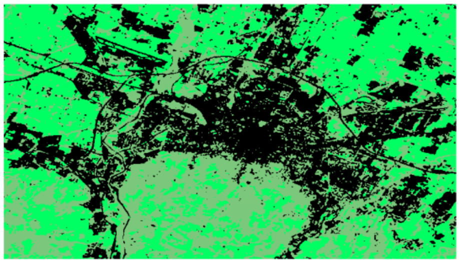
Beyond methodological experimentation, this novel approach contributes to the broader objectives of official statistics by enabling the derivation of new or improved territorial indicators. For instance, the masks generated by the CNN models could support the estimation of indicators such as urban green area per capita, which can be derived by overlapping the vegetation maps with resident population grids published at the census section level. This integration would allow a spatially detailed representation of green space availability per inhabitant, enhancing the accuracy and policy relevance of urban sustainability indicators. Moreover, this approach could further enhance future experimental statistics on urban green areas that ISTAT is expected to publish, by differentiating the various types of urban vegetation identified through deep learning classification.

Future research directions may also focus on integrating higher-resolution datasets, such as aerial orthophotos, to improve segmentation accuracy. The U-Net model trained on Sentinel-2 images, could be, for instance, used to support the labeling of a new high resolution orthophoto-based dataset. Indeed, although the model trained on satellite images performs poorly at inference time on orthophotos, the masks created automatically could be then manually corrected, notably reducing the time needed for the annotation process.

Fig. 1: A Comparison between the Results of the Two Methodologies Tested to Study the Vegetation in the City of Bologna.



(a) A Binary Mask Built with NDVI Thresholding.



(b) The Segmentation Mask Built by the U-Net.

Source: our elaboration on Sentinel 2 data

Cfr. Fig 1: (a) built-up areas in black, green areas with vegetation. (b) black correponds to built-up areas, light green to low vegetation and dark green to trees.

5. Conclusion

This research demonstrates the effectiveness of deep learning models in the analysis of urban vegetation from satellite imagery. The application of U-Net and DeepLabv3+ models for semantic segmentation significantly enhances the ability to identify and classify urban greenery, providing valuable insights for urban planners and policymakers. As remote sensing technology and deep learning methodologies continue to evolve, their integration will play a critical role in promoting sustainable urban development and enhancing the quality of urban life.

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INTEGRAZIONE DI MODELLI *EXPERT-BASED* E *DATA-DRIVEN* A SUPPORTO DELLA PRODUZIONE DEI RISULTATI CENSUARI

LEVERAGING EXPERT KNOWLEDGE AND DATA-DRIVEN CLASSIFICATION FOR DECISION-MAKING: A CASE STUDY IN OFFICIAL POPULATION STATISTICS

Antonella Bernardini[1], *Angela Chieppa*[2], *Nicoletta Cibella*[3], *Fabrizio Solari*[4]

Sommario

La stima della popolazione residente è essenziale per l'allocazione delle risorse, le politiche pubbliche e gli studi demografici. Il Censimento Permanente integra dati amministrativi e rilevazioni campionarie per produrre risultati a diversi livelli territoriali. I dati amministrativi, raccolti per fini non statistici, vengono armonizzati nell'archivio integrato e trasformati in "Segnali di Vita", utili alle elaborazioni censuarie. La stima richiede l'identificazione degli individui candidati a essere abitualmente dimoranti e la loro classificazione in "residenti" o "non residenti", seguendo regole deterministiche basate sulla conoscenza degli esperti. Queste regole, sebbene trasparenti e interpretabili, possono risultare rigide e non rilevare pattern complessi, mentre i modelli statistici possono soffrire di minore interpretabilità o distorsioni. Lo studio propone un framework metodologico e operativo per integrare la conoscenza degli esperti tematici con modelli statistici data-driven. L'obiettivo non è dimostrare la maggiore efficacia di un metodo rispetto a un altro, ma evidenziare come impostare correttamente il loro uso congiunto per supportare i processi decisionali in contesti complessi, come la gestione dei dati censuari, caratterizzati da estrema eterogeneità informativa e da comportamenti diversi a seconda dei gruppi di popolazione considerati. Dopo aver definito il contesto applicativo e metodologico, si descrive una prima sperimentazione basata sulla combinazione adattiva di regole tematiche deterministiche e modelli predittivi basati su alberi decisionali. In questo approccio, le metriche di qualità dei singoli modelli non rappresentano un fine a sé stante, ma uno strumento per guidarne l'integrazione efficace e orientare scelte operative precise. Il framework rafforza l'uso statistico dei dati amministrativi nella metodologia censuaria italiana e offre spunti applicativi per altri contesti caratterizzati da fonti informative eterogenee.

[1] Istat - Italian National Institute of Statistics, Rome, Italy - e-mail: anbernar@istat.it

[2] Istat - Italian National Institute of Statistics, Rome, Italy - e-mail: chieppa@istat.it (corresponding author)

[3] Istat - Italian National Institute of Statistics, Rome, Italy - e-mail: cibella@istat.it

[4] Istat - Italian National Institute of Statistics, Rome, Italy - e-mail: solari@istat.it

Abstract

Reliable population counts are vital for governance, resource allocation, and public policy. Italian Permanent Population Census integrates administrative and survey data. Administrative data, initially collected for non-statistical purposes, are harmonized in the Integrated Administrative Data Base and converted into "Signs of Life", which indicate individuals' presence across sources. Estimating the usual resident population involves identifying potential residents and classifying them as "residents" or "non-residents" using expert-defined deterministic rules. These rules ensure transparency and interpretability but may be too rigid to capture complex patterns. Conversely, statistical models offer flexibility but can lack interpretability and struggle with imbalanced data. This study proposes a methodological and operational framework to integrate domain experts' knowledge with data-driven statistical models, with particular focus on the mixture of experts approach for adaptively combining thematic rules and decision trees. The goal is not to demonstrate the superior effectiveness of one method over another, but to show how to correctly set up their joint use to support decisionmaking processes in complex contexts, such as census data management, which is characterized by extreme informational heterogeneity and by behaviours that vary across population groups. In this perspective, quality metrics of individual models serve as tools specifically designed to guide their effective integration and to inform operational decisions.

This framework reinforces the statistical use of administrative data within the Italian census methodology and offers insights for applications in other contexts characterized by heterogeneous information sources.

Parole chiave: conteggi di popolazione, conoscenze degli esperti, metodi di classificazione, dati amministrativi.

Keywords: *census population counts, expert knowledge, classification methods, administrative data.*

1. Introduction

Accurate population counts from censuses are necessary for efficient resource distribution, governance, and policy formulation. Therefore, the estimation process should be transparent and easily understandable to non-statisticians to fully meet their needs. With the shift to a permanent census system, population counts in Italy are now produced yearly, integrating administrative and survey data. The census process for determining the resident population involves several phases. First, administrative sources are processed within the Integrated Database of Usual Residents (named AIDA) and converted into simplified statistical information called *Signs of Life* (SoL). After selecting only SoL occurrences referring to individuals eligible to be residents, each individual in this set is labelled as *resident* or *non-resident* according to a set of classification rules. The rules currently used are based on expert knowledge. Ongoing knowledge discovery from administrative data and annual census surveys helps experts define classification rules, while Audit surveys ensure quality assessment. Expert-driven approaches provide transparency and interpretability, especially for non-statisticians, but may miss subtle patterns. Statistical learning can complement this by uncovering additional insights. To combine these strengths, we propose a hybrid classification model that integrates expert rules with data-driven methods. This model aims to improve the accuracy of resident population estimates and establish a feedback loop using audit data to refine the estimation process.

The aim of this work is not to identify the best classification method for population count estimation. Rather than assessing the effectiveness or superiority of individual classification approaches, this work proposes a general framework to support decision-making in census contexts, showing how evaluation metrics and model diagnostics can be used to guide the integration of expert-driven and data-driven methods. The paper is organized in the following way. Section 2 describes the methodological context and outlines the theoretical framework. Section 3 presents the experimental study and its main findings. Finally, section 4 is devoted to the final remarks and conclusions, including operational and strategic implications for organizational choices and census operations.

2. Context

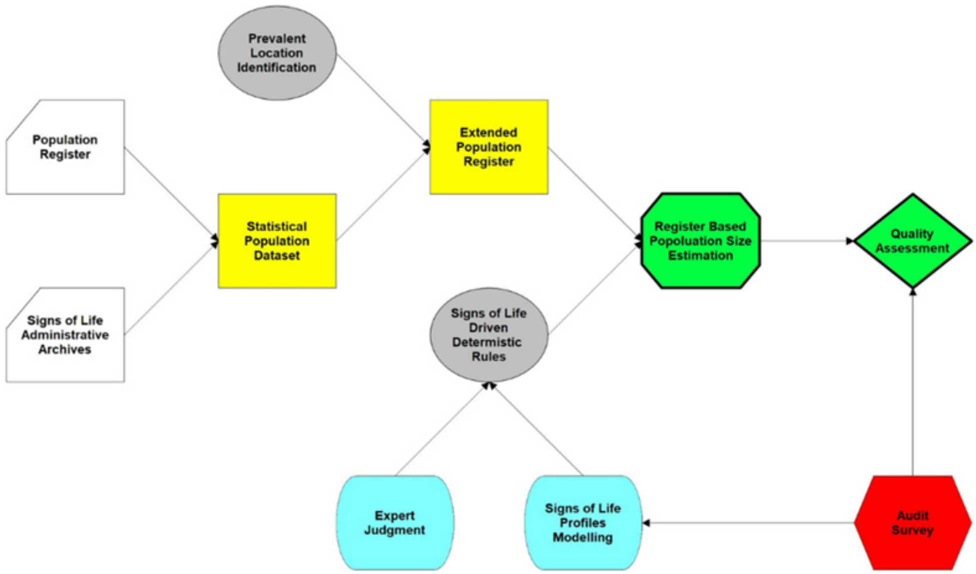
2.1 The application framework: population counts estimation in a multisource framework

The current strategy of the Italian Permanent Population Census relies on Istat statistical registers, which integrate several administrative sources and surveys. A key component is the Population Register (PR), which consolidates data from municipal administrative registers and other sources. Annual sample surveys play an important role in improving the accuracy and reliability of census estimates, while also enhancing the quality of Istat registers in both thematic and coverage aspects. In 2020, due to the suspension of field surveys caused by the COVID-19 emergency, ISTAT adopted a fully register-based approach to estimate the resident population. Previously, a combined survey-register approach was used. This new method relies on SoL-based methodology, where administrative SoL, categorized by type, duration, reliability, and geographical relevance, are pivotal in accurately counting usual residents (UNECE, 2018). The AIDA database plays a crucial role by centralizing SoL data and cross-referencing PR with other administrative sources.

The estimation process employs deterministic rules that combine results from exploratory data analysis and statistical modelling with expert knowledge to classify individuals according to residence patterns emerging from SoL. This classification determines which population groups are included in the resident population.

The shift to a fully register-based estimation process required the establishment of a proper statistical framework and outlines the main features of surveys designed to enhance the quality of register-based estimates and provide quality assessment (Solari *et al*., 2023). Figure 1 provides a visual overview of the framework.

Figure 1. Population size estimation process



Source: Istat 2021

Data resulting from the integration of all the variables in PR and AIDA can be considered as an Extended Population Register (EPR), in which information related to different SoL coming from different administrative sources is registered. The EPR is assumed not to suffer from under-coverage, or at most to be affected only by negligible under-coverage compared to over-coverage. This hypothesis was validated with the help of 2021 sample survey data.

A set of deterministic classification SoL-based rules allows to remove from the EPR of the individuals who are considered not to belong to the usually resident population, thereby adjusting the EPR for over-coverage. The audit survey is specifically designed to assess the quality of registerbased population size estimates by measuring estimation errors and collecting data to refine the classification rules, under the assumption that the target population is fully included in the EPR.

2.2 The need for combining expert knowledge and statistical classification models

Since 2020, Istat experts have combined their thematic expertise with continuous knowledge discovery from administrative data to identify meaningful patterns for estimating population counts. In 2021, Istat introduced advanced statistical techniques, such as latent class models, to support rule definition. To further improve estimation accuracy, Istat has been testing new methodologies and incorporating additional data sources. Among these, machine learning methods and novel data types have shown promise in enhancing the classification of SoL, as demonstrated by Laureti *et al*. (2024). However, these models face challenges, particularly with imbalanced datasets, where the dominance of registered individuals in municipal records can bias classifiers against underrepresented groups.

To address such biases and data gaps, Istat is piloting an audit survey. This includes assessing over-coverage within the EPR and conducting targeted studies to identify population segments that are underrepresented in administrative sources.

A promising solution is a hybrid model that integrates expert-defined deterministic rules with data-driven statistical models trained on survey data. This approach acknowledges that both expert knowledge and training data quality can vary across subpopulations. For instance, administrative sources may fail to capture certain foreign workers, while survey data might suffer from non-response bias. Expert judgment remains essential where survey data are sparse, while machine learning can uncover hidden patterns beyond human recognition. Literature in artificial intelligence supports this integrative approach, highlighting the benefits of combining human expertise with algorithmic learning (Wilder, Horvitz, & Kamar, 2021; von Rueden *et al*., 2023).

The hybrid model also strengthens the audit framework by offering a tool that integrates survey results directly into classification logic, refining expert models and improving SoL accuracy. However, this integration presents key challenges. Ensuring comparability across methods requires consistent evaluation metrics. Reliable benchmarks are needed to accurately assess misclassification rates. Moreover, the methodological complexity of combining distinct approaches must be managed carefully to avoid uncertainty.

Designing the hybrid model involves formalizing expert rules into explicit classification logic and developing statistical models using SoL enhanced survey data. Clear benchmarks and outcome metrics should be defined, derived from audit surveys or administrative signals. Training samples must be carefully constructed to ensure representativeness and interpretability. Finally, a robust statistical strategy must guide the integration of expert and data-driven components, combining empirical experimentation with theoretical insights to balance strengths and mitigate limitations.

2.3 Methodological context for the integration of predictive models

A common challenge in statistics is making a choice among multiple candidate estimation models. Here the term 'model' denotes both statistical models and heuristic classification derived from expert knowledge. Often none of the possible choices can be considered optimal according to some relevant criteria. Model accuracy may not be uniform across the population, each model likely having optimal properties for segments of the population representing some critical profiles but not for other critical profiles.

This non-uniform behaviour suggests the need to segment the population and apply tailored models for each group. In this context, hierarchical mixtures of experts (Hastie *et al*., 2009) offer a statistical solution for handling model selection across different population segments. In the standard mixtures of experts' algorithm, population segmentation is defined using a classification/regression tree, which provides an interpretable structure that can be easily translated into rules for better expert understanding. In similar experimental cases, where a hybrid model combining expert-driven rules and other statistical classifiers is tested, a hierarchical mixture of experts' approach has yielded very promising results (Pradier *et al*., 2021). Alternatively, a plausible solution is provided by model averaging (Hastie *et al*., 2009), which aims to define an optimal combination of all candidate models. Among model averaging we can distinguish Bayesian and frequentist model averaging. The former is based on posterior probabilities computation and naturally emanating from the Bayesian paradigm, while in the latter, model weights are usually determined to obtain desirable properties of the resulting estimators under repeated sampling and asymptotic optimality. Notice that in the Bayesian context, expert knowledge can also be used to elicit informative priors for the different model parameters.

Within this framework, the expert-driven classification itself can be considered one of the possible expert functions or learning processes. This allows for the integration of expert knowledge as a key component in the overall model, ensuring that both expert insights and data-driven methods contribute to the final classification.

3. Experimental settings and first results

3.1 Available data and training samples

From a statistical point of view, the estimation of the usual resident population is a classification problem. The units to be classified are all the individuals who are eligible to be residents, referring to a specific time t, i.e. all occurrences in the EPR. The target variable is a dichotomous indicator, denoting whether an individual is usually living in Italy. Information about an individual's usual place of residence is a key focus of annual census surveys and is explicitly collected for individuals in the survey samples. Among the current annual surveys, the so-called ‘L survey’ (where ‘L’ stands for ‘list’) collects detailed information on the usual residence for a sample of individuals registered in the population register. Additionally, other census surveys may capture information about individuals who are not registered.

The availability of administrative data and census surveys facilitates the creation of data-driven prediction and classification models. Key covariates include territorial variables and demographic indicators, validated in recent studies (Bernardini *et al*., 2024). Among these, the type and pattern of SoL emerge as the most significant predictors. The quality and availability of data, however, differ substantially between individuals recorded in municipal registers and those unregistered. Municipal registers provide detailed demographic and household variables, such as household composition and foreign citizenship status, and offer a direct measure of the dependent variable, albeit with potential errors. Conversely, for unregistered individuals, fewer covariates are available, and no direct feature representing usual place of living exists, complicating predictive modelling. To address these disparities, the population is segmented into two groups: registered and unregistered individuals, each requiring distinct supervised learning models. For registered individuals, census survey data serves as the primary training set, with outcome variables derived directly from survey results (e.g., detected, not detected, uncertain cases). For unregistered individuals, training samples are defined using a longitudinal approach, analysing administrative signals over multiple years. This segmentation ensures better representation of underrepresented subpopulations and improves model accuracy. The experimental framework is summarized in Table 1.

Table 1. Experimental settings for statistical learning

Training samples	Main Inputs	Supervising variable
Set 1: individuals recorded in the Population Register at date *t* sampled in Census Survey of same year	Territorial covariates: demographic size of the municipality, degree of urbanization, administrative and territorial reference. Variables from PR: gender, age, citizenship, foreign citizenship status, municipality of residence, number of family members. Variables from AIDA: signal type, signal source, signal location.	Survey outcome (detected, not detected, uncertain outcomes)
Set 2: individuals with consistent SoL at date *t* not recorded in the Population Register at that date	Territorial covariates. Variables from PR *t*: gender, age, citizenship, area/foreign country of birth. Variables from AIDA *t*: signal type, signal source, signal location. Survey Variables: survey outcome (detected, not detected; uncertain outcomes) of people enumerated in census surveys.	Variables from PR *t*+1: resident flag, municipality of residence. Variables from AIDA *t*+1: signal type, signal source, signal location

Source: Istat 2021

Further key insights from first experimentations on available training data highlight the importance of SoL as predictors. Their relevance, however, varies across subpopulations due to interactions with other variables, such as demographic and territorial characteristics. Table 2 illustrates the distribution of SoL profiles among eligible residents and the corresponding census survey response rates.

Certain subpopulations, such as individuals without SoL or those with weak signals, are at risk of being overshadowed in generalized models due to their low representation. For example, as shown in Table 2, individuals without SoL account for only 1.84% of eligible residents and exhibit low response rates (71.10% for Italians and 35.89% for foreigners), underscoring the need for balanced sampling strategies.

Predictive determinants differ significantly across groups such as foreigners, youths, or individuals with incomplete signals. Tailored models are necessary to capture these variations accurately. For instance, response rates in the census survey vary not only by SoL profile but also by citizenship: certain SoL profiles, such as "rental contracts," exhibit markedly different response rates for Italians (69.17%) compared to foreigners (49.63%). This variability underscores the need for subgroup-specific modelling to prevent misclassification and improve prediction accuracy.

Table 2. SoL classes and Census survey response rate

SoL Profiles	**Eligible as residents in Istat databases**			**Response rate at L Survey**	
	Nr. instances	%		Italians	Foreigners
Steady signs of work/study	31.620.418	52,94%		89,17%	68,32%
Retirement/income source signs	16.926.345	28,34%		90,92%	74,34%
Fiscally dependent family member	4.479.095	7,50%		88,23%	72,34%
Weak signs of work/study	1.932.287	3,24%		85,14%	52,83%
Indirect signs of life (several sources)	1.218.389	2,04%		86,19%	48,35
Rental contract	1.042.950	1,75%		69,17%	49,63%
Signs of university studies	991.543	1,66%		92,17%	74,70%
Signs of work/study episodic	422.545	0,71%		84,49%	55,73%
No signs of life	1.096.850	1,84%		71,10%	35,89%

Source: Data extracted from AIDA database and L Census Survey, Istat 2021

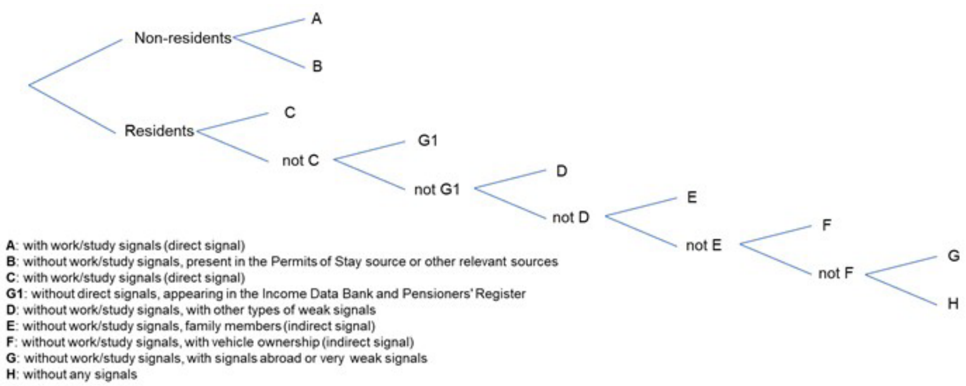
3.2 Expert-based classification rules

Administrative data sources are a key component for many National Statistical Institutes in the production of population censuses. As mentioned earlier, by integrating multiple data sources, it is possible to identify consistent indicators of individual presence in the national territory, which correspond to the previously defined SoL. SoL are categorized as follows:

- direct signals of presence (e.g., rental contracts, pensions, income support);
- indirect signals (e.g., tax dependency, vehicle ownership);
- signals of presence abroad (from administrative, income, or pension records);
- residual signals (e.g., residence permits, household composition from registry data).

To produce census statistical results, individuals are classified according based on hierarchical assessment of SoL attributes. The reference population includes both residents and non-residents who, in the two years preceding the census reference date, exhibited work- or study-related signals, held active rental contracts, possessed valid residence permits, received pensions or income support, or declared income in Italy during the previous fiscal year. Classification is performed through a decision tree (Figure 2) developed according to deterministic criteria defined by domain experts within a Knowledge Discovery from Database (KDD) framework (Chieppa *et al.*, 2018). The process begins by distinguishing individuals registered in the population register (residents) from those not registered (non-residents) and proceeds hierarchically through signal categories, starting with direct indicators of presence, followed by indirect and residual signals. The latter are not always sufficient to confirm actual residency for enumeration purposes.

Figure 2. Expert-based classification of individual administrative Sol



Source: Istat 2021

The initial classification process separates individuals into two broad categories: those potentially undercounted and those at risk of overcounting. While minimal signals may confirm the presence of registered individuals, stronger, consistent evidence is required to include unregistered individuals. To overcome the limitations of a purely hierarchical, univariate method, supplementary deterministic rules have been added. These rules use multivariate and family-based criteria, such as household composition and housing status, to improve classification in complex or borderline cases. Operating independently from the initial decision tree, this complementary framework allows for a more holistic assessment of individual situations. These expert-defined rules are continually refined through a learning process involving comparison, validation, and updates, guided by empirical findings and evolving administrative data. The following are illustrative examples of multivariate and family-based rules used to refine the inclusion or exclusion of individuals from the population count:

- rules to include individuals in the Population Count (examples). Individuals meeting any of the following conditions are considered part of the usually resident population:
  - registered in the population register, with no life signals, but holding a residential rental contract or owning a dwelling in the municipality of registration;
  - registered in the population register, with no life signals, but living in a multi-member household that includes students under the age of 16;
  - not registered in the population register, foreign nationals holding a valid residence permit and a residential rental contract in a non-touristic municipality;
- rules to exclude individuals in the Population Count (examples). Individuals with the following profiles are excluded due to a low likelihood of actual presence in the territory:
  - not registered in the population register, showing stable work or study-related signals, but residing in a border municipality (e.g., likely cross-border commuters);
  - registered in the population register, with no life signals, living in a multi-member household with no students under 16, no dwelling available to the household (either owned or rented), and no household member exhibiting life signals.

These criteria are instrumental in improving count accuracy, especially for ambiguous or borderline situations that cannot be resolved through hierarchical logic alone.

3.3 Classification models

In this analysis, we developed classification models to predict the resident status using decision tree methodologies. For the analyses carried out and to show the effectiveness of the proposal, the region of Latium was selected from the training sample described in section 3.1, which has approximately 175,000 sampled records out of a total of 3.5 million. Latium is also very representative of the problem under study due to the specificities of its territory and the characteristics of the municipalities there.

Latium data includes several categorical predictors: age class, sex, municipality size, citizenship and province in addition to variables related to the presence of administrative signals with their duration and strength. The objective was to identify patterns and significant predictors influencing the response outcome, while maintaining model simplicity and interpretability.

We first constructed a parsimonious classification tree, hereafter referred to as the basic tree. The model was trained on the full dataset using the Gini impurity criterion for splitting. The choice of a parsimonious model, i.e., one with fewer and more meaningful splits, was intentional and aimed at striking a balance between predictive power and interpretability. As previously noted, the outcome categories were highly unbalanced, and specific modelling strategies were required to avoid the systematic misclassification of units as residents. The final model generated 502 terminal nodes and achieved a substantial reduction in deviance. Importantly, the selected model effectively distinguished between outcome categories, including the less frequent category "0", which comprised 424 units, demonstrating that minority categories were not overlooked. The dominant splitting variables leading to different predicted outcomes are age class, citizenship, and municipality size.

Subsequently, we constructed a second classification model, hereafter referred to as the advanced tree, which provides greater control over tree complexity through parameters such as the minimum number of units required for splitting and the complexity parameter. This approach was intended to assess whether a more granular model could achieve higher classification accuracy or reveal more nuanced relationships. The advanced tree was deeper and more complex than the basic tree, while maintaining interpretability, particularly when branches were visualized with node counts and predicted class probabilities. The model performed well across multiple categories, both resident and non-resident, and appeared to reflect the underlying structure of the data appropriately. In summary, both models provided valuable insights into the drivers of the survey outcome variable. The basic tree offered a parsimonious and easily interpretable structure, whereas the advanced tree allowed for more precise tuning and potentially stronger predictive performance.

3.4 Combining models to improve classification quality

Here we illustrate how different integration strategies perform in a real-world context through an experimental study based on the data and models partially discussed in the previous sections. The aim of the experiment was to test and highlight the main processing steps and to demonstrate how to manage the key elements involved in the statistical combination of different models, rather than to provide a simple comparison or ensemble of predictive models. Performance metrics are therefore used not only for model evaluation but also as analytical tools to support informed decisions on model integration, particularly within census validation processes.

Moreover, these metrics offer insights into how expert-based rules and data-driven classifiers contribute differently across population profiles characterized by heterogeneous data quality, with potentially important implications for data acquisition and management strategies.

We considered three classification approaches introduced in the previous sections:

- the thematic rule-based classifier (expert rules);
- the basic classification tree, survey-trained statistical model (basic tree);
- the advanced tree, survey-trained statistical model (advanced tree).

All models were applied to classify all eligible individuals as resident (1) or non-resident (0), in the Latium data

Each statistical model and rule-based classifier defined by experts can be evaluated using specific measures of predictive performance. Given the highly imbalanced nature of the data, global accuracy alone provides limited insight into model behavior, as it is dominated by the majority class (Provost & Fawcett, 2013). For this reason, we also focus on metrics such as sensitivity that could be meaningful for the identification of the minority class of non-resident.[5] As shown in Table 3, while all models achieved high accuracy, the expert-based classifier exhibited substantially higher sensitivity in detecting the minority class. This finding highlights the critical role of thematic knowledge in contexts where administrative covariates are not sufficiently informative for fully automated classification.

Table 3. Summary performance of selected models

Model	Accuracy	Sensitivity/Recall Category 0 'Non- Resident'	Specificity Category 1 'Resident'	F1 Score Category 0 'Non- Resident'
Expert rules	0.9288	0.1138	0.9986	0.2015
Basic tree	0.9215	0.0178	0.9989	0.0345
Advanced tree	0.9215	0.0167	0.9990	0.0325

Source: Experimental results on Latium data, AIDA and Census Survey, 2021

5 Accuracy indicates the overall percentage of correctly classified observations. Sensitivity (recall) represents the model ability to correctly identify true positives, while specificity measures the model's ability to correctly identify true negatives. In this study, sensitivity is primarily evaluated for the non-resident class (category 0), whereas specificity refers to the resident class (category 1). The F1 Score, defined as the harmonic mean of accuracy and sensitivity, provides a balanced assessment of model performance, which is particularly useful in imbalanced scenarios.

A deeper subgroup analysis confirms that model performance varies substantially across population profiles. Table 4 reports accuracy for the expert-rule classifier and the advanced tree, stratified by citizenship, age, municipality size, and type of administrative signal. The results reveal marked heterogeneity: statistical classifiers underperform among foreign nationals and individuals lacking administrative signals, with sensitivity falling below 0.99 and accuracy decreasing by more than five percentage points in some cases. In contrast, the expert-rule model maintains consistently high sensitivity and superior accuracy, particularly within administratively weak profiles. For instance, among individuals with no administrative signals, the expert rules outperform the advanced tree by more than four percentage points in terms of accuracy.

Table 4. Classification quality metrics by population profile

Group		Accuracy Expert rules	Accuracy Advanced Tree
Citizenship	Italian	0.943	0.942
	Foreign	0.769	0.699
Municipality Size	up to 10k	0.954	0.949
	10k–99k	0.919	0.912
	100k–249k	0.790	0.782
	over 250k	0.896	0.884
Age Class	18-34	0.919	0.908
	35-64	0.923	0.914
	65-74	0.953	0.949
Admin. SoL	No Sign	0.854	0.806
	Work	0.932	0.932
	Study	0.957	0.957
	Pension /Fiscal Dependent	0.948	0.948

Source: Experimental results on Latium dataset, AIDA and Census Survey, 2021

These findings highlight the limitations of relying solely on one specific statistical or data-driven model and motivate the adoption of a combined modeling approach that leverages the complementary strengths of expert knowledge and survey-trained classifiers. In particular, the observed variation across population profiles provides guidance for designing a Mixture-of-Experts (MoE) framework, in which the contribution of each model can vary according to individual characteristics rather than applying a uniform ensemble. Features such as citizenship, the presence of administrative signals, and potentially other individual-level covariates emerge as promising candidates for the gating function.

Following these considerations, the experiment next focused on combining models to improve classification quality. Four integration strategies were tested, including two ensemble-based approaches and two Mixture-of-Experts (MoE) frameworks.

The ensemble strategies included

(i) majority voting, which assigns the final class based on the most frequent prediction among models,

(ii) weighted voting, which gives more weight to the best-performing classifier, identified here as the expert-rule model.

Ensembles offer a straightforward approach for aggregating predictions; however, they combine predictions uniformly across all individuals and therefore do not explicitly account for the heterogeneity observed among population subgroups. To address this limitation, we implemented two versions of a Mixture of Experts (MoE) model. In both cases, a simple gating mechanism selects the classifier that achieves the highest sensitivity for the class to which a given individual belongs:

- the first MoE uses a simple gating criterion based solely on citizenship (MoE_Citizenship): for all non-residents, the classifier that best identifies this class is applied,
- the second MoE extends the gating mechanism to jointly consider citizenship and the presence of administrative signals, reflecting the subgroup patterns highlighted in Table 4. These variables were identified as key discriminants of model performance, particularly in administratively weak or otherwise hard-to-classify profiles.

Table 5 summarizes the performance of the four combined strategies. Majority voting confirms its inadequacy in highly imbalanced settings, yielding very low sensitivity for non-residents. Weighted voting substantially improves sensitivity and F1 score by prioritizing the expert-rule classifier, but remains a global strategy. Both MoE approaches achieve comparable or improved overall performance, while allowing model selection to vary across population groups. The MoE based on citizenship alone performs similarly to the weighted ensemble, whereas the extended MoE incorporating administrative signals attains the highest sensitivity and F1 score, with only a marginal reduction in specificity.

Table 5. Summary performance of combined models

Combination strategy	Accuracy	Sensitivity/Recall (Class 0 'Non-Resident')	Specificity (Class 1 'Resident')	F1 Score (Class 0 'Non-Resident')
Ensemble – Majority	0.9215	0.017	0.9989	0.033
Ensemble – Weighted	0.9287	0.1138	0.9984	0.2014
MoE1(citizenship)	0.9288	0.1139	0.9986	0.2016
MoE2(citizenship and admin sign.)	0.9287	0.1207	0.9979	0.2108

Source: Experimental results on Latium dataset, AIDA and Census Survey, 2021

Overall, these results confirm that even simple, rule-based MoE frameworks can effectively exploit subgroup-level heterogeneity, improving minority-class detection without compromising classification stability.

4. Implications and potential benefits of the proposed hybrid approach

This paper presents a theoretical analysis and proposes a hybrid model to enhance population count estimation by integrating expert knowledge with data-driven statistical learning using survey and administrative data. The objective is to provide a methodological framework, together with an operational perspective, to support their informed and complementary integration within complex census-related decision processes. Although administrative data, transformed into signs of life, have high predictive potential, experts more readily identify complex relationships within these signals, while statistical models often struggle due to data imbalance and require further processing to encode signals in a more discriminative way. Experts translate subtle interactions into deterministic classification rules, yet these may miss additional associations and patterns that statistical models can detect. Conversely, statistical models face challenges such as strong imbalance, partially addressed by the planned integration of audit survey data.

The combination of expert rules and statistical models is managed through mechanisms such as model averaging or hierarchical Mixtures of Experts. Our initial exploratory work identified useful evaluation metrics and emphasized the importance of assessing classification quality on relevant subgroups via stratified confusion matrices. Even simplified Mixture of Experts models demonstrated promising performance, motivating further development of adaptive gating strategies driven by profile-specific quality measures. To further refine the hybrid approach, supervised gating models are under development. These aim to learn optimal model assignment rules based on feature combinations and cross-validation, allowing the MoE architecture to adapt dynamically to new data without losing interpretability.

This hybrid approach bridges the gap between deterministic expert knowledge and statistical learning, turning audit data into actionable insights for population estimation. While offering significant theoretical benefits, implementation must balance complexity and interpretability to remain transparent and accessible to non-specialists.

Beyond these conceptual and methodological considerations, the experiments also point to two important strategic and operational implications, highlighting the concrete impact of methodological choices on the Census process. First, as illustrated by the simple case study in Section 3.4, model performance should be leveraged not merely as an end in itself, but as a tool to gain deeper insights into the quality of the underlying data and, crucially, to guide the integration of statistical predictive models with expert rules. For instance, the classification of non-residents based solely on statistical models proved weak when relying exclusively on administrative signals, underscoring the need for a hybrid approach.

The practical implications extend well beyond the specific application of combining expert rules and statistical models in the census context. In fact, they can be generalised to other complex domains, such as estimating the resident population, where the integration of administrative and survey data may require not only the use of statistical models but also the intervention of subjectmatter experts in order to obtain accurate and representative estimates.

The evaluation of model performance and related metrics is crucial for informing strategic decisions, such as identifying the need for additional administrative sources, which may substantially alter model coefficients, or guiding the targeting of surveys and audit activities to ensure more reliable and representative measurements across population subgroups.

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LEVERAGING INDUSTRY 5.0 FOR OFFICIAL BUSINESS STATISTICS INNOVATION

Diego Distefano[1], Paola Bosso[2], Giovanni Gualtiero Di Paolo[3], Pasquale Papa[4]

Abstract

Over the past decade, digitalisation paradigms such as Industry 4.0, Industry 5.0, and Smart Manufacturing have deeply reshaped industrial processes, fostering data-driven practices grounded in advanced technologies, system interoperability, and integrated management systems. This study explores their potential application to Italian official statistics, focusing on opportunities to reduce respondent burden, improve efficiency, and enhance data quality through machine-to-machine data exchange. Drawing on evidence of the digital maturity of Italian businesses—especially SMEs—and on current Industrial production official surveys, the analysis proposes a multi-source strategy while highlighting technological, organisational, and regulatory challenges that limit short-term benefits but promise medium- to long-term gains.

Keywords: *Industry 4.0 and 5.0; Smart Manufacturing; Official Statistics; Digitalisation of SMEs; Machine-to-Machine Data Collection. JEL: C81*

1. Background and objectives[5]

In the past decade, the development of new technologies has triggered a profound transformation of industrial processes at both national and international levels. Central to this transformation are emerging digitalisation paradigms such as *Industry 4.0*, *Industry 5.0*, and *Smart Manufacturing* (Xu *et al*., 2021). While these paradigms share many foundational principles – such as system interoperability across the supply chain, the creation of common standards, and the use of advanced technologies to enhance

1 Istat - Italian National Statistical Institute, Rome, Italy - e-mail: diego.distefano@istat.it (corresponding author)
2 Istat - Italian National Statistical Institute, Rome, Italy - e-mail: lara.fontanella@unich.it
3 Istat - Italian National Statistical Institute, Rome, Italy - e-mail: annalina.sarra@unich.it
4 Istat - Italian National Statistical Institute, Rome, Italy - e-mail: s.fontanella@imperial.ac.uk
5 Author Contributions: P. Bosso: sections 4, 5 (part) – G.G. Di Paolo: sections 2, 5 (part) – D. Distefano: sections 3, 5 (part) – P. Papa: sections 1, 5 (part).

efficiency, flexibility, and scalability – their definitions and applications are shaped by geographical context.

The *Industry 4.0* initiative, of European origin and particularly led by Germany, has had a significant impact across Europe. In contrast, *Smart Manufacturing* has gained greater traction in the United States, largely due to the efforts of the Smart Manufacturing Leadership Coalition (SMLC) - a non-profit organisation comprising representatives from the manufacturing supply chain, academia, and research institutions.

Smart manufacturing uses cloud technology, combines human creativity with machines and AI, and aims for faster, more precise, and personalised production with less waste and more flexibility (Rüßmann *et al*., 2015).

In recent years, the concept of I4.0 has evolved into I5.0, which encompasses not only the technological dimension but also the human, environmental, and resilience issues. This broader framework recognises the importance of integrating these elements to create a more sustainable and resilient industrial future [Breque *et al*., 2021]. In both I4.0 and I5.0, technological advancements drive a data-centric approach, where data management becomes a strategic business imperative.

Companies embracing digitalisation now regard data management as a strategic asset and leverage big data to optimise operational and strategic decisions.

This study aims to explore the potential implications of these digitalisation paradigms for Italian short term official statistics. It assesses both the opportunities and the challenges associated with integrating new data sources into official statistical production (Bender *et al*., 2022). A central objective is to formulate a strategy for incorporating these emerging technologies into the existing framework of Italian official statistics.

A critical element of this strategy is evaluating the *digital maturity* of Italian businesses-especially SMEs (Small and Medium-sized Enterprises) – to determine the practical feasibility of adopting innovative digital solutions. Specifically, the study investigates the implementation of a generalised Machine-to-Machine (M2M) data transmission approach. Unlike traditional M2M systems, which rely on custom-built procedures, the proposed model is designed to be scalable and based on specialised modules developed within the framework of Industry 5.0. These modules would be integrated into the most advanced Enterprise Resource Planning (ERP) platforms currently available.

Key components of the study include:

- Assessing the statistical burden posed by short-term official surveys;
- Measuring the digital maturity of Italian enterprises, with a focus on SMEs;
- Designing the primary phases of an experimental process for data integration.

Ultimately, this research seeks to contribute to a more efficient, modernised statistical system capable of leveraging digital innovation to improve the quality, timeliness, and relevance of official statistics in Italy.

2. Analysis of data

The official surveys conducted by Istat, part of the National Statistical Program, impose a variable burden depending on the size and industry of the companies. They include forty-four surveys, of which twenty-two are short-term (covering 127,482 companies), sixteen are annual, and eight are multi-year or occasional (involving approximately 395,453 companies), for a total of 452,322 companies involved[6]. As shown in Table 1, 99% of companies participating in official business surveys are SMEs (97% for short-term surveys). However, large companies have a much higher economic weight, accounting for about 23% of employment and 35% of added value.

Table 1. Businesses involved in ISTAT official surveys, by size range and type of direct survey.

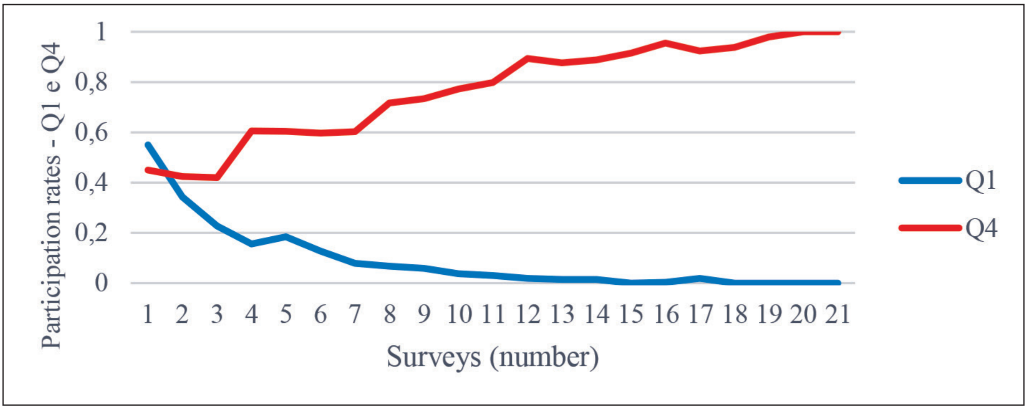
	Type of direct survey					
Businesses size range	*All*	*%*	*Structural*	*%*	*Short-term*	*%*
Micro and small	430,449	95	373,900	95	111,420	87
Medium-sized	18,425	4	18,135	4	13,036	10
Large	3,448	1	3,418	1	3,026	2
Total	452,322	100	395,453	100	127,482	100

Source: our elaboration on ISTAT data

Businesses involved in statistical surveys participate in a minimum of one survey and a maximum of 21, with many surveys repeated multiple times throughout the year, especially for weekly, monthly, and quarterly frequencies. Average survey involvement varies by size: micro and small businesses participate in an average of 1.5 surveys, while larger businesses participate in 11.8 surveys on average. Even medium-sized companies have a relatively high average involvement of 6.2 surveys. For each business involved in one or more surveys, participation rate (r) is calculated as the ratio of surveys completed to surveys requested. Than the Q1 and Q4 quartiles are calculated in relation to the number of surveys. As an example companies involved in a single survey have a first quartile of approximately 0.6, while those involved in more than 10 surveys have a first quartile below 0.1 (Figure 1). Analysing the first and fourth quartiles of participation rates reveals a direct relationship between participation and the number of surveys. This result is likely influenced by the company size, as larger companies tend to participate in more surveys.

[6] The reference is to the last completed edition of each direct survey. All surveys are conducted using the CAWI (Computer-Assisted Web Interviewing) tecnique.

Figure 1. Participation rates of businesses in Istat surveys by number of surveys, Q1 and Q4 quartiles



Source: our elaboration on ISTAT data

It is noteworthy that 84% of large enterprises fall into Q4, indicating a strong "loyalty" of large enterprises in participating in official surveys. In contrast, micro enterprises (which are typically involved in 1.5 surveys) show a near perfect balance between responding and not responding. Specifically, 53% of micro enterprises fall into Q1, while 43% are placed in Q4. Official direct surveys on businesses are becoming increasingly difficult to conduct. Respondents are becoming more reluctant to participate, and statistical agencies are struggling to afford the costs of conducting surveys. These challenges are exacerbated by the need to meet high quality standards for survey outputs. In this context, the digitalisation process and the development of the fourth and fifth industrial revolutions (I4.0 and I5.0) offer new opportunities to improve the efficiency and effectiveness of surveys (De Waal, *et al*., 2020).

3. Assessment of the degree of digitalisation of Italian companies

As part of Istat's annual survey on the use of information and communication technologies (ICT) in enterprises, the "degree of digitalisation" is measured through the Digital Intensity Index (DII). This index combines various factors to evaluate how extensively businesses with at least 10 employees have adopted 12 important digital activities. According to the methodology used, a company is considered digitally basic if it carries out at least 4 of these 12 activities. These include using the internet, having a website, engaging on social media, conducting e-commerce, providing ICT training for employees, and implementing advanced technologies such as artificial intelligence (AI). Some of these indicators are part of one of the four dimensions of the Digital Economy and Society Index (DESI), the European Commission's index that measures the level of digitalisation of EU countries. This dimension focuses on the integration of digital technologies and assesses the adoption of digital tools by businesses, such as the use of cloud services, big data and artificial intelligence, e-commerce (online sales and e-commerce turnover), and the digitalisation of business processes (e.g. ERP systems).

The 2024 ICT survey results show that among businesses using AI, the most popular applications are: extracting information from text documents (54.5%), using generative AI for creating written or spoken content (45.3%), and converting spoken language into computer-readable formats through voice recognition (39.9%). Compared to 2023, the number of companies employing at least one AI technology increased by 71%, with generative AI usage growing the fastest at 163.5%, and AI used for machine movement growing the slowest at 3.7%.

The latest data also highlight a clear digital divide between medium-small enterprises (10-249 employees) and larger companies (250+ employees):

- Basic digitalisation is achieved by most medium-small enterprises (70.2%), but nearly 30% still fall short. Among large companies, basic digitalisation is nearly universal (97.8%).
- A high level of digitalisation is reached by only 26.2% of SMEs, compared to 83.1% of large enterprises, indicating that smaller firms face more challenges adopting advanced technologies.
- Overall, 87.5% of employees in companies with at least 10 workers are employed in businesses that meet the basic digitalisation level.

These figures suggest that smaller companies still have significant potential to advance their digital transformation, often limited by financial constraints, lack of digital skills, and difficulties in implementation. Support through government incentives, training programs, and focused digital strategies could help bridge the gap with larger enterprises.

Looking at specific sectors, the manufacturing industry with the highest digitalisation level is the 'manufacture of computers and electronic and optical products' (Division 26 of NACE Rev2), which is the main focus of the experimental trial.

4. Official short-term business survey data collection based on large scale M2M application: phases of the experimental trial

A focused operational process designed to harness the benefits of digitalisation for official statistics cannot be considered exhaustive, but is necessarily part of a multi-source strategy for collecting business data. Therefore, the experimental activity focuses on: a) variables that are particularly suitable for automated data collection, as they are made available by integrated and digitalised I4.0 systems and are not directly available from alternative sources (e.g. administrative data); and b) a set of enterprises characterised by high levels of digitalisation, as they represent potential candidates for the application of automated data collection techniques involving AI-based models and machine-to-machine (M2M) transmission.

Within this multi-source approach, a component of traditional survey-based data collection remains, in the medium term, necessary for enterprises with lower levels of digitalisation, as well as for variables that are not well suited to automate collection (e.g. qualitative variables).

A targeted operational procedure aimed at exploiting the potential offered by I4.0 and I5.0 technologies for official statistical purposes fits within a multi-source approach to the collection of statistical data on businesses (Saraiva dos Santos, 2022), (Salemink *et al*., 2022). In this context, the experimental trial involves the implementation of a set of operational phases, outlined below:

- *Phase 1: Identification of the experimental domain*
    (a) *Selection of a reference variable for the trial:* The variable selected for the initial experimentation involving the new source is the industrial production expressed in volume. This choice is driven by on practical and methodological reasons. Currently, this data is only collected through direct surveys and is not available from administrative sources. Meanwhile, Industry 5.0 platforms have strong capabilities to capture this type of data, making it an ideal subject for testing new statistical processes. At present, the selected variable is obtained exclusively through direct surveys:
    - *Monthly Survey on Industrial Production* (IPI) measures changes over time in the physical volume of output produced by the industrial sector (excluding construction activities), thereby describing trends in industrial production in Italy. It is conducted monthly on a panel of approximately 6,000 enterprises, generating around 12,000 monthly production data flows.
    - *Survey on Industrial Production* (Prodcom) collects annual data on the physical volumes and/or monetary values of industrial production, broken down by detailed product categories. The survey covers all local production units (around 62,000) of enterprises with at least 20 employees, as well as a representative sample of enterprises with 3 to 19 employees.

    (b) *Identification of the experimental sector.* A possible sector selected for the experimentation is manufacturing of computers and electronic and optical products, (Division 26 of NACE Rev2). This sector stands out due to its high digitalisation level and extensive use of new technologies, with steady growth over time, consistent with ICT survey findings.

- *Phase 2: Involving ERP Providers and Companies*

  This initial assessment phase has two parts: engaging ERP platform providers and evaluating participating companies. The goals are to determine (a) if the project is operationally feasible, and (b) how acceptable it is to the involved companies:

  (a) *Identification of Advanced ERP Providers and Structured Interviews*. Advanced ERP systems integrated with Manufacturing Execution System (MES) components appear best suited for the pilot. Leading providers cover around 60% of the Italian ERP market and confirm that these platforms effectively manage the key production data needed. A questionnaire was designed to gather early feedback on the potential of the new data source, focusing on the items reported in Table 2.

Table 2. Structured interview outline for ERP providers

Interview topics	Items	
1. User Type	– – – –	Market share Business sectors and size Degree of user digitalisation Types of services offered
2. Tools Supporting Process Digitalisation	– – –	Enabling technologies for Industry 5.0 (IoT, IIoT, AI, etc.) Integrated approach across the entire production chain Process monitoring via sensors (e.g., Production, Plant Maintenance)
3. Data-Driven Process Management	– –	Reporting for statistical purposes Management of statistical data to meet Official Statistics requirements
4. Automated Tools for Measuring Production Volumes	– – – –	Use of sensors, RFID, and other technologies Measurement units for produced volumes Detailed product classification and adopted standards Secure M2M data transmission tools

Source: our elaboration on ISTAT data

  Introductory meetings are held with ERP providers to deepen understanding and explore collaboration opportunities. More detailed discussions on data security, privacy, and technical details will follow at a later stage involving Istat's technical experts.

  (b) *Acceptability assessment: Evaluation of acceptability of the new approach among a purposive sample of respondents*. Since this approach is more intrusive than traditional web surveys, it is important to gauge companies' attitudes and openness. A carefully chosen sample of businesses varying in size, sector, location, and digital maturity-drawn from participants in the Monthly Industrial Production survey-is selected. These businesses, some of which have sought digital investment incentives, will undergo in-depth interviews to assess their trust and acceptance of automated M2M data transmission, as well as to identify potential challenges and advantages for future expansion of the project.

- *Phase 3: Alignment with Statistical Information Requirements*.

  This phase evaluates whether data collected from management platforms for the chosen variable and sector can be directly used or needs adjustment to meet official statistical standards, based on EU regulations (especially Regulation (EU) 2019/2152) and national dissemination requirements. It examines differences in definitions, measurement units, timing, and sector classification to ensure consistency with international statistical regulations.

- *Phase 4: Test and Comparative Analysis*.

  The field test phase aims to verify the effectiveness of collecting data via M2M technology and compare it with traditional survey methods. The goals are to assess data reliability, quality, and process efficiency.

  (a) *Experimental Transmission Flow*. A selected group of volunteer companies will participate in an experimental data transfer process, aimed at refining procedures and evaluating timing and data quality.

  (b) *Comparative Analysis of Data Transmission Methods (Traditional vs. M2M)*. A parallel data collection will be carried out with highly digitalised companies, comparing traditional methods against M2M technology. This comparison will focus on meeting the quality and content standards required for official statistics.

5. Discussion and conclusions

The digital transformation of production chains is generating large volumes of data, opening up new possibilities for official business statistics. This study aims to assess the feasibility of using a generalised machine-to-machine (M2M) data transmission model, relying on specialised ERP modules tailored for Industry 5.0 environments. Leveraging business digitalisation presents several clear benefits, such as significantly reducing the response burden on companies, lowering the long-term costs of traditional data collection, and enhancing the overall quality and timeliness of statistical outputs by addressing multiple aspects of Total Survey Error (TSE). Government-backed incentives for digital transformation further support this shift, while the growing integration of digital processes is becoming a key competitive driver for Italian firms.

The experiment forms part of a broader research initiative increasingly embraced by leading statistical institutions worldwide. These institutes are gradually moving away from exclusive reliance on direct surveys and toward a "multi-source" model, which incorporates alternative data sources. This shift is often associated with efforts to automate and simplify statistical data collection processes, made possible by technological advances such as generative AI, machine learning, and web scraping. The approach proposed in this study aligns with this direction.

However, using new data sources in practice involves several challenges-chiefly, the upfront engineering and integration costs. Although digitalisation is gaining traction across Italian businesses, it remains uneven, especially among small and medium-sized enterprises (SMEs). The early stages require investment in adaptable technology solutions that can support automated data acquisition across a variety of management systems. In this regard, a possible impulse may come from the Italian PNRR, which allocates significant resources to the digitalisation of businesses under Mission 1 ("Digitalisation, Innovation and Competitiveness"). The most important measure is "Transizione 4.0," which supports companies' investments in digital technologies, training, and innovation through tax credits aimed at accelerating the digital transformation of production processes. In addition, maintaining consistency and compatibility among traditional survey data, administrative records, and new M2M sources demands complex statistical and organisational coordination.

Another critical issue involves potential resistance from businesses to allowing automated data transfer from their internal systems, particularly when this entails access to sensitive databases. In fact the use of a technique based on automated M2M (Machine- To-Machine) methods is more "invasive" compared to direct surveys carried out via web questionnaires (Snijkers, 2022). There are also difficulties related to aligning the definitions and classification systems used by national statistical institutes (NSIs) with those employed by data providers, which may necessitate custom conversion and transformation processes. Table 3 below outlines both the potential benefits and the key challenges, noting their respective implications for businesses and official statistics producers (NSIs). Ultimately, the advantages of the approach may not be fully realised in the short term, as much depends on how widely the solutions can be scaled and standardised. The setup of the described experimental procedure, although carried out in a limited context (single variable and specific sector), along with the involvement of two key players in the digitalisation of industrial processes (businesses and advanced ERP platform providers), is expected to provide practical insights into the strengths and weaknesses arising from the application of the new data source, as well as guidelines for its operational implementation.

Table 3. Summary table on opportunities and challenges of the M2M data transmission approach and its impact on businesses and official statistics producers

Opportunities			**Challenges**		
Item	*Businesses*	*NSI*	*Item*	*Businesses*	*NSI*
Burden	X	X	Engeneering new data source	X	X
Cost	X	X	Partiality of the source		X
TSE control		X	Heterogeneity of platforms		X
Government incentives	X		Parallel double data collection	X	X
Multi-source approach		X	Acceptability/resistance by companies		X
Leveraging tech. innovation	X	X	Consistency definitions and classifications	X	X

Source: our elaboration on ISTAT data

It's also important to acknowledge that these innovations introduce new complexities in measuring Total Survey Error. As with any pioneering effort, the early phases involve a certain level of risk and require sustained investment and resources to unlock longer-term gains in efficiency and data quality.

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APPLICAZIONI GEOSTATISTICHE E SPAZIALI PER OTTIMIZZARE LA GESTIONE DEGLI ULIVETI DA PARTE DELLE AZIENDE AGRICOLE NELLA STRATEGIA EUROPEA DI RIDUZIONE DELLE EMISSIONI DI CARBONIO

GEOSTATISTICAL AND SPATIAL APPLICATIONS TO OPTIMIZE THE MANAGEMENT OF OLIVE GROVES BY AGRICULTURAL COMPANIES WITHIN THE EUROPEAN CARBON EMISSION REDUCTION STRATEGY

Angela Maria Digrandi[1] e Pasquale Cimmino[2]

Sommario

In un contesto di emergenza climatica globale, l'adozione di strumenti integrati e avanzati risulta imprescindibile per una gestione sostenibile del territorio. Il presente studio analizza l'impiego combinato di intelligenza artificiale, geostatistica e dati multi-fonte per la valutazione del potenziale di sequestro del carbonio e di produzione di bioenergia nei sistemi olivicoli, con particolare attenzione alle aree protette della regione Campania. Il modello analitico si basa su dati Copernicus-Corine, elaborati tramite algoritmi di intelligenza artificiale, integrati con fonti statistiche ufficiali provenienti da ISTAT, ISPRA e ARPAC. È stato sviluppato un indicatore composito di "potenziale bioenergetico", che sintetizza informazioni riguardanti la produzione agricola, dati ambientali e variabili socio-economiche, offrendo uno strumento quantitativo efficace per supportare le politiche pubbliche di mitigazione climatica e sviluppo sostenibile.

Abstract

In the context of a global climate emergency, the adoption of integrated, advanced tools is essential for sustainable territorial management. This study examines the synergistic application of artificial intelligence, geostatistics, and multi-source data to assess the carbon sequestration potential and bioenergy production in olive-growing systems, particularly those located within protected areas of the Campania region. The analytical framework utilizes Copernicus-Corine data processed through artificial intelligence algorithms, complemented by official statistical data from ISTAT, ISPRA, and ARPAC. A composite indicator of "bioenergy potential" was develo-

[1] CNR, Centro Nazionale delle Ricerche, Napoli, Italia - e-mail: a.digrandi@iriss.cnr.it

[2] Former Istat - Istituto Nazionale di Statistica, Napoli, Italia - e-mail: cimmino.linopasquale@gmail.com

ped, synthesizing information on agricultural production, environmental data, and socio-economic variables, providing an effective quantitative tool to support public policies for climate mitigation and sustainable development.

Parole chiave: Geostatistica, Intelligenza artificiale, Sequestro del carbonio, Indicatore composito, Potenziale bioenergetico.
Keywords: Geostatistics, Artificial intelligence, Carbon sequestration, Composite indicator, Bioenergy.

1. Introduzione

Il cambiamento climatico impone l'adozione di soluzioni efficienti e sostenibili sia nelle aree urbane che in quelle rurali, coinvolgendo terreni agricoli e foreste. L'intelligenza artificiale offre strumenti avanzati per migliorare la sostenibilità e l'efficienza delle risorse, grazie all'elaborazione di grandi dataset e allo sviluppo di modelli predittivi in grado di ottimizzare l'uso del suolo in relazione alle condizioni ambientali e alle esigenze socio-economiche.

Il modello analitico utilizzato si basa sull'integrazione della fonte CORINE Land Cover con fonti statistiche ufficiali georefenziate provenienti da ISTAT, ISPRA e ARPAC. I dati ottenuti da tale integrazione sono stati sottoposti ad analisi geostatistiche il cui approccio specifico consiste nell'individuare indicatori pertinenti allo scopo della ricerca ai vari livelli di scala territoriale in cui sono disponibili ed effettuare la sintesi attraverso indicatori compositi che mantengono e valorizzano il riferimento territoriale. Gli autori hanno adattato il concetto di geostatistica delle scienze naturali, in cui viene utilizzato per stimare valori in punti non campionati, per modellizzare variabili socio-economiche complesse, considerando la loro distribuzione sul territorio e le loro relazioni a diversi livelli di scala geografica.

Tratta di processi iterativi durante i quali le varie scale di analisi contribuiscono ad arricchire la coerenza complessiva dell'operazione di sovrapposizione di strati informativi provenienti dai satelliti e da dati statistici georeferenziati.

Il caso di studio sulla Campania mira a dimostrare come questa integrazione possa generare opportunità per un'economia resiliente e rispettosa dell'ambiente, con particolare attenzione al ruolo degli uliveti nelle aree protette. Questo approccio risulta coerente con le politiche europee in materia agro-ambientale, finalizzate a promuovere pratiche sostenibili e a ridurre le emissioni di CO_2, attraverso sistemi informativi territoriali molto accurati e a scala molto granulare.

2. Fonti, normative e metodologie

2.1 Fonti statistiche e cartografiche

Il dataset CORINE Land Cover (di seguito CLC) fornisce una classificazione geograficamente dettagliata della copertura e dell'uso del suolo in Europa, aggiornato regolarmente dal programma Copernicus. Il CLC integra tecnologie avanzate di intelligenza artificiale attraverso algoritmi di machine learning e reti neurali per analizzare grandi quantità di dati geospaziali, climatici e geo-idrologici, consentendo il monitoraggio in tempo reale delle modifiche del suolo e permettendo interventi proattivi e sostenibili. Tuttavia, è stato necessario approfondire il sistema di classificazione usato nelle analisi delle immagini satellitari, che si basa su un modello predittivo in cui un algoritmo assegna un'etichetta o categoria a un dato nuovo in base a dati precedentemente etichettati. Infatti, solo attraverso un modello robusto di classificazione, a partire da immagini satellitari, si identificano i diversi tipi di uso del suolo (aree agricole, foreste, zone urbane, ecc.).

Le elaborazioni delle immagini spaziali, in particolare quelle prodotte dai satelliti Sentinel-2 lanciati tra il 2015 e il 2017, hanno migliorato la risoluzione spaziale della mappa CLC (da circa 100 metri a 10 metri nelle bande ottiche più rilevanti). E' aumentata, pertanto, la capacità di dettaglio territoriale e i dati CLC del 2018, utilizzati in questo studio, incorporano tale innovazione e offrono un inventario dettagliato della copertura e dell'uso del suolo in Europa, con 44 classi tematiche che vanno da ampie aree forestali a singole coltivazioni, diventando uno strumento cruciale per il monitoraggio ambientale, la pianificazione territoriale e la gestione delle emergenze. La conoscenza adeguata del sistema di classificazione adottato nel CLC ha permesso di integrarlo con i dati statistici ufficiali in Italia, ma il processo di integrazione non è un percorso semplice.

I dati satellitari offrono ampia copertura geografica ma mancano della componente informativa socio-economica che l'analisi di dati georeferenziati derivanti da censimenti, indagini e dati amministrativi, consente. Per avere strumenti di controllo adeguati, in questo lavoro si è fatto ricorso alle microzone ISTAT (rilasciate nel 2024) che, per la loro elevata risoluzione spaziale, sono state utilizzate per definire con precisione le aree a maggiore vocazione agricola e forestale e per affinare la costruzione degli indicatori sintetici[3].

L'uso congiunto dei dati CLC e delle microzone ha reso evidenti le aree di mancata sovrapposizione e dal confronto di tali aree con le informazioni socio-economiche, qua-

[3] Le microzone sono suddivisioni territoriali dettagliate, definite in modo omogeneo a livello nazionale, che consentono una lettura granulare delle caratteristiche socio-economiche e ambientali dei micro-territori. La scala di restituzione varia da 1:5.000 nelle zone urbane a 1:25.000 nelle aree a minore densità abitativa.

li espansione residenziale e produttiva, si evidenziano sia le aree di sostituzione tra aree agricole e aree urbanizzate, in particolare nelle zone prossime ai centri abitati nonché quelle di potenziale abbandono. In questo studio, è stata la sovrapposizione con le mappe delle sottosezioni delle Ecoregioni che si è rivelato utile a supportare l'ipotesi che le aree di abbandono siano caratterizzate talvolta da una minore vocazione ad uliveto per motivi climatici e altimetrici. Si tratta presumibilmente di uliveti coltivati in passato (rilevati dal censimento dell'agricoltura del 2010) che, per difficoltà di accessibilità, minore produttività e maggiori costi, sono stati gradualmente abbandonati (il censimento del 2021 rileva una elevata diminuzione di aree olivetate in Campania).

La sovrapposizione dei layer delle microzone a quelle delle sottosezioni delle Ecoregioni e a quelle dell'uso del suolo CLC, è stata fondamentale per analizzare le aree critiche così come quelle di potenziale riattivazione degli uliveti e ricostruire, in tal modo, il mosaico territoriale utile alle politiche agro-ambientali.

2.2 Normative di riferimento

Gli autori hanno tenuto presenti le normative europee e italiane (Crea, ISPRA) che definiscono standard e pratiche per i beneficiari di aiuti alla sostenibilità in agricoltura, tra cui gli eco-schemi della nuova Politica Agricola Comune (PAC 2024) che promuovono incentivi e requisiti per pratiche agricole a basso impatto ambientale, con particolare rilievo per i sistemi olivicoli di valore paesaggistico e naturalistico. Le normative europee evidenziano i benefici economici, ambientali e sociali, la qualità dei dati e la necessità di competenze specifiche («Regolamento UE 2024/1689»), richiamando l'opportunità offerta dall'IA di intercettare fenomeni di greenwashing tramite monitoraggio e supporto decisionale in agricoltura e ambiente. Le normative europee e le applicazioni italiane definiscono standard e pratiche per i beneficiari di aiuti alla sostenibilità includendo indicatori quantitativi basati su dati aziendali e statistici per monitorare azioni a tutela della biodiversità e della sostenibilità ambientale.

In base a precedenti lavori sugli ecosistemi forestali e sul rischio idro-climatico a livello di analisi delle Ecoregioni («Digrandi & Cimmino, 2023»), è stato avviato un progetto di misurazione del potenziale degli ecosistemi forestali nell'assorbimento di CO_2, ampliando l'analisi al contributo, meno studiato in letteratura, delle coltivazioni arboree e in particolare degli uliveti, diffusi in tutta l'area del Mediterraneo.

2.3 Metodologia

L'approccio metodologico si fonda su una pre-elaborazione accurata dei dati, sulla base dell'allineamento spaziale e temporale delle diverse fonti. Dopo aver effettuato le opportune verifiche sui sistemi di classificazione adottati dalle fonti utilizzate (anche tra le fonti statistiche nazionali e quelle amministrative regionali), si è proceduto all'elaborazione di un indicatore sintetico il cui obiettivo era quello di fornire una misura della potenzialità delle foreste e delle coltivazioni di olivo nell'offrire un supporto strategico per lo stoccaggio di CO_2.

La pre-elaborazione dei dati ha comportato una successione di step fondamentali per combinare informazioni satellitari e statistiche e ha riguardato:

- il ritaglio dei dati satellitari in base alle aree di interesse;
- l'allineamento spaziale dei dati satellitari e dei dati statistici georeferenziati;
- la normalizzazione dei dati georeferenziati.

L'accuratezza di questa fase è risultata determinante per la successiva costruzione dell'indice sintetico che, nel caso di studio in esame, ha consentito di giungere a misurare la capacità di foreste e coltivazioni di ulivo di stoccare CO_2, integrandosi con il contributo esercitato dal suolo stesso nell'assorbimento di CO_2. Dopo aver preso in considerazione numerosi indicatori di base, la scelta è stata circoscritta alla quantità stimata di residui da potature e sfalci, alla superficie olivetata, alla superficie forestale, alla quota di territorio in aree protette e agli indicatori sulla densità territoriale della popolazione residente e delle attività produttive e turistico-ricettive.

La procedura per la scelta dell'indicatore sintetico ha previsto anche una serie di controlli sulla coerenza tra output cartografici e dati di riferimento. Fondamentale è stato il processo sovrapposizione delle microzone ISTAT con i dati satellitari CLC e con la rappresentazione cartografica degli indicatori di base e dell'indicatore sintetico che ha permesso di:

- localizzare con precisione le aree a maggiore vocazione agricola e forestale, in particolare quelle destinate a uliveto;
- analizzare la distribuzione e la consistenza delle superfici olivetate e forestali a una scala sub-comunale, superando i limiti delle tradizionali analisi aggregate;
- raffinare la costruzione dell'indicatore sintetico, consentendo di identificare micro-partizioni territoriali con specifiche potenzialità di sequestro di CO_2 e produzione di bioenergia;
- contestualizzare i risultati rispetto alle peculiarità socio-demografiche delle diverse microzone, migliorando la capacità di indirizzare le politiche e gli interventi di rigenerazione territoriale.

L'analisi geostatistica dell'intero ciclo di produzione costituisce, di fatto, un punto fondamentale nelle politiche di transizione energetica in quanto fa emergere il contributo complessivo del ciclo vegetazionale delle piante in progetti di riduzione dell'impatto climatico e di generazione di energia verde.

3. Caso di studio: sequestro di CO2 negli uliveti della Campania e individuazione del loro potenziale bio-energetico

3.1 Contesto e dati utilizzati

Il contesto geografico di analisi è rappresentato dalla regione Campania, caratterizzata dalla presenza di ampie superfici a uliveto in aree naturali protette. Sono stati utilizzati i dataset CORINE Land Cover, i dati delle microzone ISTAT, i dati del censimento dell'agricoltura dell'anno 2021, i dati sul consumo di suolo e i dati in serie storica 2020-2022 elaborati ad hoc dall'ARPAC sui rifiuti biodegradabili da sfalcio e potatura. Il mix di fonti ha permesso un'analisi integrata e ad alta risoluzione, che evidenzia territori con alto potenziale di recupero energetico e sequestro di carbonio.

L'uso congiunto del sistema di classificazione del territorio dato dalle Ecoregioni e dei dati satellitari CLC offre un supporto nel comprendere la localizzazione delle specie arboree, sia quelle forestali per macro tipologia, sia quelle dell'arboricoltura da frutto. Il collegamento tra i dati satellitari (ottenuti attraverso le rilevazioni del satellite Sentinel 2), le statistiche ufficiali sulle coltivazioni arboree, fornite dal censimento dell'agricoltura dell'anno 2021, e il riferimento a partizioni specifiche quali le aree naturali protette e le sottosezioni delle Ecoregioni, consente viste territoriali fini utili alle politiche e alle verifiche sul campo degli impatti delle scelte di investimento.

Un ulteriore passo dell'analisi, rispetto a quanto disponibile in letteratura, è stato reso possibile dal rilascio delle statistiche ufficiali sulle microzone nel 2024 (con riferimento alle basi territoriali e ai dati del censimento della popolazione del 2021), attraverso le quali si evidenziano le micro-partizioni territoriali con vocazioni specifiche quali le coltivazioni ad uliveto.

Nel presente caso di studio, si è scelto come primo livello di analisi l'utilizzo dei dati di Corine Land Cover per misurare la diffusione territoriale degli uliveti e il ruolo che tali coltivazioni rappresentano anche ai fini di riduzione del rischio climatico. Non ci si è limitati al calcolo del valore economico che la presenza dell'albero di ulivo rappresenta, misura che può essere utilizzata nell'ambito dei sistemi di pagamento (PES) e per compensare il bilancio di produzione e stoccaggio della CO_2. Si è ampliato lo studio all'intero processo di vita delle coltivazioni olivicole, enucleando e misurando l'uso, da parte delle aziende agricole, degli scarti di manutenzione e delle potature, focalizzando l'analisi sulle aree protette e discriminando i risultati a livello di sottosezioni delle Ecoregioni.

In tale contesto multi-fonte, la costruzione dell'indice sintetico ha comportato diverse fasi preparatorie (cfr. paragrafo 2.3):

- fasi iterative di scelta ragionata degli indicatori di base disponibili;
- standardizzazione attraverso la costruzione di indicatori rapportati alla popola-

zione residente per quanto riguarda i dati disponibili sui rifiuti CER 2001201 provenienti dalla raccolta dei rifiuti urbani;
- standardizzazione della superficie forestale e di quella ad uliveto rapportate alla superficie totale del comune e calcolo della quota di superficie di area protetta a livello comunale.

Al termine del processo di standardizzazione, si è proceduto al confronto degli output delle diverse procedure di calcolo dell'indicatore sintetico. Sono stati valutati vari metodi non compensativi per la costruzione di indici sintetici: il Mazziotta-Pareto Negativo (IMP neg.), il Positivo (IMP pos.), il metodo Min-Max e l'indice Mazziotta-Pareto (Mz). Tutti si fondano sul principio di non sostituibilità, ossia impediscono che un deficit in una variabile venga compensato da un surplus in un'altra. Il metodo Min-Max mantiene la non compensatività tramite soglie basate sui valori estremi, ma rischia di enfatizzare outlier, svantaggioso quando si intendono identificare potenzialità di miglioramento anziché misurare performance assolute. L'indice Mz, essendo calcolato su scale normalizzate tra valori estremi, risulta più sensibile agli outlier e meno stabile in presenza di distribuzioni distorte. Inoltre, l'Mz può restituire valori simili per unità statistiche con diversa distribuzione interna degli indicatori, riducendo la sua capacità discriminante rispetto all'IMP neg.

Sebbene tutti questi metodi condividano il principio di non compensatività, un confronto basato sulla matrice di cograduazione e sulla sovrapposizione cartografica degli output degli indicatori sintetici rispetto agli indicatori elementari[4] ha dimostrato che l'IMP neg. è il più coerente e rappresentativo nel sintetizzare i fenomeni multidimensionali oggetto dello studio e si rivela robusto, in quanto evita distorsioni dovute a valori estremi. L'indicatore sintetico "potenziale bioenergetico", elaborato con il metodo Mazziotta-Pareto (Mazziotta & Pareto, 2016), è un approccio che equilibra la distribuzione degli indicatori senza enfatizzare né i valori massimi né quelli minimi. Questa caratteristica lo rende particolarmente adatto quale indicatore di potenzialità, capace di evidenziare in modo stabile e significativo le unità suscettibili di miglioramento, senza essere influenzato da outlier.

Per facilitare una lettura più approfondita e sistematica del territorio di riferimento e per illustrare gli indicatori chiave utilizzati nell'analisi, di seguito vengono presentate le cartografie tematiche elaborate che documentano le diverse fasi del processo di analisi geostatistica. L'elaborazione del progetto è stata possibile grazie ai dati elaborati ad hoc dalla direzione Catasto Rifiuti dell'Arpac che ha estratto i dati da O.R.SO. (Osservatorio

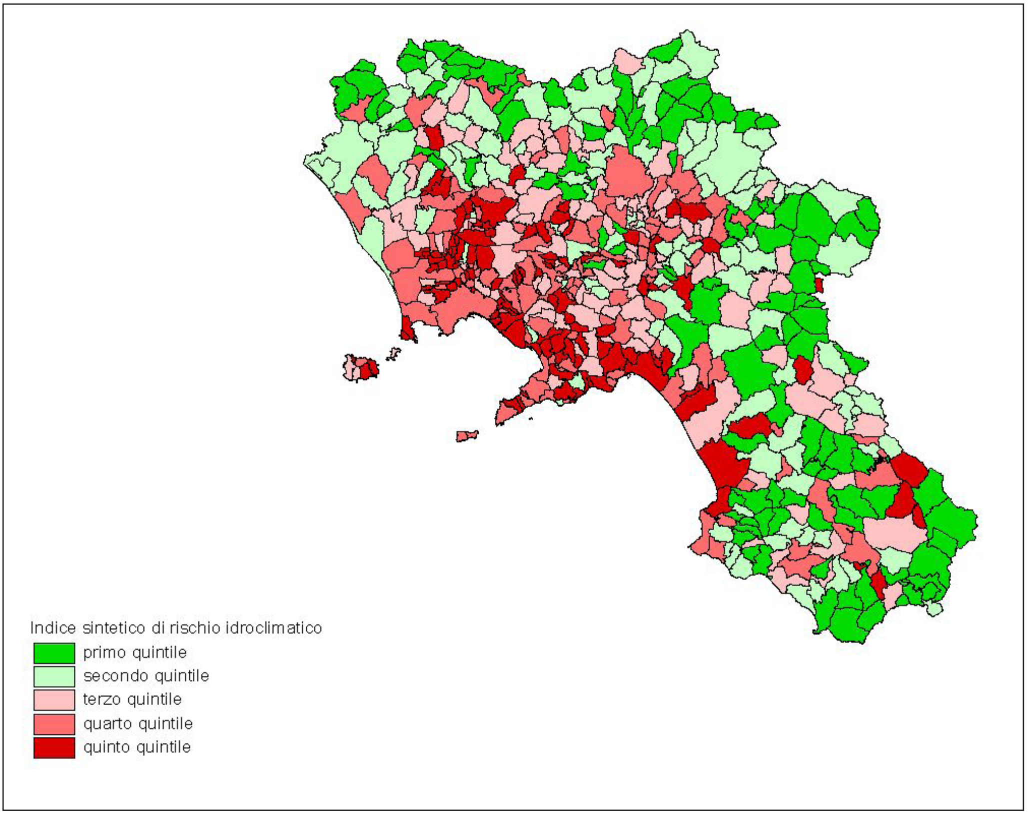
[4] Per garantire la validità dei risultati, gli autori hanno effettuato anche un confronto in serie storica (tra CLC 2015 e censimento agricoltura 2010), ottenendo la confermando la robustezza dell'approccio utilizzato.

Rifiuti Sovraregionale) un applicativo web-based che raccoglie i dati di produzione e gestione dei rifiuti urbani dei comuni campani (550 soggetti) e degli impianti di trattamento dei rifiuti ubicati in Campania (circa 1.000). Grazie all'elaborazione di questi dati è stato possibile conoscere in serie storica la produzione, la gestione e i flussi dei rifiuti urbani a livello di singolo comune per il CER specifico dei rifiuti da sfalcio e potatura nell'ambito dei rifiuti urbani organici conferiti.

L'inserimento sequenziale dei cartogrammi da 1 a 9 consente di seguire in modo trasparente l'evoluzione dell'indagine, dalla costruzione degli indicatori di base fino alla sintesi finale, offrendo uno strumento di supporto sia all'interpretazione scientifica sia alla definizione di strategie operative.

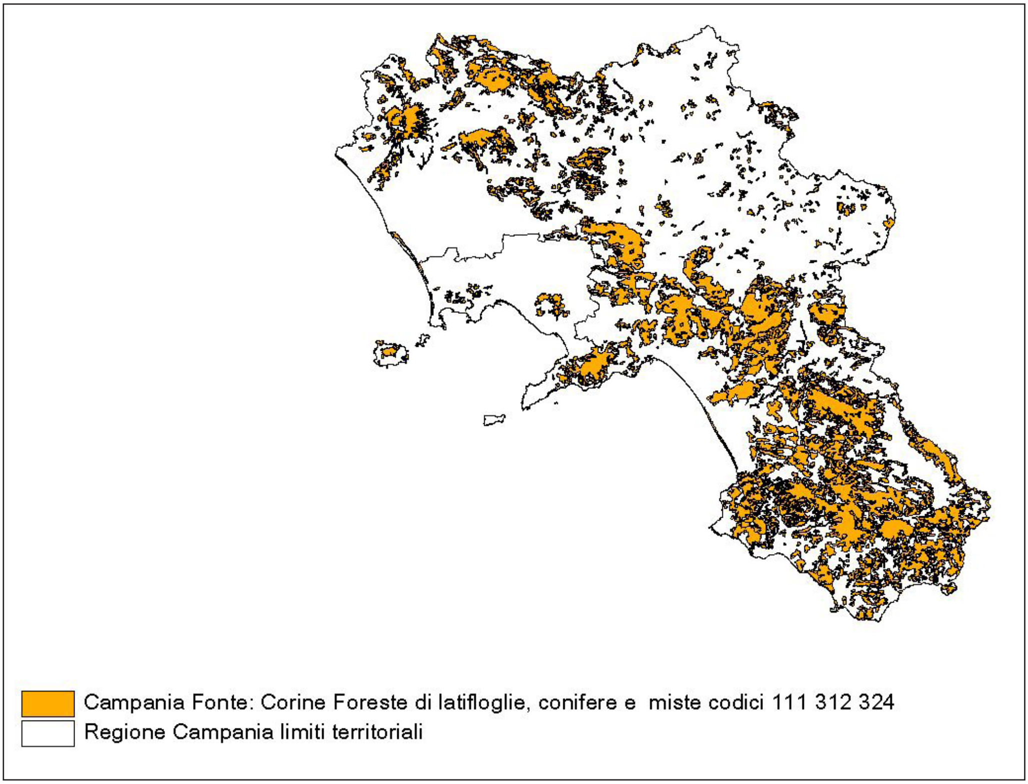
La Figura 1 mostra l'indice sintetico di rischio idro-climatico e la Figura 2 la localizzazione delle foreste di latifoglie, miste e di conifere.

Figura 1. Indice sintetico di rischio idro-climatico (valori espressi in quintili dell'IMP)



Fonte: Elaborazione degli autori. Indice sintetico su dati ISPRA e ISTAT

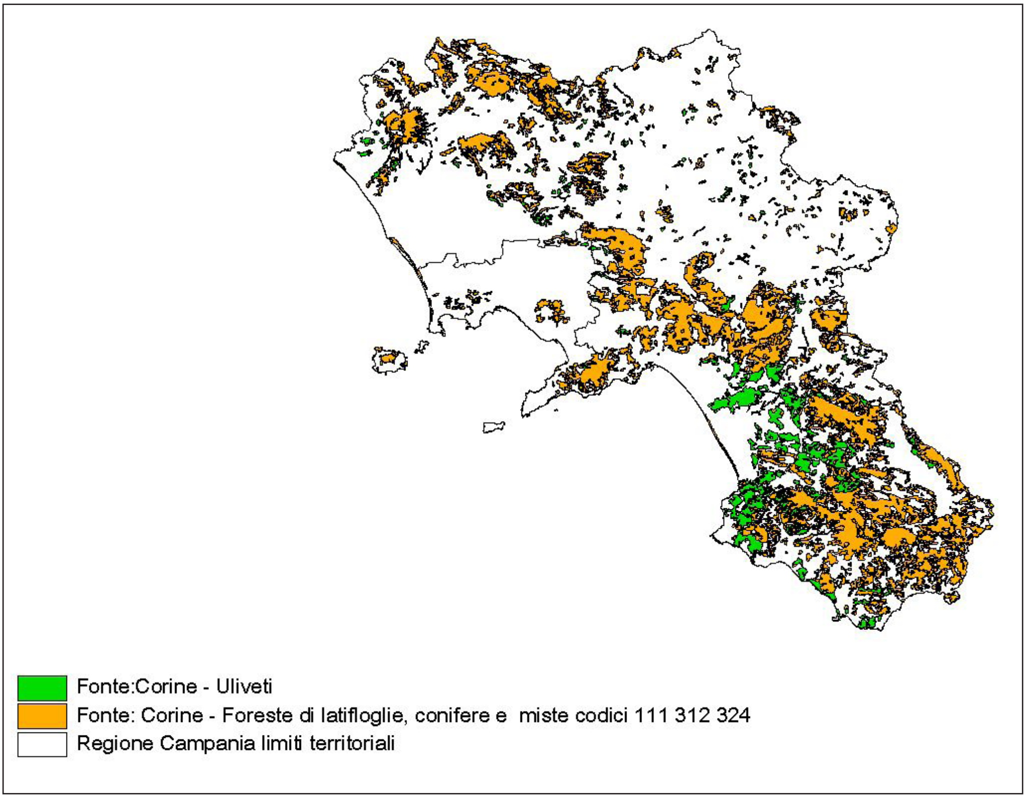
Figura 2. Foreste di latifoglie, conifere e miste



Fonte: Elaborazione degli autori su fonti CLC e ISTAT

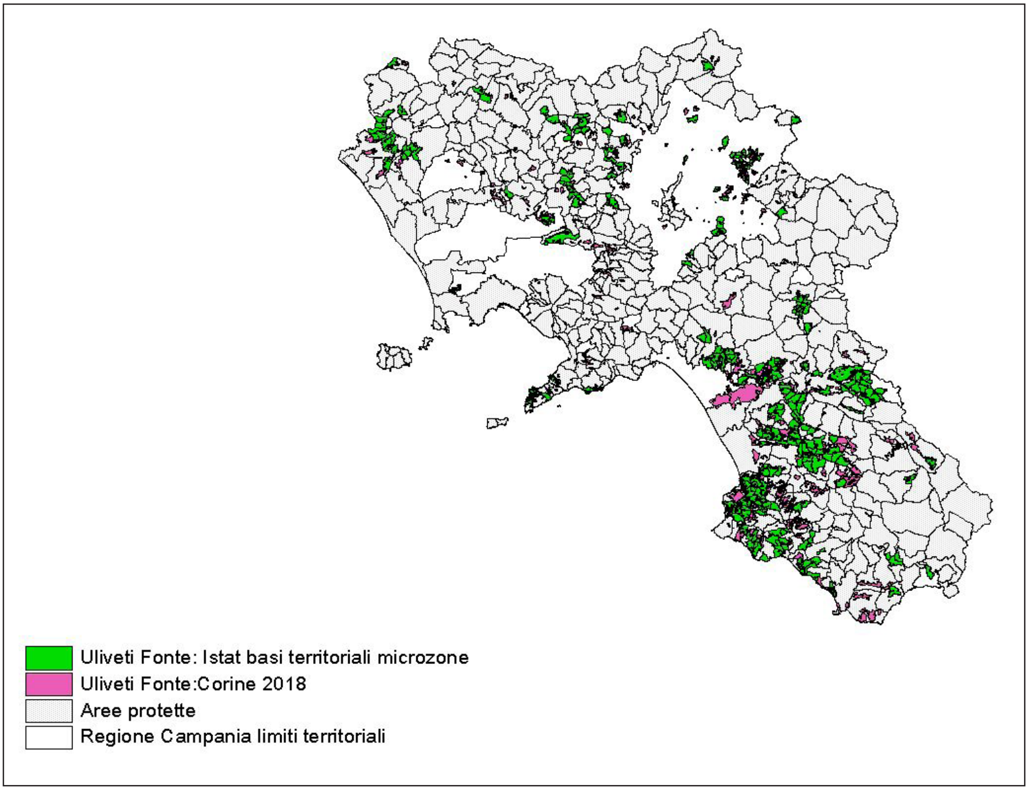
L’uso congiunto dei dati satellitari elaborati da Copernicus di classificazione del suolo consente di evidenziare la localizzazione specifica delle specie arboree, sia quelle forestali per macro tipologia, sia quelle dell’arboricoltura da frutto con particolare riferimento alla localizzazione degli uliveti (cfr. Fig. 3). La sovrapposizione del layer delle microzone Istat evidenzia la localizzazione specifica degli uliveti (cfr. Fig.4) ottenuta attraverso le basi territoriali del censimento del 2021. Il layer delle sezioni delle Ecoregioni (cfr. Fig. 5) aggiunge un’informazione di natura geo-climatica sulla localizzazione degli uliveti: essi sono specificamente e maggiormente diffusi nella sezione 2B2b che afferisce alla Divisione Mediterranea delle Ecoregioni.

Figura 3. Uliveti e Foreste di latifoglie, conifere e miste



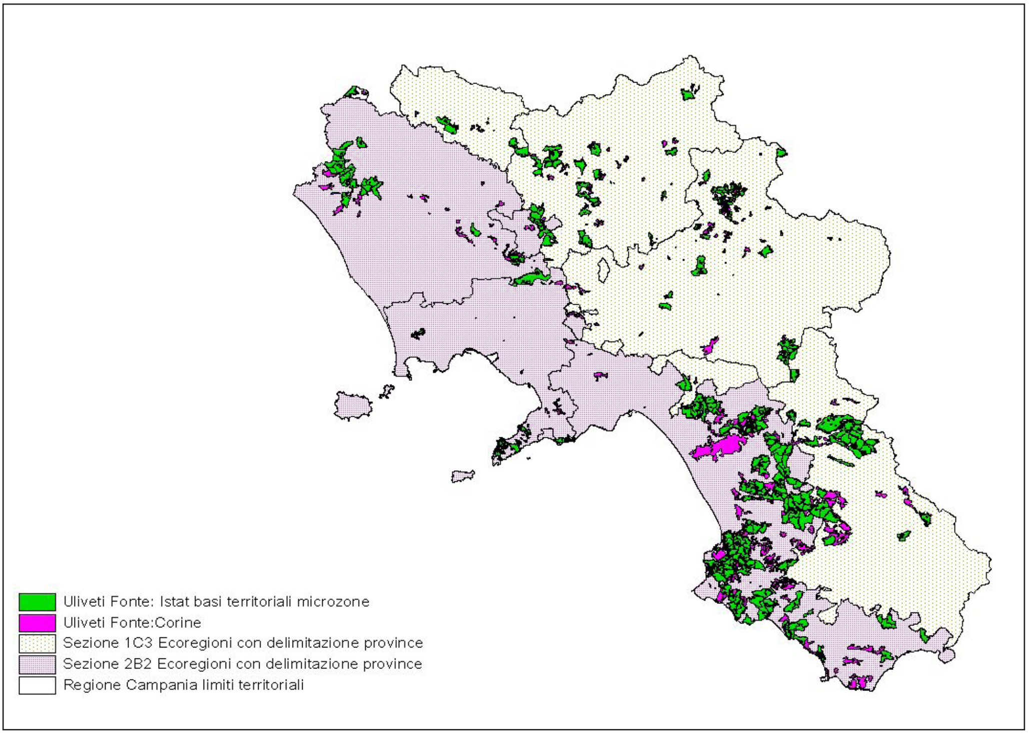
Fonte: Elaborazione degli autori su fonte CLC

Figura 4. Uliveti nelle aree protette linkage fra fonte Istat microzone e fonte CLC



Fonte: Elaborazione degli autori su fonte CLC

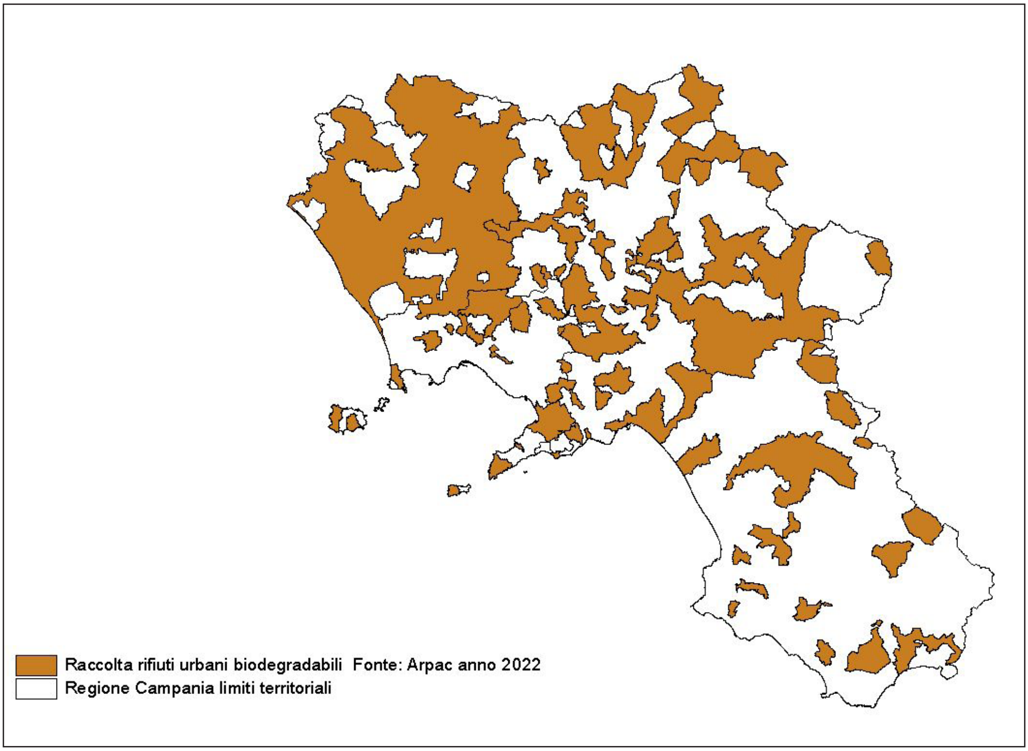
Figura 5. Uliveti - Microzone per sottosezione delle Ecoregioni



Fonte: Elaborazione degli autori su fonti CLC e ISTAT Microzone ed Ecoregioni

Nella Figura 5 si evidenzia, peraltro, come l'utilizzo delle microzone ISTAT si sia rivelato essenziale per aumentare il livello territoriale dell'analisi (cfr. paragrafo 2.1), offrendo una base informativa solida per la definizione di strategie mirate di gestione sostenibile del suolo e di valorizzazione dei servizi ecosistemici. D'altro lato, le immagini satellitari CLC coprono aree più ampie e includono variabili climatiche utili per validare e integrare le informazioni derivate dalle microzone Istat per cui è doveroso porsi in un'ottica di continuo raffronto fra le fonti. Per l'obiettivo di studio, è risultato utilissimo poter disporre dei dati dettagliati sulla raccolta dei rifiuti biodegradabili da sfalcio e potatura (cfr. fig.6), resi disponibili ad hoc per questa finalità dall'ARPAC.

Figura 6. Raccolta rifiuti urbani biodegradabili da sfalcio e potatura

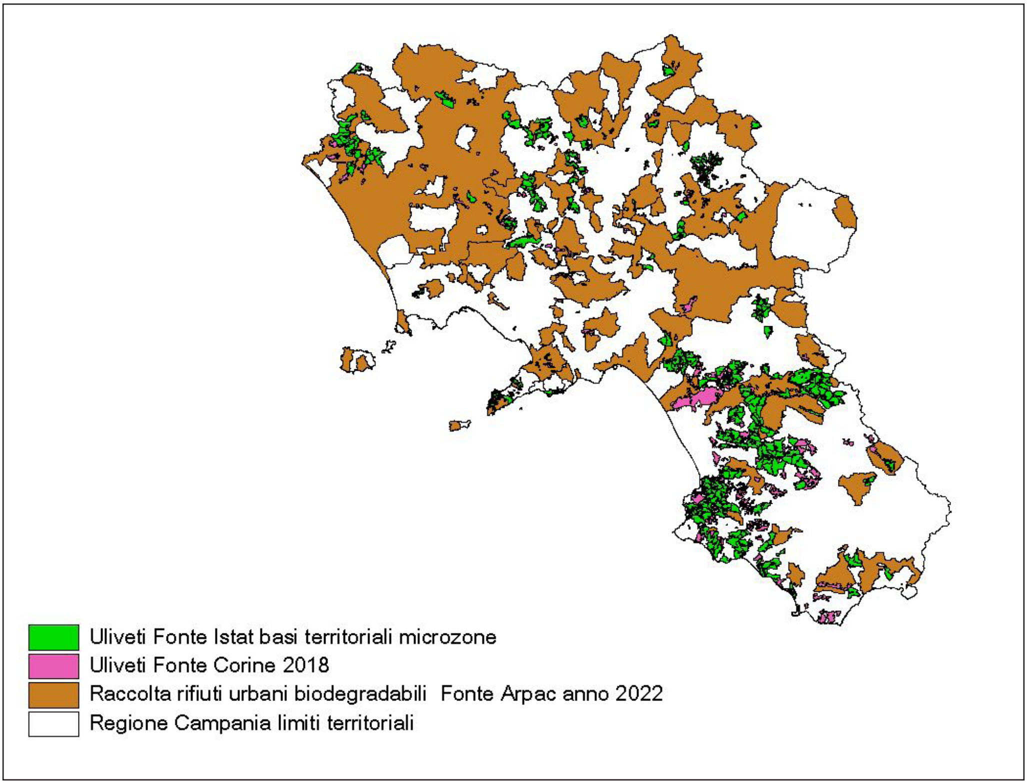


Fonte: Elaborazione degli autori su dati ARPAC e ISTAT

3.2 Costruzione dell'indicatore sintetico

La costruzione dell'indice sintetico ha comportato diverse fasi iterative di scelta ragionata degli indicatori di base disponibili attraverso uno studio geostatistico sulla significatività dell'integrazione fra strati geografici di fonte satellitare, dati censuari delle microzone e statistiche sulla raccolta dei rifiuti urbani biodegradabili (cfr. Fig. 7).

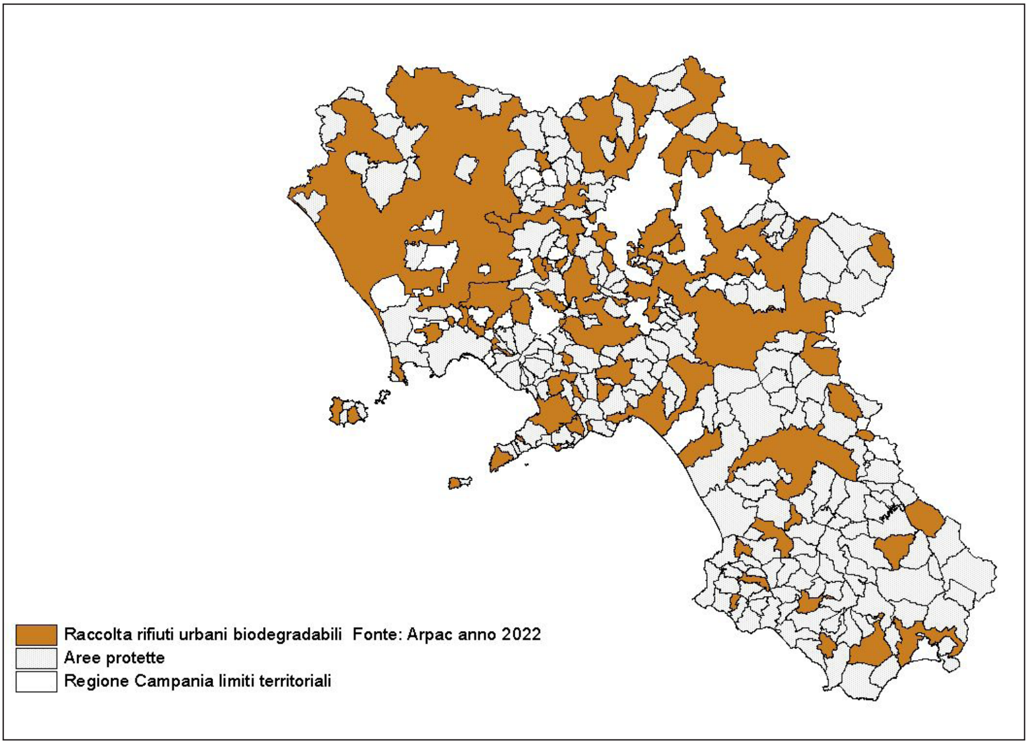
Figura 7. Raccolta rifiuti urbani biodegradabili da sfalcio e potatura - linkage con i dati satellitari e dati di fonte censuaria (microzone)



Fonte: Elaborazione degli autori su dati ARPAC, CLC e ISTAT microzone

Il confronto fra la Figura 7 e la Figura 8 pone in evidenza il contrasto fra aree fortemente urbanizzate, che nel cartogramma della Figura 1 (in cui viene rappresentato l'indice sintetico di rischio idro-climatico) sono caratterizzate da un forte livello di rischio idro-climatico e le aree in cui la raccolta di rifiuti biodegradabili da sfalcio e potatura è consistente. Le mappe descrivono altresì aree naturali protette che, sebbene siano caratterizzate da elevata presenza di foreste e di coltivazioni ad olivo, non hanno ancora attivato adeguati processi di raccolta del rifiuto verde.

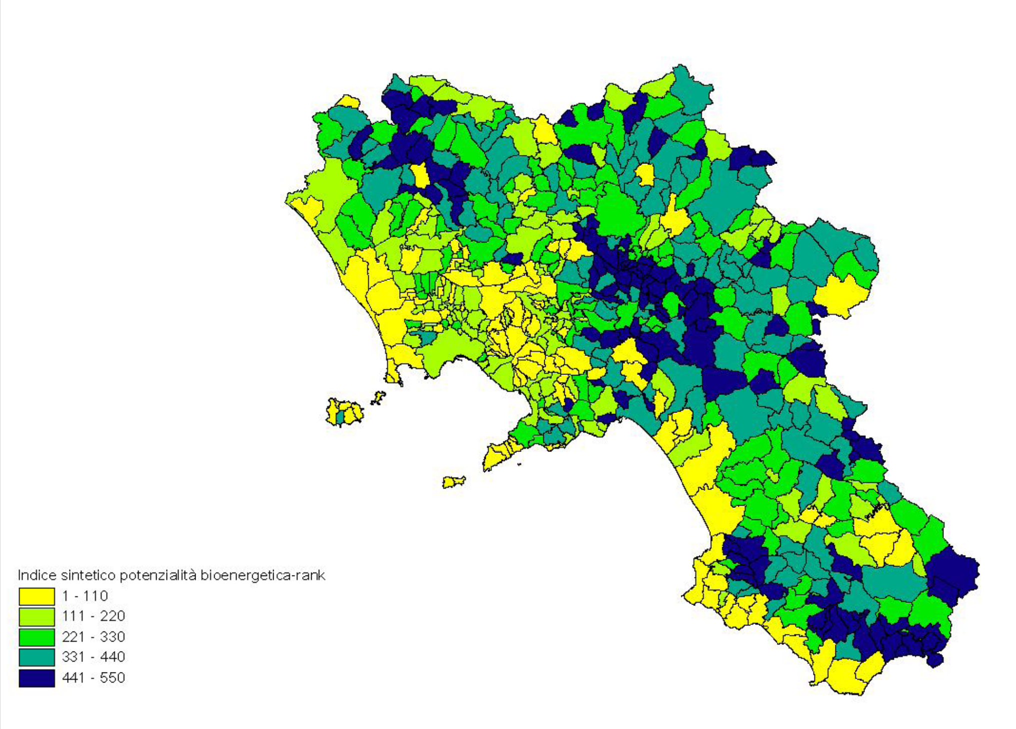
Figura 8. Raccolta rifiuti urbani biodegradabili da sfalcio e potatura e Aree protette



Fonte: Elaborazione degli autori su dati ARPAC e ISTAT

Per la costruzione dell'indicatore sintetico, è stato adottato un processo di standardizzazione finalizzato a garantire la comparabilità tra i diversi comuni. In particolare, sono stati sviluppati indicatori normalizzati rispetto alla popolazione residente per quanto riguarda i dati disponibili sui rifiuti con codice CER 2001201 (rifiuti urbani derivanti da sfalci e potatura). Sono stati, inoltre, considerati la superficie forestale in rapporto alla superficie totale del comune e la superficie olivetata, sulla base delle diverse fonti disponibili (Istat e Regione Campania, rilevazioni satellitari e microzone ISTAT), il consumo di suolo (ISPRA), l'indice di accessibilità ai servizi essenziali e alle autostrade e ferrovie, la densità della popolazione e delle imprese, la densità delle unità locali e degli addetti ai servizi turistici (ISTAT). Questi indicatori sono stati scelti per rappresentare la potenzialità bioenergetica e la capacità di sequestro di CO_2 del territorio.

Figura 9. Indicatore sintetico del potenziale bioenergetico



Fonte: Elaborazione degli autori Indice sintetico su dati ARPAC, ISPRA e ISTAT

L'indicatore sintetico, rappresentato nel cartogramma di figura 9 e definito dagli autori come "potenziale bio-energetico", evidenzia le aree di potenziale incremento del ruolo di sequestro di CO_2 da parte delle aree forestali e olivicole attraverso la trasformazione del rifiuto verde in biogas.

Tenendo presenti le stime realizzate da Nesticò (Nesticò et al3 2022) per stimare l'apporto economico delle foreste nell'assorbimento di CO_2, le normative europee e l'introduzione degli eco-schemi nelle pratiche sostenibili di coltivazione degli olivi (citati nella nota n.4 nel paragrafo 2.2), la possibilità di utilizzare i risultati di questa ricerca per quantificare il valore economico intrinseco degli uliveti è fondata anche su studi recenti effettuati in altri paesi del Mediterraneo. Gómez-Muñoz *et al*. (2022) hanno quantificato la fissazione di carbonio nelle colture di copertura spontanee temporanee negli oliveti di Andalusia, evidenziando valori medi di sequestro di CO_2 compresi tra 2,5 e 3,5 tonnellate di CO_2 equivalente per ettaro all'anno legato soltanto all'inerbimento. Considerando un prezzo di mercato dei crediti di carbonio tra 20 e 40 euro per tonnellata di CO_2 sequestrata, ciò si traduce in un valore economico potenziale di circa 50-140 euro per ettaro all'anno. Questi dati sottolineano il ruolo strategico delle pratiche agro-ecologiche nella mitigazione dei cambiamenti climatici e nella necessità di supporto economico agli agricoltori che intraprendono pratiche colturali sostenibili.

Emerge un approccio alla valutazione economica degli ecosistemi naturali fondamentale per supportare politiche di rigenerazione territoriale. Queste analisi offrono spazi di simulazione per una nuova politica economica che integri due visioni del futuro: quella naturalistica ed ecologica e quella tecnologica che utilizza l'intelligenza artificiale non solo come strumento di analisi di big data, ma anche come luogo di interazione tra intelligenza tecnologica e intelligenza umanistica.

Peraltro, oltre al valore degli uliveti come sottrattori di CO_2 e come fonte di produzione di biogas, va evidenziato il valore edonico del paesaggio olivicolo storico, caratteristico del bacino mediterraneo, che può essere calcolato tramite prezzi ombra correlati al valore immobiliare nelle compravendite abitative in prossimità di paesaggi storici.

4. Discussione e Conclusioni

4.1 Discussione

I risultati confermano che l'integrazione di dati multi-source, metodi avanzati di IA applicati ai dati satellitari e l'approccio geostatistico consentono di sviluppare strumenti utili e affidabili per la gestione sostenibile.

Lo studio evidenzia che la misura della perdita economica, derivante da eventi climatici avversi o dalle epidemie delle piante di ulivo, si deve estendere oltre la sola mancata produzione di olio e deve includere i costi di reimpianto e la diminuzione del valore immobiliare, senza tralasciare di contabilizzare il valore del turismo rurale lento, spesso legato ai cammini storici, che risulta fortemente penalizzato dalla distruzione di foreste, uliveti, vigneti e frutteti storici.

L'indicatore sintetico "potenziale bio-energetico" rappresenta una sintesi efficace per la pianificazione territoriale di interventi di mitigazione del rischio climatico ma la complessità dei dati e le limitazioni temporali degli aggiornamenti richiedono continui miglioramenti e implementazioni.

Nel presente lavoro, la possibilità di analizzare le coltivazioni arboree a livello sub-comunale consente di affinare la valutazione micro-territoriale del sequestro di carbonio e del valore economico associato, nonché del potenziale bioenergetico del ciclo vitale degli alberi, offrendo una base solida per indirizzare politiche di sostenibilità mirate e interventi di valorizzazione ambientale.

I risultati ottenuti confermano che l'integrazione di intelligenza artificiale, dati geospaziali e analisi geostatistiche rappresenta un approccio metodologicamente avanzato e promettente per la gestione sostenibile del suolo e per la quantificazione del sequestro di CO_2 a scala territoriale granulare. L'impiego di indicatori sintetici costruiti su dati armonizzati e multilivello, nel caso di studio attraverso l'adozione dell'indicatore Mazziotta-Pareto MP1neg., ha permesso di superare le limitazioni delle analisi tradizionali e di restituire una rappresentazione più affidabile e dettagliata delle potenzialità bioenergetiche e di assorbimento del carbonio nei diversi contesti territoriali.

Il valore aggiunto del metodo è la scalabilità e l'adattabilità a diversi contesti territoriali e colture, con potenziali applicazioni in ambito rurale e forestale a scala sub-comunale, comunale, regionale e nazionale.

L'applicabilità del metodo ad altri ambiti territoriali è influenzata da due principali limiti:

- la reperibilità dei dati, che talvolta richiede richieste specifiche agli enti produttori e una verifica approfondita dei metadati tramite documenti metodologici che non sempre sono accessibili contestualmente ai dati;
- l'aggiornamento dei dati, che è annuale per la maggior parte delle fonti, fatta eccezione per il censimento dell'agricoltura (attualmente in fase di transizione verso un rilascio annuale continuo), per quelli sull'uso del suolo di fonte Corine Copernicus il cui rilascio è periodico, così come per i dati a livello sub comunale delle microzone, connessi agli aggiornamenti delle basi censuarie;
- il dettaglio territoriale è condizionato dalla risoluzione spaziale dei dati satellitari, dei dati delle Ecoregioni e di quelli delle microzone, dei dati di fonte censuaria e amministrativa. Rimane compito del ricercatore individuare nelle singole fasi le fonti da utilizzare in funzione del tipo di verifica che si vuole ottenere dal confronto/integrazione.

Tuttavia, si è dimostrato in questo studio che sfruttare al massimo l'apporto di varie fonti, consapevoli di limiti e ricchezza informativa dei vari strati informativi, consente di offrire informazione significativa. Peraltro, il metodo è ampiamente replicabile in altri contesti regionali e agricoli, poiché i dati utilizzati (cartografie ISTAT e CLC-ISPRA, dati censuari su famiglie, imprese e addetti alle specifiche attività economiche) sono disponibili per tutto il territorio nazionale a livello granulare.

4.2 Conclusioni

L'analisi condotta sul caso studio della Campania, con il focus sulle aree protette e sulle coltivazioni ad uliveto, evidenzia come la disponibilità di dati ad alta risoluzione – quali CLC e microzone ISTAT – consenta di individuare con maggiore precisione le aree prioritarie per interventi di valorizzazione ambientale e di sviluppo di filiere bioenergetiche. In particolare, la metodologia proposta permette di:

- identificare le zone in cui la raccolta del rifiuto verde può essere incrementata per la produzione di biogas, anche in contesti urbani e periurbani;
- evidenziare le aree, soprattutto nelle zone protette, dove il contributo alla mitigazione delle emissioni di CO^2 deriva prevalentemente dall'assorbimento da parte delle foreste e degli uliveti, suggerendo la necessità di strategie integrate di gestione del verde e di promozione della raccolta differenziata degli scarti vegetali e dell'inerbimento;
- fornire strumenti di supporto alle decisioni per la pianificazione territoriale e la definizione di politiche pubbliche mirate alla transizione ecologica e alla resilienza climatica.

In prospettiva, l'approccio qui descritto si configura come una piattaforma replicabile e scalabile, in grado di essere estesa ad altri contesti regionali e a diverse tipologie di colture arboree o forestali.

L'integrazione tra fonti dati eterogenee, tecniche di IA e indicatori geostatistici, rappresenta un contributo significativo alla ricerca applicata e all'implementazione di strategie di mitigazione e adattamento ai cambiamenti climatici, in linea con le più recenti direttive europee e con gli obiettivi di sviluppo sostenibile. L'analisi delle discrasie rilevate dalla sovrapposizione delle varie fonti di layer costituisce il mosaico cartografico che la metodologia di integrazione degli indicatori contestualizza, individuando i territori e le aziende/imprese agricole da coinvolgere in comunità bioenergetiche.

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ALLEANZE TRA IMPRESE E BACKBONE DELLE RETI SPAZIALI: UN'ANALISI SU SCALA NAZIONALE DEI CONTRATTI DI RETE

BUSINESS ALLIANCES AND SPATIAL NETWORK BACKBONES: A NATIONAL-SCALE ANALYSIS OF FORMAL COLLABORATIONS

Andrea Enrico Vurro[1], Alessio Bumbea[2], Annamaria Giuffrida[3], Andrea Mazzitelli[4], Giuseppe Espa[5]

Sommario

Lo studio analizza gli accordi di collaborazione tra imprese (Formal Collaboration Agreements) in Italia, concentrandosi sulle loro dimensioni spaziali e settoriali facilitate dai contratti tra di rete tra imprese. Inizialmente concepiti per sostenere le piccole e medie imprese (PMI), i contratti di rete coinvolgono spesso aziende di varie dimensioni. Utilizzando un set di dati delle Camere di Commercio italiane, questo studio esamina i modelli di distribuzione geografica e di specializzazione settoriale tra le imprese partecipanti. Strumenti di analisi di rete, come i grafi bipartiti e le tecniche di estrazione del backbone, aiutano a studiare il tessuto economico. I risultati dimostrano una chiara relazione tra la prossimità geografica e la specializzazione economica, evidenziando cluster regionali definiti da specifiche attività industriali; inoltre, le metriche di centralità identificano i comuni e i settori che fungono da nodi cardine, cruciali per la diffusione delle informazioni e l'integrazione economica. L'analisi di rilevazione delle comunità sottolinea un forte allineamento tra la specializzazione economica e il raggruppamento geografico, rivelando modelli significativi nella distribuzione territoriale delle attività economiche. Queste intuizioni forniscono ai decisori politici prove pratiche per promuovere iniziative di sviluppo regionale mirate, sostenendo così la competitività delle PMI attraverso il rafforzamento delle collaborazioni tra imprese.

1 Universitas Mercatorum, Department of Engineering and Science, Rome, Italy - e-mail: andrea-enrico.vurro@studenti.unimercatorum.com

2 Universitas Mercatorum, Department of Engineering and Science, Rome, Italy - e-mail: alesssio.bumbea@studenti.unimercatorum.com

3 Universitas Mercatorum, Department of Engineering and Science, Rome, Italy - e-mail: annamaria.giuffrida@studenti.unimercatorum.com

4 Universitas MercatorumDepartment of Economics, Statistics and Business, Rome, Italy - e-mail: a.mazzitelli@unimercatorum.it

5 University of Trento, Department of Economics and Management, Trento, Italy - e-mail: giuseppe.espa@unitn.it

Abstract

This paper investigates Formal Collaboration Agreements (FCAs) in Italy, focusing on their spatial and sectoral dimensions as facilitated through contracts between businesses ("contratti di rete"). Initially designed to support small and medium-sized enterprises (SMEs), FCAs often involve firms of varying sizes. Using a dataset from the Italian Chambers of Commerce, this study examines the geographic distribution and sectoral specialization patterns among of participating firms. Network analysis framework, such as bipartite graphs and backbone extraction techniques, help to identify clusters of municipalities.

The findings demonstrate a clear relationship between geographic proximity and economic specialization, highlighting regional clusters defined by specific industrial activities and centrality metrics identify municipalities and sectors functioning as pivotal nodes, crucial for information dissemination and economic integration.

The community detection analysis emphasizes a strong alignment between economic specialization and geographic clustering, revealing notable patterns in the territorial distribution of economic activities. These insights provide policy-makers with practical evidence to promote targeted regional development initiatives, thereby supporting SMEs' competitiveness through strengthened interfirm collaborations.

Keywords: *Bipartite network, Formal collaborations, Community detection, Spatial clustering, Backbone analysis, Leiden algorithm.*

1. Introduction

Following the European Commission's Communication (European Commission, 2008), commonly referred to as the "Small Business Act," several European countries introduced complementary national measures aimed to follow the european guidelines at fostering innovation and co-operation among small and medium-sized enterprises (SMEs). In Italy, this initiative was performed through the introduction of Formal Collabo-ration Agreements (FCAs) called 'network contracts' ("contratti di rete"), a legal and organizational instrument established by Law n. 33 of 2009 (Cabigiosu, 2025). FCAs provide a structured and flexible framework enabling two or more firms to form a strategic collaboration, creating a "community of purpose", with objectives centered on collective growth, innovation, and enhanced competitiveness (Cohen & Levinthal, 2000; Dickson, Espa, Gabriele, & Mazzitelli, 2021) such as the "reseaux d'enterprises." implemented in France. A FCA represents a strategic opportunity for SMEs aiming to establish alliances that facilitate the sharing of resources, expertise, and information, while preserving the organizational autonomy. Such agreements enable access to external assets, knowledge, technological capabilities, and skills, favoring joint R&D initiatives, coordinated marketing and procurement, and rapid entry into new markets. Through these collaborative networks, SMEs can strengthen their market position, enhance competitiveness, and maintain operational flexibility, thus combining strategic cohesion with adaptive independence (Burlina, 2020; Latham & Le Bas, 2006; Laurell, Achtenhagen, & Andersson, 2017; Malecki & Veldhoen, 1993; Rubino & Vitolla, 2016).

Several research underscores the positive relationship between SMEs' engagement in FCAs and their improved economic performance, particularly in terms of increased sales growth (Cisi, Devicienti, Manello, & Vannoni, 2020; Rosenfeld, 1996; Schoonjans, Van Cauwenberge, & Vander Bauwhede, 2013).

Nevertheless, quantifying the long-term impacts of SMEs' involvement in agreements remains challenging due to limited data availability (Huggins, 2001; Mazzitelli, Vurro, Giuffrida, Bumbea, & Espa, 2025). Given the relatively recent implementation of FCA legislation, the benefits, such as knowledge absorption and enhanced learning capabilities, typically become more evident over long periods. Despite these challenges, FCAs remain critically important to SMEs, allowing them to effectively exchange information, co-create products, engage in joint marketing and procurement, and collaboratively enter or develop new market segments (Cohen & Levinthal, 2000).

This study has two main objectives. First, it explores Italy's economic landscape by analyzing geographical clustering among firms involved in FCAs, using 6-digit ATECO 2007 codes and municipality where the firms are based and secondly, it employs a backbone extraction methodology in order to simplify the original bipartite graph, increasing density to improve data clarity and discover latent phenomena.

2. Data and variables

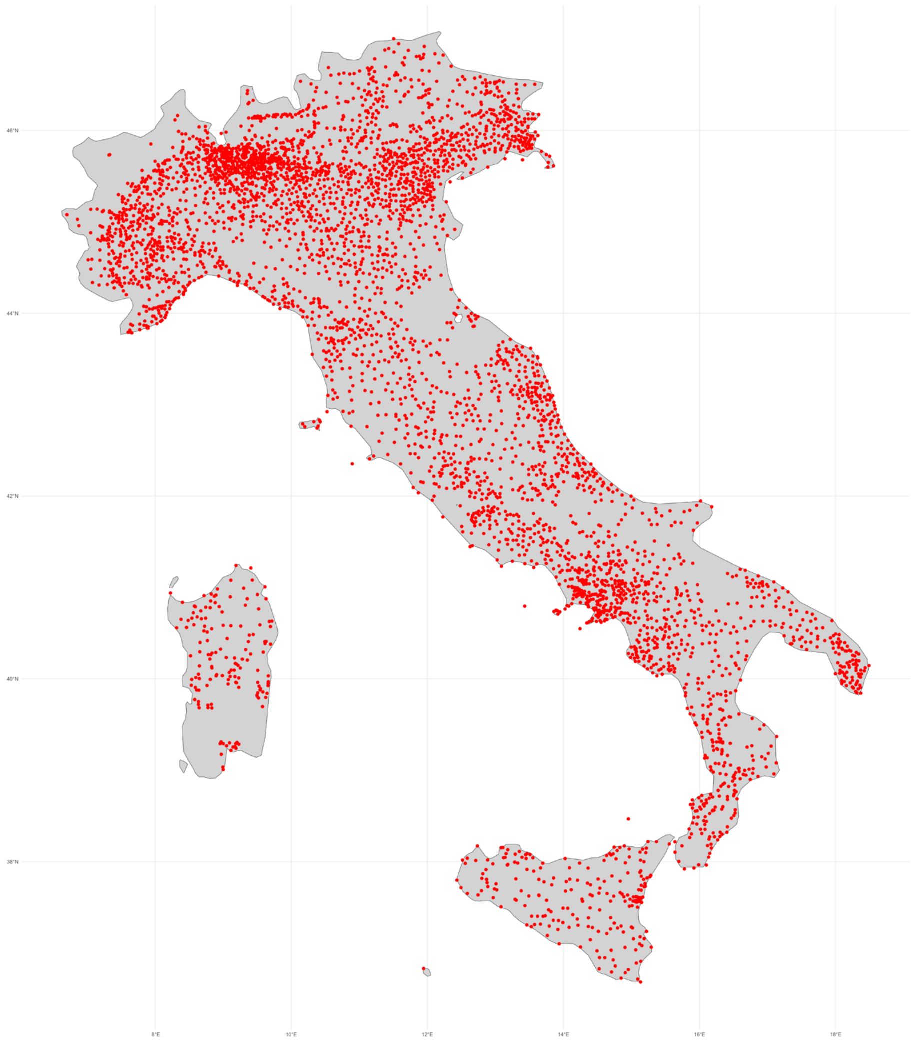
This section describes the dataset of active FCAs obtained from the open-data portal managed by InfoCamere on behalf of the Italian Chambers of Commerce (InfoCamere, accessed 03/05/2025.), which publishes a monthly-updated snapshot of FCA. The analysis incorporates data from FCAs, distinguishing between agreements with and without legal entity, both types of organizational profiles are considered in this research.

Several variables including firms' geographic identifiers (municipality and province) and economic classification codes (six-digit ATECO 2007) were extracted, standardized, and organized into a coherent dataset. Observations missing ATECO codes were removed to ensure analytical consistency. Subsequently, geographic coordinates were added through a reverse geocoding process, using OpenStreetMap, thereby enabling geographic analysis of firms involved in (FCAs) (Kolaczyk & Csárdi, 2020).

The final dataset includes 50,972 firms, each linked to a specific location and associated with an ATECO sector classification. These firms are spread across a total of

4,772 municipalities. The analysis will focus exclusively on the municipalities and ATECO codes included in this dataset. As illustrated in Fig. 1, the spatial distribution of firms involved in FCAs reveals a marked concentration in the northern regions of Lombardy, Piedmont, Veneto, and Friuli Venezia Giulia, a moderate presence is observed in Campania and along the Adriatic coast, while smaller clusters emerge in Apulia, Liguria, and Tuscany.

Fig. 1. Locations of firms participating in FCA



3. Methodology

In this section, the analytical framework is presented.

3.1 Bipartite network

Let $G = (V, E)$ be a graph specified by its vertex set V and edge set E. If the vertex set V can be partitioned into two disjoint sets V_i and V_j such that every edge E has one endpoint in V_u and the other in V_v the graph is an undirected bipartite graph:

$$G = (V_i \cup V_j, E_{i,j}) \tag{1}$$

where in $E_{i,j} \subseteq V_i \times V_j$. In this paper the sets V_i and V_j represent geographic location and the ATECO classification.

3.2 Topology measures

Graph theory offers a rigorous framework for characterizing the macroscopic structure of social networks through a range of topological measures. Among the most widely used are degree-based metrics – such as degree centrality – and path-based indices like betweenness, which quantify a node's immediate connectivity (Zhang & Luo, 2017). To capture the broader architecture of a bipartite network, it is possible to compute global indices including network density and assortativity, alongside node-level measures such as eigenvector centrality. Together, these metrics reveal how connectivity patterns vary across municipalities and economic sectors, identify those nodes that act as critical intermediaries. A systematic analysis of these indices delineates the key structural features responsible for maintaining network cohesion, highlighting the municipalities and ATECO codes most pivotal to its integrity.

The density of the network indicates overall connectivity and is defined as the ratio of the actual number of edges $|E|$ to the maximum possible number of edges ($|V_i| \times |V_j|$), it describes how connected the graph is:

$$Density = \frac{|E|}{|V_i| \times |V_j|} \tag{2}$$

The degree of a generic node n measures its connectivity, calculated by summing the presence of edges connecting it to nodes in the opposite partition:

$$D(n) = \sum v_i \neq v_j \, \alpha_{uv} \tag{3}$$

where $u \in V_i \neq v \in V_j$ and $\alpha_{uv} = 1$ if node u is connected to node v, and 0 otherwise.

Betweenness centrality quantifies the importance of a node connecting different parts of the network, based on how frequently it appears on the shortest paths between two generic nodes s and *t*. Formally, the betweenness centrality *BC*(*n*) of a node *n* is:

$$BC(n) = \sum_{s \neq n \neq t} \frac{\sigma_{st\,(n)}}{\sigma_{st}} \tag{4}$$

where σ_{st} is the total number of shortest paths from node to node and $\sigma_{st\,(n)}$ represents the number of those paths passing through *n*.

Eigenvector centrality captures a node's influence based on its connections to other highly influential nodes. For node *u*, eigenvector centrality *EC*(*i*) is determined by:

$$EC(u) = \frac{1}{\lambda} \sum_{j \in N(u)} EC(j) \tag{5}$$

where *N*(*u*) denotes the set of neighbors of node *u*, and λ is the largest eigenvalue associated with the adjacency matrix of the network; the nodes connected to many influential nodes receive higher eigenvector centrality scores.

Assortativity measures the degree correlation between connected nodes, reflecting whether nodes with similar degrees tend to connect more frequently. It is quantified as the Pearson correlation coefficient of degrees across the edges:

$$r = \frac{\sum_{(i,j) \in E})(k_i - \bar{k})(k_j - \bar{k})}{\sqrt{\sum_{(i,j) \in E} (k_i - \bar{k})^2 \sum_{(i,j) \in E} (k_j - \bar{k})^2}} \tag{6}$$

where E denotes the set of edges, k_i and k_j the degrees of nodes i and j and k ¯ the average degree of nodes in the network.

These metrics collectively provide comprehensive insights into the overall structure, connectivity, and relative importance of municipalities and sectors within the bipartite network.

3.3 Backbone analysis

Bipartite graphs are particularly effective in capturing complex and structured interactions between two distinct sets of entities; however, their high density can hinder the detection of meaningful structural patterns. A widely adopted solution is to project the bipartite network onto one of its node sets, resulting in a unipartite graph where two nodes are connected if they share one or more common neighbors in the original bipartite structure. This projection reduces dimensionality and shifts the analytical focus toward within-layer relationships. Nonetheless, even such projections often retain superfluous or noisy edges that impede computationally intensive algorithms, clutter visualizations, and mask core structure (Coscia & Neffke, 2017). To address these challenges, one extracts the backbone, a sparse, unweighted subgraph that preserves only the most salient connections. By filtering out statistically or structurally insignificant edges, backbone extraction sharpens interpretability, diminishes noise, and supports more efficient computation and clearer visualization of the network's essential architecture (Neal, 2022; Neal, Domagalski, & Sagan, 2022).

Unlike projection-based methods, backbone models operate directly on the bipartite network, preserving its intrinsic structure. In a bipartite graph

$G = (V_u \cup V_v, E_{u,v})$, where edges link nodes across two disjoint sets V_u and V_v, projection is achieved by multiplying the adjacency matrix B by its transpose, producing $P = BB^T$. The resulting unipartite graph $G_u = (V_u, E_{u,u})$, connects nodes in based on shared neighbors in V_u, thereby capturing co-occurrence patterns.

The backbone analysis applied to the bipartite graph follows the methodology proposed by Neal (Neal *et al.*, 2022). This facilitates the detection of hierarchical structures, communities, and relevant associations. To minimize information loss, the observed co-occurrence frequencies are evaluated against a null model that preserves node degree sequences through random edge assignment. Given the large dataset, the Stochastic Degree Sequence Model (SDSM) is used as a computationally efficient alternative to the Fixed Degree Sequence Model (FDSM) (Neal *et al.*, 2022).

Although SDSM does not maintain exact degree values, it preserves expected degree distributions and key global attributes such as mean degree and heterogeneity. This makes it a practical choice for identifying spatial and sectoral clustering in large networks.

3.4 Community detection

Community detection methods can be applied to identify densely connected municipalities in the network and collect them into cohesive communities so that it is possible to evaluate whether these groupings correspond to geographic contiguity (Bedi & Sharma, 2016). In particular, modularity–maximization algorithms such as Louvain and its improved variant Leiden are widely used to uncover community structure and subsequently assess its alignment with spatial proximity (Hairol Anuar *et al.*, 2021).

The Leiden algorithm overcomes several limitations identified in the Louvain method (Cimini *et al.*, 2015), offering improved guarantees of well-connected clusters and enhanced modularity optimization. This approach enables the detection of structurally coherent clusters that may also exhibit geographical cohesion. Both the algorithms rely on modularity (Q), a metric quantifying how the network is structured into well-defined communities with fewer inter-community connections.

In addition to spatial evaluation, modularity (Q) was computed to quantify the degree to which the network is structured into well-defined communities. Modularity is defined as:

$$Q = \frac{1}{2m} \Sigma_{ij} \left[A_{ij} - \gamma \frac{k_i k_j}{2m}\right] \delta (c_i, c_j) \quad (7)$$

where m is ($|V_i| \times |V_j|$) the total number of the edges in the network, A_{ij} is the adjacency matrix, γ is the resolution parameter that defines the size of the communities, k_i and k_j represent the degrees of the nodes i and j, c_i and c_i denote the communities to which nodes and $\delta(c_i, c_j)$ belong and is the Kronecker delta function, which equals 1 if nodes are in the same community, and 0 otherwise. Modularity values near zero indicate no meaningful community structure beyond randomness, values above 0.3–0.4 indicate clear community structures, meanwhile values near 1 represents strongly distinct communities. The resolution parameter of the Leiden algorithm was tuned to maximize the modularity score, a key quality function in community detection. This process enabled the extraction of an optimal partitioning that delineates groups of municipalities sharing intense collaborative links. The robustness and computational scalability of the algorithm allowed for the reliable identification of meaningful communities while maintaining manageable computational complexity.

A quantitative assessment of the geographical consistency of the identified communities was performed by calculating the average pairwise geographic distance among municipalities within each community. This metric served as a proxy for spatial coherence, enabling a direct evaluation of the algorithm's capacity to capture territorial proximity within the network-derived clusters.

4. Results

In this section, the results of the research are presented.

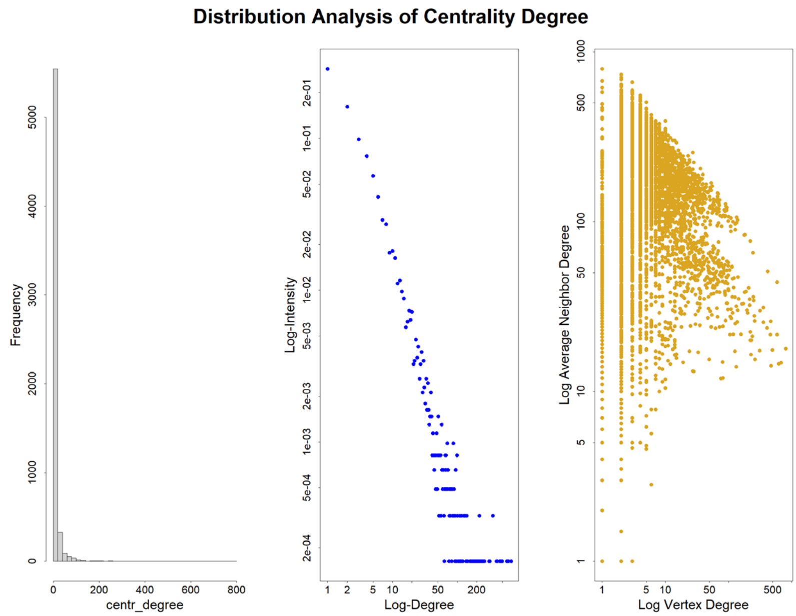
4.1 Topological properties of the bipartite graph

The bipartite graph analyzed has 6,132 nodes and 30,608 edges, connecting municipalities and economic sectors. The topological characteristics of the graph give insights into the network's structural properties and dynamics. The diameter of 9 implies that the maximum distance between any two nodes is short, reflecting high interconnections and efficient accessibility among municipalities and economic activities. The network density value of 0.0016, indicates that the graph is very sparse, indicating specialized territorial distribution and selective connections between municipalities and economic sectors. The average path length of 3.6029 indicates that, on average, just over three steps are needed to link any two nodes. This underscores a generally good level of connectivity despite the sparsity of the graph.

The assortativity coefficient of -0.0935 suggests a weak disassortative tendency, or a slight preference for nodes to be connected to those with different degrees. However, given the proximity to zero, the graph does not exhibit pronounced assortative or disassortative structures, suggesting that connectivity patterns are likely influenced by territorial and economic factors beyond degree similarity alone.

The analysis of node degrees provides additional insights into the structure of the network. The degree distribution, which is displayed in a set of graphs (Fig. 3), comprises a histogram of frequencies, a log-scale plot to emphasize variation and a plot of the average neighbor degree against node degree, revealing how low and high degree nodes interact. The municipalities with the highest degrees are Roma (581) and Milano (413), confirming their pivotal position within the national economic system. In terms of economic connectedness, the most connected ATECO codes include sectors like building construction (410000), cereal and vineyard cultivation (011100, 012100), electrical installations (432101), vegetable cultivation (011300), mixed agricultural practices (015000), traditional restaurants (561111), and road freight logistics services (494100). These nodes reflect the pivotal position of agriculture, construction, and local services in the Italian economy, linking municipalities through key productive functions and emphasizing the weight of traditional sectors in regional development.

Fig. 2. Representation of degree of the bipartite network. (Left) Histogram of the node degree distribution; (Center) Log-log plot of degree ver-sus intensity; (Right) Log-log correlation between vertex degree and the average degree of its neighbors. These plots characterize the structural connectivity and scaling properties of the bipartite network

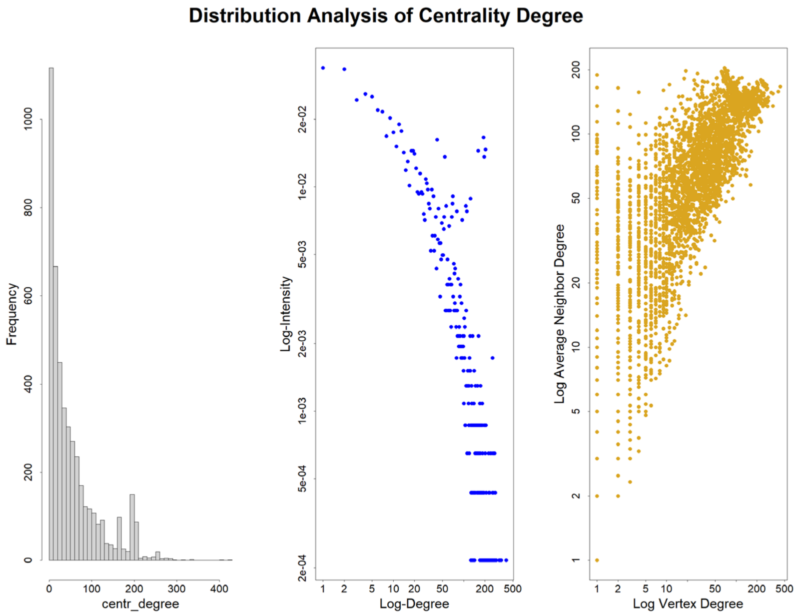


As illustrated in Fig. 2, the degree distribution reveals a pronounced initial concentration, where a limited number of nodes exhibit very high degrees, followed by a rapid decline across the rest of the network. The objective of the study is to ensure that these dominant nodes do not distort the overall interpretation of the network's structure. However, this disparity is less visually evident in the logarithmic plots, where the transformation compresses scale differences and provides a more nuanced view of distributional variability.

4.2 Topological properties of the unipartite graph

After extracting the backbone of the graph using a significance threshold of α = 0.05 and removing nodes with degree zero, the resulting subgraph displays structural characteristics different from the bipartite graph. The backbone's diameter increased to 12, indicating a lengthened longest shortest path. However, the average path length decreased slightly to 3.48, suggesting a more cohesive and compact structure. The density of the subgraph rose to 0.0118, demonstrating meaningful connections; sensitivity checks confirm the expected trend under alternative thresholds, with density increasing to 0.0224 at $\alpha = 0.10$ yielding a denser graph, while $\alpha = 0.05$ retains a sparser structure in which nodes are connected by more statistically significant edges. The main geographic regularities and largest communities remain qualitatively stable, whereas at $\alpha = 0.01$ proved computationally too expensive. Additionally, the assortativity coefficient became weakly positive (0.124), revealing a slight inclination for nodes to connect with others of similar degree, this tendency, known as homophily, reflects the principle that similarity of size favors connection, a common feature in both social and information networks. These shifts emphasize the backbone's effectiveness in balancing sparsity and interpretability, preserving significant relationships while enhancing clustering and global accessibility.

Fig. 3. Representation of degree of the unipartite network. Representation of degree of the bipartite network. (Left) Histogram of the node de-gree distribution; (Center) Log-log plot of degree versus intensity; (Right) Log-log correlation between vertex degree and the average degree of its neighbors



As observed in Fig. 3, the graph exhibits a more homogeneous degree distribution, pointing to a better balance in the number of connections across nodes. In particular, the final plot highlights a noticeable shift in the tendency of nodes to associate with others of similar degree, further confirming the emergence of assortative behaviors in the simplified network structure.

4.3 Leiden community detection

In order to understand the latent geographic patterns of Italian firms and FCAs, the community detection analysis was conducted utilizing the Leiden algorithm on the graph derived from the bipartite backbone extraction. Given a modularity value, quantified at around 0.6, indicating a clear community structure, the Leiden algorithm effectively returned a total of 31 distinct communities. This level of modularity indicates a robust partitioning of the network into groups with dense internal connectivity and sparser connections between groups, highlighting strong internal cohesion within identified clusters.

Fig. 4a. Representation of the unipartite network obtained after backbone extraction and community detection (the 10 largest communities)

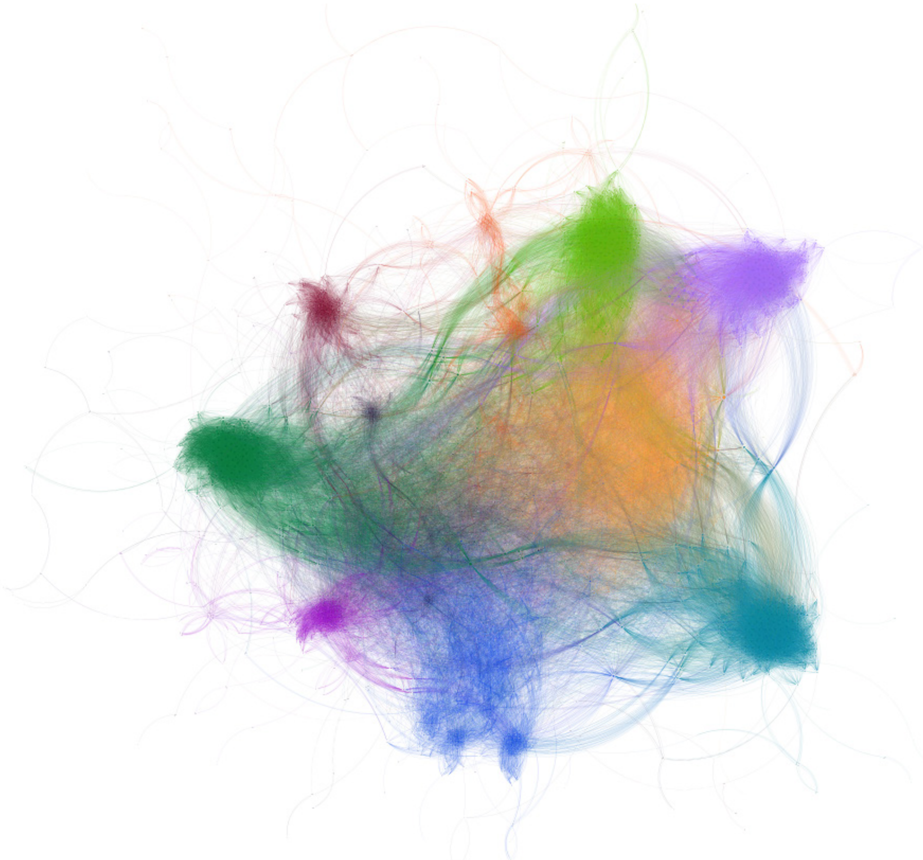
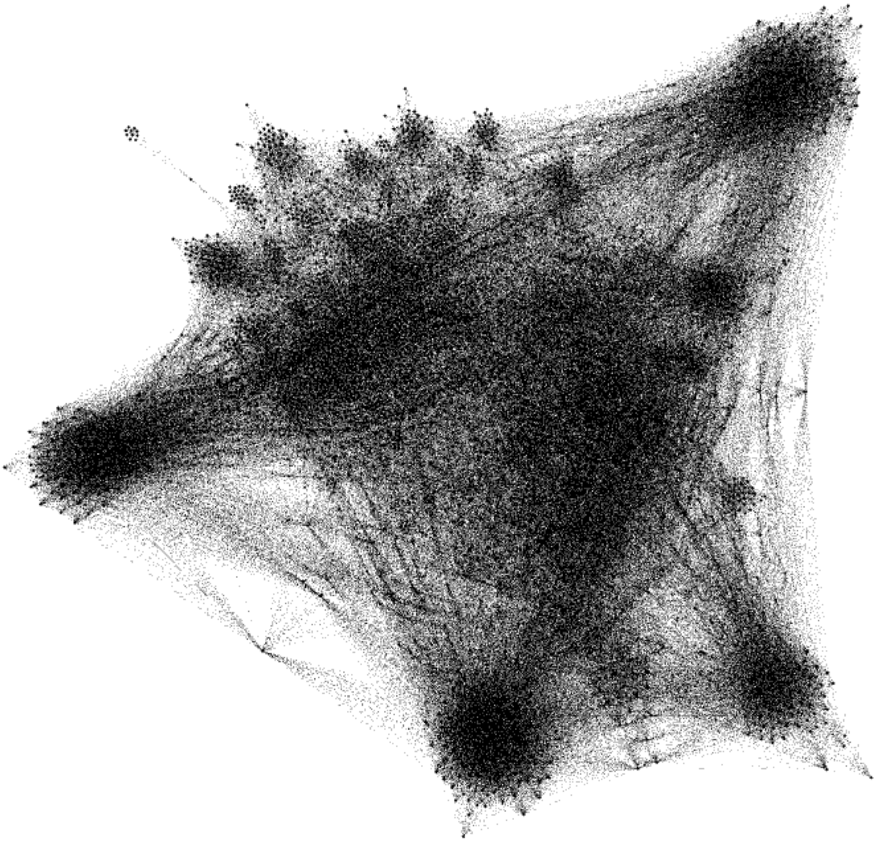


Fig. 4b. Filtered visualization of the unipartite network obtained after backbone extraction, including only municipalities with degree ≥ 10. The filtering enhances readability for visualization purposes and highlights the existence of a connected hub as identified by the Leiden algorithm



Network visualizations at the municipal scale are inherently dense, as density is a direct consequence of the large number of municipalities and their actual connectivity patterns. This limits immediate interpretability in the full graph (Fig. 4a). To further clarify the overall network structure, Fig. 4b reports a filtered representation including municipalities with degree ≥ 10, which enhances readability and highlights the main hubs and community structure, without affecting the underlying network analysis.

The global average distance across the entire network was calculated as 424.28 km, reflecting the overall spatial dispersion among municipalities involved in FCAs. In contrast, the average geographic distance within communities was notably lower, at 330.16

km. This marked difference emphasizes that communities detected by the Leiden algorithm effectively capture geographical proximity, corroborating the presence of spatially coherent clusters.

5. Conclusions

In this study, a methodological framework is presented to investigate the spatial structure of formal collaborations among SMEs in Italy through FCAs. The application of the backbone extraction method (Neal, 2022) led to a 7.36-fold increase in network density, thereby enhancing the in-formativeness and interpretability of the graph. Subsequent community detection analysis (Bedi & Sharma, 2016), achieving a modularity index of 0.6, indicating a well-defined structure, revealed the presence of 31 spatially coherent clusters, each exhibiting strong internal connectivity. Moreover, the clusters displayed a pronounced alignment with geographical proximity: the average intracommunity distance between municipalities was significantly lower than the average distance observed across the entire network.

These results reinforce the notion that FCAs among SMEs naturally organize into geographically cohesive communities reflecting existing patterns of regional industrial agglomeration (Huggins, 2001), providing insights into the interplay between geographic proximity and sectoral specialization. This spatial coherence underscores the potential of FCAs to foster localized economic integration, potentially amplifying regional competitiveness and innovation capabilities through geographically concentrated collaborative dynamics (Cabigiosu, 2025). Local aggregation of FCAs can strengthen regional economic integration by fostering the emergence of innovative clusters, thereby generating positive externalities that enhance territorial competitiveness and spur investment in R&D, in line with Porter’s theory of competitive clusters (Porter, 1998).

Future research may extend this framework along several directions. First, integrating external socio-economic indicators, such as growth, R&D, export performance, and territorial specialization indices (Cimini *et al.*, 2015), would allow a more comprehensive assessment of the economic complexity and territorial impact of collaborative clusters. Second, the analysis could be expanded to a temporal dimension to investigate the evolution and persistence of communities over time. Additional refinements include the adoption of weighted backbone methods, in fact the Neal backbone algorithm is structurally defined for unweighted graphs (Neal, 2022), and the use of functional territorial units, such as Labour Market Areas (LMAs), can align the analysis with current economic geography approaches (European Commission. Statistical Office of the European Union., 2020), enhance both interpretability and increase policy relevance.

Finally, extending the bipartite network analysis into a tripartite graph (Murata, 2010) or multilayer graph (De Domenico, 2022), adding layers such as the participation in specific formal collaboration agreements, could enrich the analysis, since it preserves the identity of each agreement, uncovers "polymodal" communities of firms, municipalities and contracts (Lambiotte & Ausloos, 2006), and thus delivers a far richer picture of how specific contractual instruments drive regional collaboration.

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LA GOVERNANCE DELLE IMPRESE E LE STRATEGIE DI FORMAZIONE: SPUNTI DI RIFLESSIONE DALLA STATISTICA UFFICIALE

ENTERPRISES GOVERNANCE AND VOCATIONAL TRAINING STRATEGY: INSIGHTS FROM OFFICIAL STATISTICS

Roberto Di Manno[6], Manuela Nicosia[7], Emanuela Trinca[8]

Sommario

L'attenzione che le imprese a controllo estero hanno verso il capitale umano è confermata dai risultati della Rilevazione sulla formazione nelle imprese nel 2020, che Istat svolge in maniera armonizzata a livello europeo e grazie alla quale è possibile fornire indicatori necessari per le politiche di supporto al mercato del lavoro e all'occupazione. Il paper si propone di descrivere il legame tra le strategie di formazione professionale messe in atto dalle imprese e la loro governance in termini di tipologia di controllo. A tal fine, le imprese italiane sono state profilate in quattro gruppi: gruppi multinazionali esteri, gruppi multinazionali italiani, gruppi nazionali e gruppi indipendenti. Attraverso l'utilizzo di diverse fonti di dati, è stato possibile evidenziare la diversa performance delle imprese, classificate in base al tipo di governance, in termini di risultati economici. Per approfondire ed evidenziare i risultati, è stato realizzato un modello probabilistico (basato sulla regressione logistica) al fine di mettere in connessione la performance economica e le strategie di formazione. I risultati hanno confermato che le imprese multinazionali con un alto livello di performance economica hanno una maggiore propensione ad attuare una strategia per la formazione dei propri addetti.

Abstract

The most recent results of Continuing Vocational Training Survey, a harmonised European survey through which the Italian Institute of National Statistics collected data on training activities carried out by enterprises in 2020, confirmed the focus that foreign-controlled enterprises have on human capital. The paper aims to describe the relationship between the vocational training strategies implemented by enterprises and their governance in terms of type of control. For this purpose, Italian enterprises are profiled in four groups: foreign multinational groups, Italian multinational

6 Istat - Istituto Nazionale di Statistica, Roma, Italia, e-mail: dimanno@istat.it

7 Istat - Istituto Nazionale di Statistica, Roma, Italia, e-mail: mnicosia@istat.it (corresponding author)

8 Istat - Istituto Nazionale di Statistica, Roma, Italia,, e-mail: trinca@istat.it

groups, domestic groups and independent groups. Data gathered from various data sources are analysed. The descriptive analysis revealed differences in the performance of enterprises, based on their governance type, in terms of economic performance and training strategy. Multinational enterprises, particularly those controlled by foreign enterprises, achieved the best results compared to other types of enterprise groups. To deepen and highlight these results, a probabilistic model based on logistic regression was performed. The results confirmed that multinational enterprises with a high level of economic performance probably have a higher level of training activities.

Parole chiave: controllo estero, imprese multinazionali, performance economica, attività formative.
Keywords: *foreign-control, multinational groups, economic performance, training activities.*

1. Introduction[9]

According to the theoretical literature, which emphasises the higher economic performance of foreign-controlled enterprises compared to domestically controlled ones, the analyses conducted over time on the production system have consistently highlighted significant differences in economic performance between the two types of enterprise (Bandick-Hansson 2009, Aitken-Harrison 1999). In this article, we analysed the enterprise population by dividing it into four groups: enterprises belonging to foreign multinational groups (MNEs foreign govervance), enterprises belonging to Italian multinational groups (MNEs Italian govervance), non-internationalized enterprises, and independent enterprises. Based on these premises, our work aims to describe the connection between governance and the training strategy adopted by enterprises in 2020. The paper is structured as follows: Section 2 presents the various data sources and the methods applied in order to analyse the data. Section 3 presents the main results, based on the descriptive analysis of different data sources and the logistic model, which provides a more in-depth analysis of indicators. Section 4 finally refers to the main conclusions.

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9 Although the contribution is the joint responsibility of the authors, sections 2.1.1, 2.1.2, 3.1 are attributed to Emanuela Trinca, section 2.1.3, 3.2 are attributed to Manuela Nicosia, section 3.3.1 is attributed to Roberto Di Manno. The authors are collectively responsible for sections 1, 2.1, 2.2, 3.3.2 and 4.

2. Data source and methods

2.1 Data from Business Group Register and structural business surveys

In order to proceed with the analysis it was necessary to integrate data from various statistical sources. In particular, the Business Register of Enterprise groups was used to define the enterprises' governance and the Statistical Register "Frame SBS" was used to obtain the economic variables necessary for studying enterprise performance. Other sources of data included the survey on foreign-controlled enterprises resident in Italy (Inward FATS), the survey on foreign-controlled enterprises with national control (Outward FATS), and the Continuing Vocational Training Survey (CVTS). Table 1 shows the breakdown by governance of the companies included in the analysis.

Table 1. Number of enterprise by governance. Year 2020

Governance	Number of enterprises
MNEs foreign governance	2,102
MNEs Italian governance	3,155
Domestic groups	6,015
Independent enterprises	8,843
Total	20,205

Source: Elaborations on Istat data - Business Register of Enterprise groups, 2020

2.1.1 Data from the Statistical Register of Groups

The Business Register of Groups is the reference for the governance definition. The Register provides information on control relationships between legal units and is based on European Regulation No. 177/2008. The Register of Groups provides control links between enterprises at both national and multinational levels, as well as highlighting some of the group's key features. The methodology involves integrating different administrative and statistical sources that have been harmonised and approved by Eurostat. Starting from elementary data on the structure of direct shareholdings of all capital companies, this methodology identifies the control links, both direct and indirect, to which each capital company is subject. The next parent enterprise of each subsidiary is identified and defined as "the first physical or legal entity in the hierarchy to exert direct or indirect control over it". Finally, the group's structure is reconstructed by tracing the sequence of links between immediate parent companies up to the ultimate parent company. The SBS framework, used in this article to analyse economic and structural variables, is an integrated system of administrative and statistical data, annually compiled by Istat to evaluate enterprise performance.

2.1.2 Data from business statistical surveys

The system of statistical surveys on the multinational activities of enterprises consists of two annual surveys carried out by Istat and named 'Survey on the activities of foreign-controlled enterprises resident in Italy' (Inward Fats) and 'Survey on the foreign activities of domestically controlled enterprises' (Outward Fats). These statistics are produced at European level in accordance with Regulation No. 2019/2152/EU of 27 November 2019. The aim of this regulation is to establish a common framework for the collection, processing and transmission of data to Eurostat in order to produce harmonised statistics at European level for assessing the structure, activity and competitiveness of foreign affiliates or enterprises controlled by non-residents within the same country. The survey on foreign-controlled enterprises resident in Italy, which meets the requirements of the European regulation for Inward Fats statistics, targets enterprises and local units (branches) resident in Italy that are ultimately controlled abroad and active in sectors B to N and P-Q-R-S of the Ateco2007 classification of economic activities. Information on the foreign control of enterprise is collected every two years via a special survey that supplements and updates other information already available at Istat. The survey, which had a reference period of 2021-2022, involved 8,935 enterprises achieving a response rate of 69%. The survey on domestically controlled enterprises resident abroad that responded to "Out-ward Fats" has as its target population enterprises and local units (branches) resident abroad that are subject to ultimate domestic control. Company financial statements (statutory and consolidated financial statements filed by companies with the Chambers of Commerce) were used to identify the target universe for the survey. In this study, this source was used to identify the top Italian multinational group and to integrate it with the Register of Enterprise Groups, ensuring that all companies in Italy belonging to Italian multinational groups were included.

2.1.3 Data from Continuing Vocational Training Survey

Data from Continuing Vocational Training Survey (CVTS) were analysed in order to include information about training activities provided by enterprises for their own employees. The CVTS is a European Union-wide survey on continuing vocational training, coordinated by Eurostat and carried out by Istat (with an outline questionnaire, common definitions and common recommendations with respect to the fieldwork). The CVTS provides comparable data on vocational training within the EU enterprises with at least ten or more employees and belonging to a certain group of economic activities. The objectives are to assess the provision of vocational training in businesses in terms of the types of training offered, the number of employees involved in the training and the training costs. As well as providing some structural information on enterprises, the CVTS's main variables related to internal and external courses, as well as other forms of continuing vocational training, such as participation in conferences, job rotation, exchanges and learning/quality circles.

2.2 The integration of different data sources and methods applied

Thanks to the integration of data from the statistical register and the surveys, the first analyses were conducted to describe the main characteristics of the four groups based on governance, in terms of both performance and training activities. Data from the CVTS Survey were synthetized using a methodological approach recognised for taxonomic purposes. The Wroclaw approach was applied to synthetize ten indicator into one index, for use in subsequent steps. Each governance type was then profiled based on the selected economic indicators and the training index obtained in the previous step. The final phase of the analysis involved performing logistic models to further analyse and highlight the results.

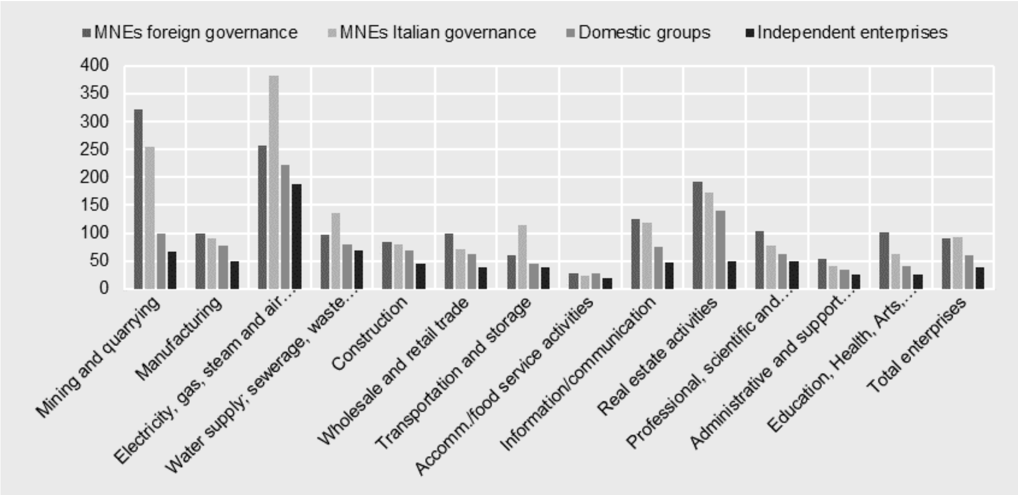
3. Results

3.1 Governance and economic indicators

The descriptive analysis confirms the trend of better performance among multinational enterprises, in terms of apparent labor productivity, as measured by the ratio of added value to the number of employees. They also reveal that the largest disparities occur when multinational companies are compared to non-internationalized firms and, especially, to independent companies. Similarly, multinational enterprises tend to offer higher wages per employee than non-internationalized firms.

For the entire economy, labor productivity is nearly 90,000 euros for foreign-controlled companies, over 93,000 euros for companies belonging to Italian multinational groups, 59,000 euros for domestic groups, and 37,000 euros for independent firms (see Figure 1). However, the figures vary significantly across sectors, both industrial and service sectors. The best performances alternate between foreign and Italian multinationals.

Fig. 1. Labour productivity by governance - Year 2021

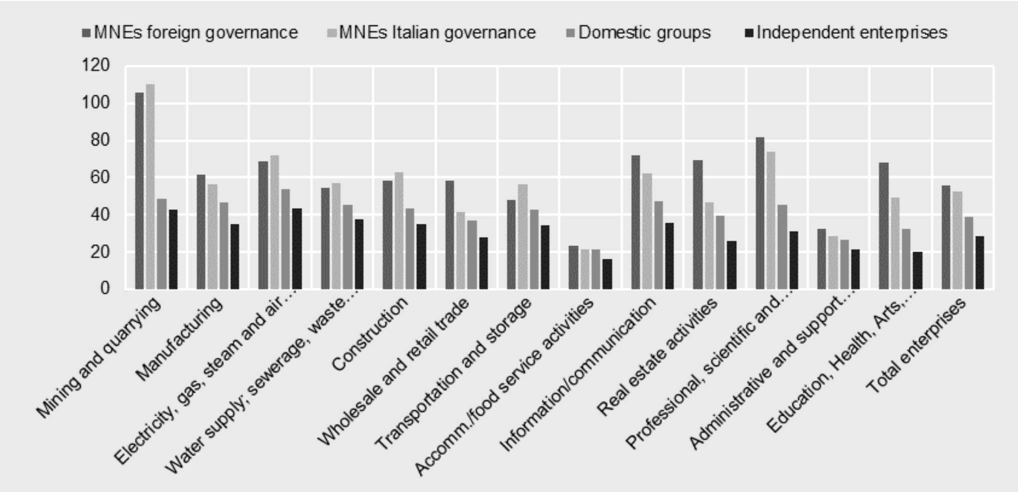


Source: Elaborations on Istat data - Survey on the activities of foreign-controlled enterprises in Italy 2020 and SBS advance frame 2021

At the level of large sector groups, foreign multinationals are more productive in mineral extraction (in the following order: 323 thousand, 254 thousand, 98 thousand, and 66 thousand) as well as in many service sectors, including information and communication (125 thousand, 119 thousand, 74 thousand, and 46 thousand), real estate activities (193 thousand, 172 thousand, 140 thousand, and 50 thousand), professional, scientific, and technical activities (104 thousand, 78 thousand, 62 thousand, and 49 thousand), and commerce (97 thousand, 71 thousand, 63 thousand, and 39 thousand). Italian multinationals show better productivity in electricity, gas (256 thousand, 382 thousand, 222 thousand, and 188 thousand) and water supply (97.9 thousand, 135.7 thousand, 80.6 thousand, and 67.7 thousand). Among the services sectors, they only prevail in transportation and warehousing (60.2 thousand, 113.3 thousand, 44.1 thousand, and 39.5 thousand).

The same trend is observed with the indicator of remuneration per employee, where multinational companies consistently outperform other firms (see Figure 2). For the entire economy, per capita remuneration values are 56 thousand for foreign multinationals, 52 thousand for Italian multinationals, 39 thousand for domestic groups, and 28 thousand for independent companies. At the sectoral level, the same pattern that observed for productivity, with the exception of the construction sector, where Italian multinationals dominate (58 thousand, 63 thousand, 44 thousand, and 35 thousand). The same trend is observed with the indicator of remuneration-per-employee, in which multinational companies always have an advantage over other firms. For the entire economy, per capita remuneration values are 56 thousand for foreign multinationals, 52 thousand for Italian multinationals, 39 thousand for domestic groups, and 28 thousand for independent companies. At the sectoral level, the same productivity pattern is observed, except in the construction sector, where Italian multinationals dominate with 58 thousand, 63 thousand, 44 thousand, and 35 thousand.

Fig. 2. Wages per employee by type of governance. Year 2021

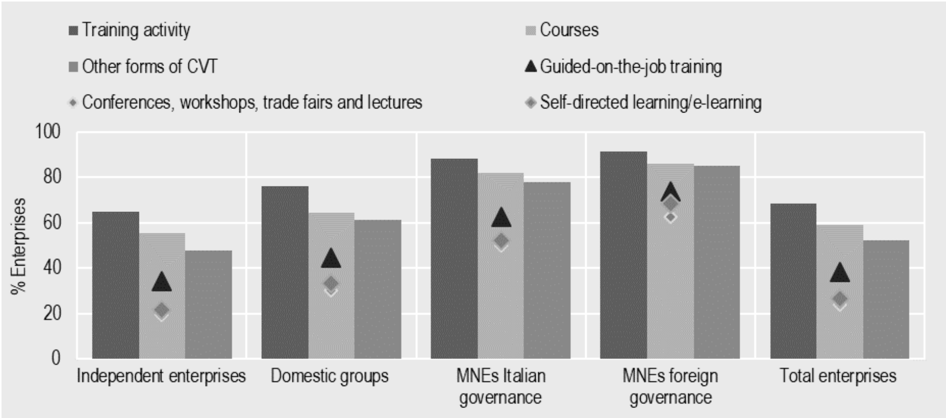


Source: Elaborations on Istat data - Survey on the activities of foreign-controlled enterprises in Italy 2020 and SBS advance frame 2021

3.2 Governance and continuing vocational training

It is well known that the vocational training provided by the enterprises helps to boost their performance and competitiveness. Despite the health emergency, in 2020, nine out of ten foreign multinational enterprises provided continuing vocational training (CVT) to their employees, compared to 68.9% of total enterprises with more than 10 employees. MNEs foreign governance provided continuing vocational training to the current staff, much more frequently than other types: CVT courses 86.0% and other forms of CVT 84.9% (see Figure 3). Among the other forms of CVT, foreign multinational enterprises show greater use of other training methods, such as on-the-job guidance, conferences, workshops, trade fairs and lectures, self-directed learning/e-learning than other types of governance. MNEs foreign governance capabilities in digital and management skills facilitate the use of different and flexible tools in order to update employees' knowledge and competencies. Foreign multinational enterprises pay attention to the human capital from the planning step onwards. 67.6% of foreign MNEs have a written training plan, compared to the 58.3% of Italian MNEs. This figure falls to 46.5% for domestic groups and to 37.5% for independent enterprises. 68.5% of foreign MNEs adopts an annual training budget compared to 25.5% of all enterprises.

Fig. 3. Enterprises providing training and type of governance - year 2020



Source: Elaborations on Istat data - CVTS Survey, year 2020

Foreign MNEs' significant investment in training is also evident in the participation rate of training courses, with foreign multinational enterprises reaching 62.8%, compared to 53.4% of all enterprises. In terms of female participation, half of foreign multinational enterprises (51.7%) has involved over 66% of women in training courses, compared to 35% of total enterprises. Furthermore, 54.1% of foreign MNEs assess future skill needs as part of the overall planning process. This figure drops to 28.1% for domestic groups and 22.9% for independent enterprises. In terms of assessing the outcomes of CVT activities, foreign multinational enterprises account for 60.9% of total enterprises, compared to 50% of Italian multinational enterprises, 42.7% of domestic groups, and 36.9% of independent enterprises. To summarise all aspects of the vocational training provided by enterprises to their employees and to better classify the four groups based on governance type, we applied the Wroclaw taxonomic method to ten indicators. The Wroclaw method is based on the concept of an 'ideal unit', which assumes the best values for each of the indicators considered. The indicators were synthesised by calculating the 'Euclidean distance' between the actual values of the elementary indicators and those of the ideal unit. According to this approach, the index is equal to zero when the distance between a given unit and the 'ideal unit' is zero (when all the values coincide). The greater the difference between the two units, the higher the index (see Appendix A).

The main weakness of this method lies in the criterion used to define the 'ideal unit'. Table 2 shows the list of indicators selected for implementing the synthetic index.

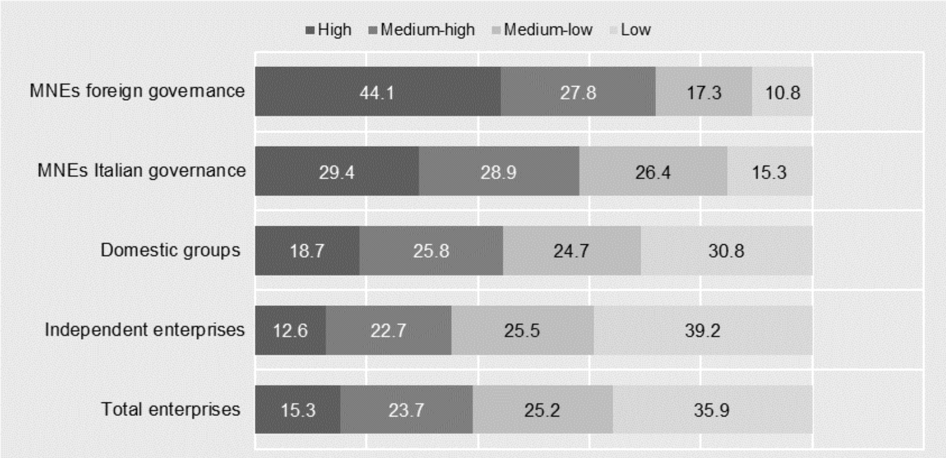
Table 2. Indicators selected to be synthetized into the index of "Level of training"

Indicator	Real value	Ideal value
CVT forms: provision of internal or external courses and other forms of CVT	0=no; 1=yes	1=yes
Provision of internal courses	0=no; 1=yes	1=yes
Regular assessment of future skill needs of the enterprise	0=no; 1=yes	1=yes
Training plan or programme	0=no; 1=yes	1=yes
Annual training budget, which usually includes provision for CVT	0=no; 1=yes	1=yes
Assessment of the outcomes of CVT activities	0=no; 1=yes	1=yes
Specific person or unit within the enterprise having the responsibility for the organisation of CVT	0=no; 1=yes	1=yes
Female participation rate	0=no courses; 1=0-33%; 2=33-66%; 3=>66%	>66%
Total participation rate	0=no courses; 1=0-33%; 2=33-66%; 3=>66%	>66%
CVT hours for mandatory courses (environment, safety and health)	0=no courses; 1=0-33%; 2=33-66%; 3=>66%	0-33%

Source: Elaborations on Istat data - CVTS Survey, year 2020

The output of the analysis is a synthetic index, representing the "reached level of training strategy" which enabled us to categorise the groups based on their respective scores (see Appendix A). Four levels of training strategy were thus identified (high, medium-high, medium-low, low) in order to classify the groups and obtain a new variable for processing in subsequent analysis steps. Figure 4 shows that four out of ten foreign multinational enterprises have a high level of training strategy compared to 15.3% of total enterprises. Considering foreign multinational enterprises with a high or medium-high level of training strategy, we can see that they account for 71.9% of all foreign multinational enterprises and 85% of large foreign multinational enterprises (those with 250 or more employees). Looking at Italian enterprises, one third (29.4%) have a high level of training, and 28.9% have a medium-high level (58.2% in total). The other types of governance have a lower share: 18.7% for domestic groups and 12.6% for independent enterprises.

Fig. 4. Level of training activity and governance – year 2020 (percentage values)



Source: Elaborations on Istat data - CVTS survey and Register of Group of Enterprises

3.3 The connection between governance and vocational training strategy

3.3.1 The Logistic regression Model performed

In order to deepen and highlight the above results, a probabilistic model (based on Logistic regression) was used, by using the synthetic index as the response variable. The linear logistic model describes the relationship of dependence between a random variable Y (dichotomous or polytomous), which a given probability distribution, and a set of "m" non-stochastic explanatory variables V_1...V_m (quantitative, ordinal, or nominal). Assuming n units, Yi observations result as tests on Yi random variables, which are independent between each other. The relationship between the expected value of the response variable (the probability p of the j-th mode of Y) and the values of the explanatory variables is given by the logistic linear form. A logistic model was chosen over a simple linear model to obtain a probability estimation that remains within the range (0, 1) and varies nonlinearly according to a sigmoidal curve that declines asymptotically near the extreme values. The estimates are provided by the model parameters and the theoretical values of the probability of the event occurring. In the case of a dichotomous stochastic variable Y, the probability that the i^(th) variable Yi equals 1 (i.e. that the event occurs) given the Xi explanatory variables, is defined as follows:

$$\Pr(Y_i = 1 | \mathrm{x}_i) = \frac{exp\,(\beta' \mathrm{x}_i)}{1 + exp\,(\beta' \mathrm{x}_i)}$$

being β the vector of explanatory variable parameters x, arranged in matrix form. Explanatory variables are usually made up of quantitative indicators. However, it is possible to use a nominal variable in this form, by converting each category into a dichotomous variable (i.e. a variable that takes on the value 1 or 0 to indicate the presence or absence of the characteristic). To obtain our response variable, the synthetic index obtained in the previous analysis step was transformed into a dichotomous variable, where the value "1" means "yes" and the value "0" means "no"[1]. The independent variables chosen to describe the relationship with the enterprise training strategy were: type of governance, productivity (4 levels), salaries, presence of R&D, sector of economic activity (according to the NACE classification).

3.3.2 The propensity of having a training strategy and type of governance

The first step involved including the four governance groups in the model (number of observations: 20,205 units). The first results (see Table 3) show the significance of type of governance in connection with the training strategy: foreign and Italian multinational enterprises have both a high propensity to adopt a training strategy, compared to Domestic groups. In addition, the sector of economic activity are positively (C19T21, F) or a negatively association (C13T18) with the propensity of enterprises to carry out training activities for their employees. A positive association of implementing a training strategy is also associate with a high productivity and become negative with a lower level of the economic indicator.

Table 3. First logit[2] with four types of governance: maximum likelihood estimation[3]

Parameter	Category	Estimation	Std. Err.	Wald chi-square statistic	Pr > chi-square
Governance	**Domestic**	**-0.3994**	**0.0270**	**218.8298**	**<.0001**
Governance	**Foreign**	**0.7821**	**0.0445**	**309.3040**	**<.0001**
Governance	**Italian**	**0.2746**	**0.0360**	**58.0598**	**<.0001**
Sector of activity	B	-0.8034	0.1793	20.0672	<.0001
Sector of activity	C10T12	0.0311	0.0783	0.1576	0.6914
Sector of activity	**C13T18**	**-0.5802**	**0.0688**	**71.1324**	**<.0001**
Sector of activity	**C19T21**	**0.4939**	**0.1524**	**10.4964**	**0.0012**
Sector of activity	C22_25	-0.1545	0.0574	7.2331	0.0072
Sector of activity	C26_28	-0.0174	0.0789	0.0485	0.8257

1 In particular, value 1 was assigned to those units with training activity level equal to High" or "Medium-high", value 0 was assigned to those units with training activity level equal to "Low" or "Medium-low".

2 See Appendix B about logit model information.

3 Note that the parameters' categories are shown in NACE classification labels. For further details, see the legend in Appendix B.

Parameter	Category	Estimation	Std. Err.	Wald chi-square statistic	Pr > chi-square
Sector of activity	C29_30	0.1126	0.1382	0.6630	0.4155
Sector of activity	C31_33	-0.2245	0.0936	5.7543	0.0164
Sector of activity	DE	0.4545	0.0613	55.0523	<.0001
Sector of activity	**F**	**0.2729**	**0.0464**	**34.5400**	**<.0001**
Sector of activity	G	-0.3192	0.0372	73.6645	<.0001
Sector of activity	H	-0.0817	0.0616	1.7624	0.1843
Sector of activity	IJ	0.1962	0.0474	17.1384	<.0001
Sector of activity	LMN	0.3213	0.0483	44.2982	<.0001
Labor productivity	**High**	**0.1304**	**0.0379**	**11.8580**	**0.0006**
Labor productivity	**Medium-high**	**0.1623**	**0.0263**	**37.9647**	**<.0001**
Labor productivity	**Medium-low**	**-0.0534**	**0.0252**	**4.5085**	**0.0337**
Salaries per employer	-	0.00999	0.000586	290.3540	<.0001
R&D	-	0.5559	0.0528	110.8756	<.0001

Source: Elaborations on Istat data

In order to analyse the relationship between training strategies and type of control, four logit models were performed for each of governance type (number of observations for each model: 3,155 units for those belonging to Italian groups, 2.102 units for those belonging to foreign groups, 6,105 units for the domestic groups, 8,843 for the independent enterprises). Table 4 shows the results of model with Italian multinational enterprises, in which we can see how economic indicators such as salaries per employer and R&D activities become crucial for the propensity of enterprises to implement a training strategy. The same indicators show a positive association by analysing foreign governance (see Table 5).

Table 4. Second logit on Italian governance: maximum likelihood estimation[4]

Parameter	Category	Estimation	Std. Err.	Wald chi-square statistic	Pr > chi-square
Sector of activity	B	0.2267	0.6295	0.1297	0.7187
Sector of activity	C10T12	0.1750	0.2202	0.6312	0.4269
Sector of activity	**C13T18**	**-0.6713**	**0.1550**	**18.7614**	**<.0001**
Sector of activity	C19T21	-0.00422	0.2499	0.0003	0.9865
Sector of activity	C22_25	-0.3560	0.1276	7.7841	0.0053
Sector of activity	C26_28	-0.1955	0.1359	2.0679	0.1504
Sector of activity	C29_30	0.8572	0.2922	8.6079	0.0033
Sector of activity	C31_33	-0.2245	0.2334	0.9250	0.3362

4 Note that the parameters' categories are shown in NACE classification labels. For further details see the legend in Appendix

Parameter	Category	Estimation	Std. Err.	Wald chi-square statistic	Pr > chi-square
Sector of activity	DE	0.4831	0.2350	4.2243	0.0398
Sector of activity	F	0.1145	0.2012	0.3241	0.5691
Sector of activity	**G**	**-0.7450**	**0.1084**	**47.2683**	**<.0001**
Sector of activity	H	0.2853	0.1911	2.2291	0.1354
Sector of activity	IJ	0.2076	0.1298	2.5581	0.1097
Sector of activity	LMN	-0.2008	0.1308	2.3559	0.1248
Labor productivity	**High**	-0.00199	0.0850	0.0005	0.9813
Labor productivity	**Medium-high**	0.0296	0.0674	0.1935	0.6600
Labor productivity	**Medium-low**	-0.00564	0.0787	0.0051	0.9428
Salaries per employer	-	**0.0210**	**0.00148**	**201.7302**	**<.0001**
R&D	-	**0.2979**	**0.1031**	**8.3455**	**0.0039**

Source: Elaborations on Istat data

Table 5. Third logit on Foreign governance: maximum likelihood estimation[5]

Parameter	Category	Estimation	Std. Err.	Wald chi-square statistic	Pr > chi-square
Sector of activity	B	-2.7449	0.6474	17.9776	<.0001
Sector of activity	C10T12	0.2140	0.3194	0.4486	0.5030
Sector of activity	C13T18	-0.0120	0.2676	0.0020	0.9642
Sector of activity	C19T21	0.6989	0.3349	4.3556	0.0369
Sector of activity	C22_25	0.2974	0.2449	1.4744	0.2247
Sector of activity	C26_28	0.4980	0.2331	4.5652	0.0326
Sector of activity	C29_30	0.0474	0.3082	0.0236	0.8778
Sector of activity	C31_33	0.4104	0.3635	1.2752	0.2588
Sector of activity	DE	0.3239	0.2997	1.1684	0.2797
Sector of activity	F	-0.2505	0.3251	0.5937	0.4410
Sector of activity	G	-0.0834	0.1225	0.4638	0.4958
Sector of activity	H	0.0448	0.2425	0.0341	0.8534
Sector of activity	IJ	-0.0430	0.1660	0.0673	0.7953
Sector of activity	LMN	0.4634	0.1748	7.0293	0.0080
Labor productivity	High	-0.1040	0.1082	0.9245	0.3363
Labor productivity	Medium-high	0.2124	0.0926	5.2661	0.0217
Labor productivity	Medium-low	0.0560	0.1129	0.2461	0.6199
Salaries per employer	-	**0.0188**	**0.00157**	**143.9169**	**<.0001**
R&D	-	**0.5160**	**0.1783**	**8.3738**	**0.0038**

Source: Elaborations on Istat data

5 Note that the parameters' categories are shown in NACE classification labels. For further details see the legend in Appendix

Table 5 and 6 show the results of logistic models performed by taking in consideration the other types of governance, which are domestic enterprises and independent enterprises, separately. Based on the results, we can assume that for both type of governance, factors that count on the training strategy are the sector of economic and the level of productivity. Among the economic sectors, the so- called "Made in Italy sector", which include the textiles, seems to be less inclined to implement effective training strategies. Conversely, the Chemical industry emerges as one of the sectors with a greater potential on improvement in training. Furthermore, the domestic or independent enterprises that carry out activities of research and development have a higher probability of achieving a high level of training activity (see Table 6 and 7).

Table 6. Fourth logit on Domestic enterprises: maximum likelihood estimation[6]

Parameter	Category	Estimation	Std. Err.	Wald chi-square statistic	Pr > chi-square
Sector of activity	B	-1.1589	0.2799	17.1427	<.0001
Sector of activity	C10T12	0.1152	0.1514	0.5790	0.4467
Sector of activity	**C13T18**	**-0.3695**	**0.1251**	**8.7238**	**0.0031**
Sector of activity	**C19T21**	**1.3251**	**0.4069**	**10.6052**	**0.0011**
Sector of activity	C22_25	-0.1386	0.1126	1.5143	0.2185
Sector of activity	C26_28	0.1485	0.1768	0.7062	0.4007
Sector of activity	C29_30	-0.2579	0.2815	0.8393	0.3596
Sector of activity	C31_33	-0.2104	0.1800	1.3666	0.2424
Sector of activity	DE	0.4215	0.0964	19.0969	<.0001
Sector of activity	F	0.1603	0.0877	3.3406	0.0676
Sector of activity	G	-0.3480	0.0635	30.0208	<.0001
Sector of activity	H	-0.0273	0.1103	0.0614	0.8043
Sector of activity	IJ	0.0422	0.0783	0.2907	0.5898
Sector of activity	LMN	0.2772	0.0825	11.2771	0.0008
Labor productivity	**High**	**0.2547**	**0.0626**	**16.5416**	**<.0001**
Labor productivity	**Medium-high**	**0.1585**	**0.0451**	**12.3720**	**0.0004**
Labor productivity	**Medium-low**	**-0.1560**	**0.0430**	**13.1413**	**0.0003**
Salaries per employer	-	0.00254	0.00110	5.3338	0.0209
R&D	-	**0.6102**	**0.0941**	**42.0647**	**<.0001**

Source: Elaborations on Istat data

6 Note that the parameters' categories are shown in NACE classification labels. For further details see the legend in Appendix.

Table 7. Fifth logit on Independent enterprises: maximum likelihood estimation[7]

Parameter	Category	Estimation	Std. Err.	Wald chi-square statistic	Pr > chi-square
Sector of activity	B	-0.0148	0.2861	0.0027	0.9589
Sector of activity	C10T12	-0.1869	0.1111	2.8312	0.0925
Sector of activity	**C13T18**	**-0.9080**	**0.1111**	**66.8022**	**<.0001**
Sector of activity	**C19T21**	**0.9110**	**0.3219**	**8.0111**	**0.0046**
Sector of activity	C22_25	-0.2391	0.0865	7.6413	0.0057
Sector of activity	C26_28	-0.0634	0.1475	0.1851	0.6671
Sector of activity	C29_30	0.0756	0.2862	0.0698	0.7917
Sector of activity	C31_33	-0.3855	0.1377	7.8424	0.0051
Sector of activity	DE	0.3386	0.0918	13.6117	0.0002
Sector of activity	F	0.2256	0.0628	12.9138	0.0003
Sector of activity	G	-0.4198	0.0587	51.2119	<.0001
Sector of activity	H	-0.3099	0.0920	11.3482	0.0008
Sector of activity	IJ	0.2278	0.0775	8.6478	0.0033
Sector of activity	LMN	0.2502	0.0750	11.1239	0.0009
Labor productivity	**High**	**0.4691**	**0.0690**	**46.2873**	**<.0001**
Labor productivity	**Medium-high**	**0.2445**	**0.0444**	**30.2971**	**<.0001**
Labor productivity	**Medium-low**	**-0.1501**	**0.0361**	**17.2531**	**<.0001**
Salaries per employer	-	-0.00493	0.00120	16.9842	<.0001
R&D	-	**0.6714**	**0.0949**	**50.0541**	**<.0001**

Source: Elaborations on Istat data

4. Final remarks

The results confirmed that multinational enterprises, whether Italian or foreign, with a high level of economic performance are most likely to adopt a training strategy. For enterprises that do not belong to groups, the influential variables are productivity and sector of activity. Investment on R&D plays an important role in the propensity to adopt a training strategy, as well. This is the first time that data on training activity have been linked to economic performance and governance information. Nevertheless, the lack of time series data on the all aspects integrated in the analysis (productivity and level of training activity for instance) is a limit of this study. In the near future, a new round of CVTS, with reference year 2025, will provide an opportunity to update the data on training strategy data and observe changes in governance, while also considering additional training-related variables, such as competences trained and costs.

7 Note that the parameters' categories are shown in NACE classification labels. For further details see the legend in Appendix.

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Appendix A

The index performed through Wroclaw approach was divided in classes applying the standard method of quartiles, in order to transform the distance (continuous measure) into discrete interpretative categories (performance levels). In order to verify the robustness of this choice, the division into classes based on quartiles was compared with that based on mean and standard deviation, obtaining a rate of concordant units of 78.5%. The chosen approach thus proved to be robust and stable. The thresholds of 0–33%, 33–66% and >66% for assigning scores (1, 2, 3) were chosen to ensure an impartial and replicable classification into three levels: Low, Medium and High. This division into equal tertiles (33.33%) as a standard statistical method for categorisation is the best choice when universal regulatory standards are lacking. Furthermore, exceeding the 66% threshold identifies enterprises that have achieved a critical mass of participation, which is essential for the widespread effectiveness of training. In order to verify the sensitivity of the classification obtained by inserting 7 indicators ranging from 0 to 1 and 3 indicators ranging from 0 to 3, a second attempt was made with normalised values. The comparison between the two rankings based on Spearman's rank correlation coefficient (equal to 0.9) confirmed the result.

Appendix B

Table B1. Information on first logit model

Value	Level of training activity	Total frequencies
1	1	11,051
2	0	9,154
Number of observations		20,205

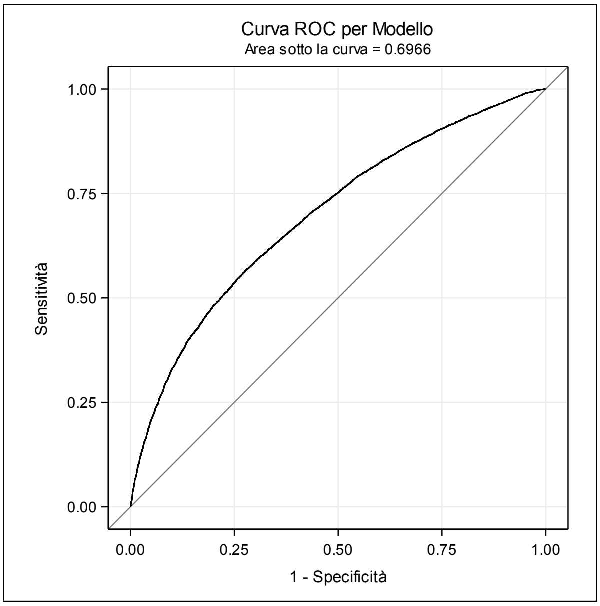
Source: Elaborations on Istat data

Table B2. Model fit statistics of first logit model

Criterion	Intercept Only	Intercept and Covariates
AIC	28010.078	25382.489
SC	28010.078	25556.590
-2 Log L	28010.078	25338.489

Source: Elaborations on Istat data

Fig. B1. ROC Curve for first logit model



Source: Elaborations on Istat data

Table B3. Legend of category labels referring to Sector of activity of units

Sector of activity label	Categories included
B	Mining and quarrying
C19T21	Manufacture of coke and refined petroleum products. Manufacture of chemicals and chemical products; manufacture of basic pharmaceutical products and pharmaceutical preparations
C22_25	Manufacture of rubber and plastic product; manufacture of other non-metallic mineral products; manufacture of basic metals; manufacture of fabricated metal products, except machinery and equipment
C26_28	Manufacture of computer, electronic and optical products; manufacture of electrical equipment; manufacture of machinery and equipment n.e.c.
C29_30	Manufacture of motor vehicles, trailers and semi-trailers; manufacture of other transport equipment
C31_33	Manufacture of furniture; other manufacturing; repair and installation of machinery and equipment. D=Electricity, gas, steam and air conditioning supply
DE	Electricity, gas, steam and air conditioning supply. Water supply; sewerage, waste management and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage
IJ	Accommodation and food service activities; information and communication
LMN	Real estate activities; professional, scientific and technical activities; administrative and support service activities.

Source: Business Register of Enterprise groups, 2020

Table B4. Information on second logit model

Value	Level of training activity	Total frequencies
1	1	2,295
2	0	860
Number of observations		3,155

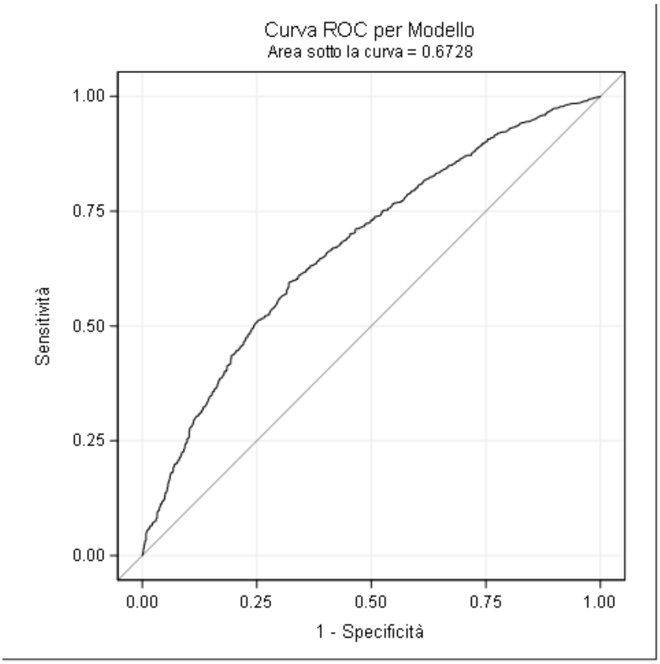
Source: Elaborations on Istat data

Table B5. Model fit statistics of second logit model

Criterion	Intercept Only	Intercept and Covariates
AIC	4373.759	3514.520
SC	4373.759	3629.598
-2 Log L	4373.759	3476.520

Source: Elaborations on Istat data

Fig. B2. ROC Curve for second logit model



Source: Elaborations on Istat data

Table B6. Information on third logit model

Value	Level of training activity	Total frequencies
1	1	1,711
2	0	391
Number of observations		2,102

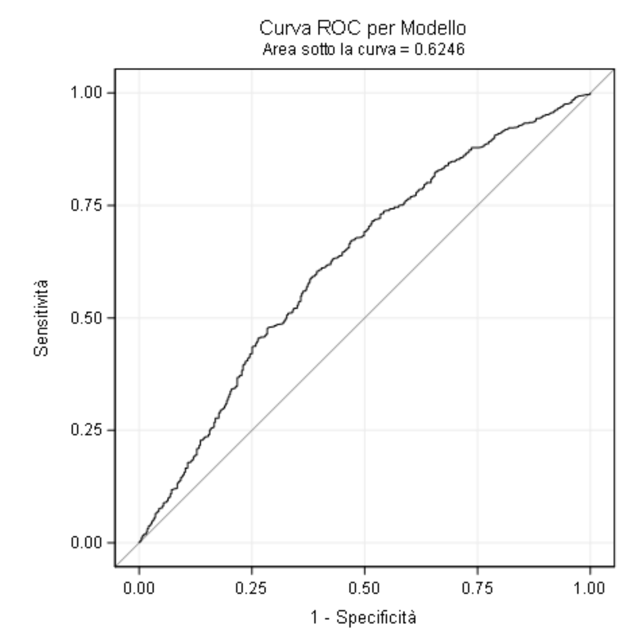
Source: Elaborations on Istat data

Table B7. Model fit statistics of third logit model

Criterion	Intercept Only	Intercept and Covariates
AIC	2913.991	2038.721
SC	2913.991	2146.083
-2 Log L	2913.991	2000.721

Source: Elaborations on Istat data

Fig. B3. ROC Curve for third logit model



Source: Elaborations on Istat data

Table B8. Information on fourth logit model

Value	Level of training activity	Total frequencies
1	1	3,210
2	0	2,895
Number of observations		6,105

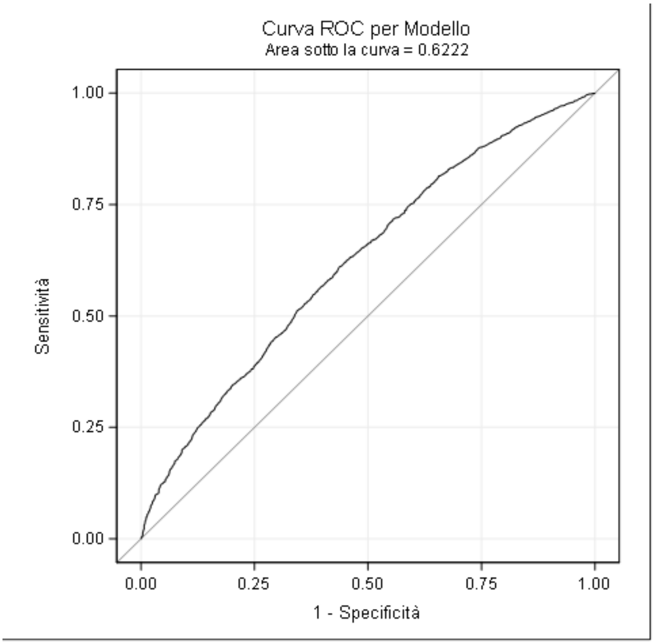
Source: Elaborations on Istat data

Table B9. Model fit statistics of fourth logit model

Criterion	Intercept Only	Intercept and Covariates
AIC	8463.327	8199.664
SC	8463.327	8327.284
-2 Log L	8463.327	8161.664

Source: Elaborations on Istat data

Fig. B4. ROC Curve for fourth logit model



Source: Elaborations on Istat data

Table B10. Information on fifth logit model

Value	Level of training activity	Total frequencies
1	1	3,835
2	0	5,008
Number of observations		8,843

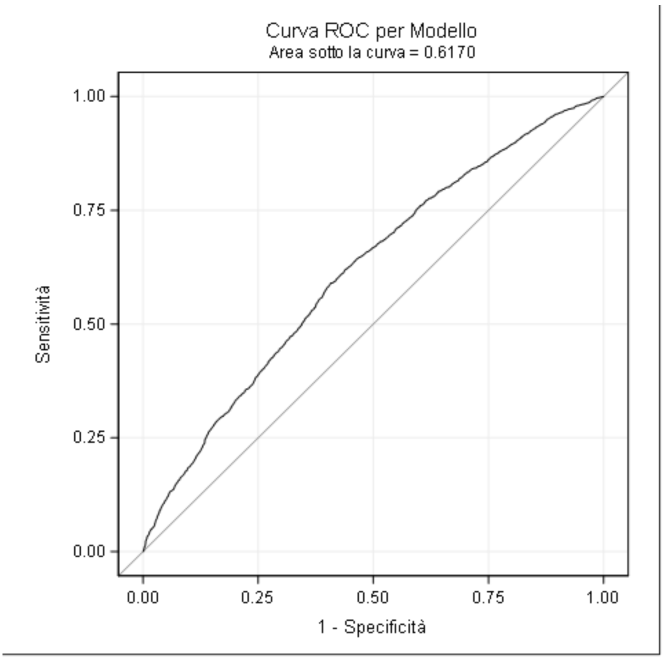
Source: Elaborations on Istat data

Table B11. Model fit statistics of fifth logit model

Criterion	Intercept Only	Intercept and Covariates
AIC	12259.001	11750.949
SC	12259.001	11885.610
-2 Log L	12259.001	11712.949

Source: Elaborations on Istat data

Fig. B5. ROC Curve for fifth logit model



Source: Elaborations on Istat data

LE AZIENDE VICINE SONO SEMPRE PIÙ VERDI? L'EFFETTO DOMINO DELLE PERFORMANCE AMBIENTALI IN EUROPA

ARE NEARBY FIRMS GETTING GREENER? THE DOMINO EFFECT OF ENVIRONMENTAL PERFORMANCE IN EUROPE

Emma Bruno[1]*, Rosalia Castellano*[2]*, Gennaro Punzo*[3]

Sommario

Il presente studio analizza in che misura le performance ambientali delle imprese europee quotate siano influenzate da caratteristiche economico-finanziarie e governance, modellando l'interdipendenza spaziale tra le stesse imprese. L'originalità del lavoro risiede nell'integrazione del paradigma ESG con una prospettiva territoriale della sostenibilità aziendale. L'analisi, riferita al 2023, riguarda le imprese incluse nello STOXX Europe 600. L'adozione di modelli spaziali consente di tener conto della componente territoriale e distinguere tra effetti spaziali endogeni ed esogeni. I risultati evidenziano una significativa dipendenza spaziale delle performance ambientali. Gli effetti diretti risultano associati sia a fattori economico-finanziari, come dimensione e redditività, sia a caratteristiche di governance, quali la diversità di genere nei board, la loro dimensione, la presenza di comitati CSR e l'adozione di politiche strutturate per la riduzione delle emissioni. Gli effetti *spillover* sono prevalentemente riconducibili a elementi di governance e policy, suggerendo una tendenza delle imprese a emulare comportamenti virtuosi presenti nei contesti circostanti. I risultati offrono spunti rilevanti per la definizione di politiche ambientali su scala locale e l'adozione di strategie aziendali coerenti con una logica territoriale interconnessa.

Abstract

This study investigates the extent to which the environmental performance of publicly listed European companies is shaped by financial and governance-related characteristics, while explicitly accounting for spatial interdependence. The novelty of the research lies in the integration of the ESG framework with a territorial perspective on corporate sustainability. The analysis, based on 2023 data from firms included

1 Università di Napoli Parthenope, Dipartimento di Studi di Management and Quantitativi, Napoli, Italia - e-mail: emma.bruno@uniparthenope.it

2 Università di Napoli Parthenope, Dipartimento di Studi di Management and Quantitativi, Napoli, Italia - e-mail: lia.castellano@uniparthenope.it

3 Università di Napoli Parthenope, Dipartimento of Studi Giuridico - Economici, Napoli, Italia - e-mail: gennaro.punzo@uniparthenope.it

in the STOXX Europe 600 index, employs spatial models to disentangle endogenous and exogenous spatial effects. The results reveals significant spatial dependence in environmental performance. Direct effects are associated both with financial factors, such as firm size and profitability, and with governance-related characteristics, including board gender diversity, board size, the presence of CSR committees, and the adoption of structured emission reduction policies. Spillover effects are primarily linked to governance and policy-related variables, suggesting that firms tend to emulate practices of nearly peers. These findings highlight the importance of including the territorial dimension into the design of local environmental policies and corporate sustainability strategies.

Parole chiave: Sostenibilità aziendale; ESG disclosure; Fattori economico-finanziari; Corporate Governance; Effetti spaziali.
Keywords: *Firm-level Sustainability; ESG Disclosure; Economic and Financial Drivers; Corporate Governance; Spatial Effects.*

1. Introduzione

Negli ultimi decenni, la sostenibilità si è imposta come una delle principali priorità nell'agenda globale (Massuga *et al*., 2024; Ladnar, 2024). Il progressivo deterioramento degli ecosistemi, la crescente scarsità delle risorse naturali, l'inasprimento delle disuguaglianze sociali e la pressione esercitata dai cambiamenti climatici hanno reso evidente la necessità di ripensare, in modo sistemico, i tradizionali modelli di sviluppo economico e sociale (Sachs, 2015; Steffen *et al*., 2015). In risposta a tali sfide, si è consolidata a livello internazionale la necessità di ricostruire un equilibrio tra crescita economica, tutela dell'ambiente e coesione sociale. Questa visione è stata formalmente articolata nell'Agenda 2030 delle Nazioni Unite e nei relativi Obiettivi di Sviluppo Sostenibile (SDGs), che costituiscono un punto di riferimento condiviso per il progresso sostenibile a livello globale (United Nations, 2015).

La sostenibilità è divenuta un principio trasversale in grado di orientare non solo le politiche pubbliche, ma anche le scelte strategiche degli attori economici e sociali (Bansal & DesJardine, 2014). In particolare, il ruolo delle imprese si è rivelato cruciale in virtù della loro centralità nei sistemi produttivi, nella gestione delle risorse e nei processi di innovazione. Le imprese sono oggi riconosciute come attori fondamentali nella transizione sostenibile, non più vincolate da un modello esclusivamente economico-finanziario, ma chiamate a integrare nelle proprie strategie degli obiettivi di lungo periodo che tengano conto delle conseguenze ambientali e sociali delle proprie attività (Ioannou & Serafeim, 2015; Eccles *et al*., 2014; Porter & Kramer, 2011). In tale prospettiva, la sostenibilità non è più percepita come un costo o un vincolo esterno, bensì un fattore strategico di creazione di valore, capace di aumentare la competitività, migliorare la resilienza organizzativa e ridurre i rischi normativi, reputazionali e operativi (Grewal & Dharwadkar, 2020; Eccles *et al*., 2014; Peloza & Shang, 2011).

L'evoluzione del quadro normativo internazionale, europeo e nazionale ha contribuito a definire un contesto sempre più strutturato per l'integrazione della sostenibilità nelle pratiche aziendali. In questo scenario, si è affermata l'adozione dei criteri ESG – *Environmental*, *Social* e *Governance* – come framework per la valutazione delle performance non finanziarie delle organizzazioni (Gillan *et al*., 2021). Il paradigma ESG si è progressivamente diffuso come strumento fondamentale per investitori istituzionali, analisti finanziari, organismi regolatori e imprese, al fine di misurare e comunicare l'impegno verso la sostenibilità (Amel-Zadeh & Serafeim, 2018; Friede *et al*., 2015; Revelli & Viviani, 2015). Tale approccio consente una valutazione più ampia della responsabilità di impresa, integrando dimensioni ambientali, sociali e istituzionali nel processo decisionale (Khan *et al*., 2021).

I criteri ESG sintetizzano tre dimensioni della sostenibilità aziendale. La prima è la dimensione *ambientale*, che riguarda l'impatto dell'attività aziendale sull'ambiente naturale, includendo fattori quali le emissioni di gas serra, il consumo di risorse naturali, la gestione dei rifiuti, la tutela della biodiversità e la capacità dell'azienda di mitigare e adattarsi agli effetti del cambiamento climatico (Ladnar *et al*., 2024; Clark *et al*., 2015). La seconda è quella *sociale*, relativa alla gestione delle relazioni con gli stakeholder interni ed esterni – tra cui dipendenti, fornitori, clienti e comunità locali – con attenzione alla promozione della diversità e dell'inclusione, al rispetto dei diritti umani, alla sicurezza sul lavoro e al contributo dell'impresa al benessere collettivo (Flammer, 2015; Servaes & Tamayo, 2013). La terza riguarda la *governance* ovvero la struttura e la qualità del governo societario, con attenzione alla trasparenza dei processi decisionali, all'integrità dei controlli interni, alla remunerazione dei vertici aziendali, alla composizione degli organi di amministrazione e alla tutela dei diritti degli azionisti (Bebchuk & Tallarita, 2022; Aggarwal *et al*., 2019).

Questo approccio integrato ha trasformato radicalmente i criteri con cui le imprese sono valutate nei mercati finanziari e nei sistemi di rating e rendicontazione. In particolare, la crescente pressione normativa – avviata con la Direttiva 2014/95/UE (*Non-Financial Reporting Directive*, NFRD), che ha introdotto l'obbligo per le grandi imprese europee di rendicontare informazioni ambientali, sociali e di governance – e consolidata attraverso strumenti come la *Corporate Sustainability Reporting Directive* (CSRD), la *Sustainable Finance Disclosure Regulation* (SFDR) e la *EU Taxonomy* – ha accelerato l'adozione di standard ambientali comuni e comparabili. Ciò ha rafforzato l'esigenza di una maggiore trasparenza nei confronti degli investitori e degli altri stakeholder e ha agevolato confronti informati e l'individuazione di strumenti orientati al supporto di un'economia sostenibile (European Commission, 2021; Kotsantonis & Serafeim, 2019).

All'interno del framework ESG, la dimensione ambientale ha assunto un ruolo centrale, soprattutto in relazione all'aggravarsi della crisi climatica (Eccles & Klimenko, 2019). Il pilastro *Environmental* dei criteri ESG rappresenta una delle metriche più utilizzate per valutare la performance ambientale delle aziende. Tali indicatori sono considerati rilevanti non solo per la responsabilità etica dell'impresa, ma anche come segnali predittivi di solidità, innovazione e capacità di adattamento nel lungo periodo (Fatemi *et al.*, 2018; Krüger, 2015). Nonostante la crescente diffusione del framework ESG, le pratiche ambientali delle imprese restano eterogenee. In Europa, come in altri contesti, si osservano significative differenze nei livelli di performance ambientale, non solo tra settori, ma anche tra imprese dello stesso settore localizzate in aree differenti (Dyllick & Muff, 2016; Marcus & Fremeth, 2009). Alcune imprese si distinguono per l'impegno nell'adozione di soluzioni innovative per ridurre il proprio impatto ecologico, mentre altre appaiono meno reattive. Le ragioni di tale eterogeneità sono complesse e riconducibili a una combinazione di fattori interni – come la cultura organizzativa, la dimensione e la struttura aziendale (Flammer, 2013) – ed esterni, tra cui il contesto normativo, la pressione competitiva, la disponibilità di infrastrutture e l'interazione con il territorio (Delmas & Toffel, 2008).

Tra i fattori esterni, un altro aspetto – sempre trascurato ma potenzialmente rilevante – è la posizione geografica delle imprese. L'assunto alla base di questo lavoro deriva proprio dalla considerazione secondo cui la prossimità territoriale può influenzare le performance ambientali attraverso meccanismi di emulazione, pressione competitiva locale, condivisione di infrastrutture, regolamentazioni regionali o presenza di distretti industriali (Anselin & Arribas-Gil, 2013; McCann & Folta, 2012). Tale ipotesi apre la strada all'introduzione di una dimensione *spaziale* della sostenibilità aziendale in base alla quale le scelte compiute da un'impresa possono influenzare o essere influenzate, direttamente o indirettamente, dalle pratiche adottate dalle imprese "vicine" secondo un effetto contagio o imitazione e attraverso meccanismi di interazione reciproca, contribuendo all'affermazione di pratiche ambientali a livello territoriale (Brandt & Holm, 2017). L'analisi delle interrelazioni spaziali in ambito ESG rappresenta un campo di ricerca ancora poco esplorato ma con un enorme potenziale (Poudyal & Zafar, 2023; Luo *et al.*, 2021). Un tale approccio consente di integrare le relazioni di prossimità nel processo di valutazione di performance aziendali e di superare, in tal modo, le tradizionali analisi settoriali o nazionali.

Il presente lavoro si inserisce in questo filone di ricerca emergente e si propone di indagare se e in che misura esistano relazioni spaziali tra performance ambientali delle aziende in Europa. In particolare, il lavoro intende verificare se le scelte ambientali di un'impresa siano influenzate dalla vicinanza spaziale con altre imprese. Lo studio si concentra sulle imprese quotate incluse nell'indice STOXX Europe 600 e, per ciascuna di esse, viene analizzato l'*Environmental Pillar Score*, un indicatore composito che misura l'impegno ambientale delle aziende sulla base di molteplici variabili. Ai fini della presente analisi, le imprese sono state geo-referenziate, permettendo l'integrazione della dimensione spaziale nello studio.

La metodologia adottata si articola in due fasi. In primo luogo, è stata condotta un'analisi esplorativa della distribuzione geografica delle aziende per verificare l'esistenza e la natura di eventuali dipendenze spaziali nelle performance di sostenibilità in Europa per identificare eventuali pattern di raggruppamento o dispersione. In presenza di correlazione spaziale, la seconda fase prevede la stima di modelli di regressione spaziale in grado di catturare esplicitamente sia gli effetti di interazione tra imprese spazialmente "vicine" sia le principali determinanti delle performance ambientali, analizzate, a loro volta, in una prospettiva spaziale. L'obiettivo del lavoro è duplice. Da un lato, identificare configurazioni spaziali nelle performance ambientali delle aziende in Europa; dall'altro, valutare l'esistenza di un possibile "effetto domino" ovvero un'influenza reciproca tra imprese "vicine" sia nell'adozione di pratiche ambientali sia nei fattori che ne determinano la performance. L'approccio proposto intende offrire un contributo teorico e metodologico al dibattito sulla sostenibilità aziendale, con implicazioni rilevanti per la definizione di politiche industriali e ambientali su scala locale e regionale.

2. Metodologia

L'analisi dei dati spaziali richiede particolare attenzione alla struttura di dipendenza tra le unità osservate. In contesti territoriali, infatti, le osservazioni difficilmente possono essere considerate indipendenti, poiché sono frequenti forme di correlazione tra unità "vicine". Tali forme di interdipendenza – note, per l'appunto, come autocorrelazione spaziale – riflettono la tendenza di unità "vicine" a presentare caratteristiche simili (o dissimili) per effetto di fattori condivisi, meccanismi di diffusione o interazioni reciproche. In tali casi, l'impiego di metodi di stima tradizionali sarebbe inadeguato, poiché la violazione dell'ipotesi di assenza di correlazione dei residui potrebbe condurre a stimatori distorti e inefficienti (Anselin, 2003). Pertanto, la strategia empirica adottata si basa su modelli di regressione spaziale in grado di modellare esplicitamente le interazioni tra le unità. A seconda del tipo di interazione spaziale – che può riguardare la variabile dipendente (endogena), le variabili indipendenti (esogena) o i residui – si ricorre a differenti specificazioni di modelli spaziali (Elhorst, 2010; Anselin, 1988), tutte riconducibili a casi particolari del modello *General Nesting Spatial* (GNS) (Manski, 1993):

$$Y = \rho WY + \alpha i_N + X\beta + WX\theta + u \tag{1}$$

$$u = \lambda Wu + \varepsilon \tag{2}$$

dove:

β è il vettore dei coefficienti associati alle covariate esogene X

α è l'intercetta e è un vettore colonna unitario

W è la matrice dei pesi spaziali

ρ è il coefficiente autoregressivo spaziale che cattura l'effetto di interazione endogena (WY)

θ è il coefficiente che cattura l'effetto di interazione esogena (WX)

λ è il coefficiente di dipendenza spaziale nei residui

λ è il vettore degli errori spazialmente autocorrelati (Wu)

ε è il vettore degli errori indipendenti e identicamente distribuiti con media zero e varianza costante.

Per identificare il modello spaziale più adeguato è stato seguito l'approccio proposto da Elhorst (2010). In una prima fase, sono stati eseguiti i test Lagrange Multiplier (LM) (Anselin, 1988) e le corrispondenti versioni robuste (RLM) (Anselin *et al.*, 1996), basati sui residui del modello OLS. Tali test consentono di rilevare la presenza di autocorrelazione spaziale, distinguendo tra effetti di interazione endogena (dipendenza spaziale nella variabile dipendente, $\rho \neq 0$) e autocorrelazione spaziale dei residui ($\lambda \neq 0$). In seguito, è stato condotto il test di verosimiglianza (*Likelihood Ratio*, LR) per verificare la presenza di effetti di interazione spaziale di tipo esogeno, ossia la presenza di autocorrelazione spaziale nelle covariate ($\theta \neq 0$), e, quindi, la possibilità di estendere il modello autoregressivo spaziale (SAR) al modello di Durbin spaziale (SDM).

Il SAR (*Spatial Auto-Regressive*) è il modello spaziale che si ottiene dal modello GNS ponendo il vincolo sia sulla struttura di autocorrelazione dei residui, ovvero ipotizzando l'assenza di autocorrelazione spaziale dei residui ($\lambda = 0$), che nelle covariate ($\theta \neq 0$). In questa specificazione, l'effetto spaziale è esclusivamente endogeno e si manifesta solo attraverso il termine autoregressivo ρ. Ciò implica che il valore della variabile dipendente rispetto a una unità è influenzato direttamente da quello delle altre unità "vicine". La relativa semplicità del SAR può rivelarsi limitante in contesti dove sono presenti anche spillover esogeni ovvero effetti spaziali trasmessi attraverso le covariate. In tali casi, trascurare questi effetti può causare un'errata specificazione del modello e portare a stime distorte. L'SDM (*Spatial Durbin Model*) è la specificazione ottenuta dal GNS assumendo solo assenza di autocorrelazione spaziale dei residui ($\lambda = 0$). Questo modello consente di modellare simultaneamente effetti endogeni tramite

WY ed effetti esogeni tramite *WX* per cui la variabile dipendente può essere influenzata – e a sua volta influenzare – da quelle delle unità "vicine" anche attraverso le caratteristiche osservabili.

Il modello SDM consente la stima di spillover spaziali sia locali, cioè tra unità "vicine", sia globali, grazie alla propagazione indiretta degli effetti, e garantisce stime consistenti anche in presenza di autocorrelazione nei residui. L'inclusione di variabili spazialmente ritardate implica che i coefficienti associati alle covariate non possano essere interpretati secondo il paradigma tradizionale del modello OLS. In presenza di interazioni spaziali, una variazione in una covariata riferita a una specifica unità può influenzare direttamente la variabile dipendente di quella stessa unità e, indirettamente, quella delle unità "vicine" (Elhorst, 2010; LeSage & Pace, 2009). Nei modelli SAR e SDM, che includono effetti autoregressivi spaziali, tali effetti variano da unità all'altra. Per tale motivo, gli effetti diretti e indiretti (spillover) sono calcolati a livello di singola unità e successivamente mediati:

- L'effetto diretto medio rappresenta l'impatto medio di una variazione in una covariata sulla variabile dipendente della stessa unità; è assimilabile al coefficiente β nei modelli OLS.
- L'effetto indiretto medio misura l'impatto medio esercitato su tutte le unità "vicine" da una variazione in una specifica unità (spillover).
- L'effetto totale medio rappresenta l'impatto medio su tutte le unità di una variazione unitaria della covariata di una singola unità.

4. Dati

L'analisi è stata condotta su un campione di imprese quotate incluse nell'indice STOXX Europe 600, uno dei principali benchmark del mercato azionario europeo. Istituito nel 1998, l'indice rappresenta circa il 90% della capitalizzazione di mercato *free-float* europea, includendo 600 società a grande, media e piccola capitalizzazione operanti in 17 paesi e in numerosi settori economici (e.g. tecnologia, sanità, energia, beni di consumo, industria, immobiliare, finanza). L'indice è sottoposto a revisioni con cadenza trimestrale per garantirne attualità e rappresentatività. L'analisi fa riferimento all'anno 2023.La scelta di utilizzare tale indice è motivata anche da ragioni normative. In particolare, l'adozione della Direttiva 2014/95/UE (*Non-Financial Reporting Directive*, NFRD) ha imposto alle grandi imprese europee l'obbligo di pubblicare informazioni non finanziarie relative a tematiche ambientali, sociali e di governance (ESG), favorendo una maggiore disponibilità e comparabilità dei dati (Velte, 2021; Ciciretti *et al*., 2023; Baboukardos *et al*., 2023). I dati derivano dalla piattaforma LSEG Workspace (già Refinitiv/Thomson Reuters), una delle principali fonti internazionali di dati finanziari e di sostenibilità.

La variabile dipendente è data dall'*Environmental Pillar Score* (EPS), un indicatore composito che sintetizza la performance ambientale delle imprese su una scala da 0 a 100. Il punteggio è costruito come media ponderata di tre componenti chiave (LSEG Data & Analytics, 2023): i) *Emissions Score*, che misura l'impegno nella riduzione delle emissioni inquinanti e di gas serra; ii) *Environmental Innovation Score*, che valuta la capacità dell'impresa di adottare tecnologie e pratiche sostenibili; iii) *Resource Use Score*, che riflette l'efficienza nell'impiego delle risorse naturali (e.g. acqua, energia, materie prime). Un punteggio pari a 0 indica assenza di iniziative ambientali documentate, mentre valori prossimi a 100 riflettono elevati livelli di impegno e trasparenza in materia di sostenibilità ambientale.

In linea con la letteratura esistente (Haque & Ntim, 2018; Nuber & Velte, 2021), le variabili indipendenti sono articolate in due gruppi. Il primo riguarda le caratteristiche finanziarie (performance aziendale):

- *Total Assets* (TASS): corrispondente al totale attivo, è usata quale proxy della dimensione aziendale. È espressa come logaritmo naturale del totale attivo.
- *Return on Assets* (ROA): indicatore di redditività aziendale, calcolato come rapporto tra utile netto (dopo le imposte) e media del totale attivo annuo, espresso in percentuale.
- *Leverage* (D/E): rapporto tra debiti totali e patrimonio netto (inclusi interessi di minoranza e debito ibrido), espresso in percentuale. Rappresenta la struttura finanziaria dell'impresa e il relativo grado di rischio.
- *Market Capitalisation* (MCAP): valore complessivo delle azioni ordinarie emesse e quotate sul mercato. Riflette la valutazione pubblica dell'impresa da parte degli investitori e rappresenta una misura sintetica della dimensione e percezione del valore societario nel mercato azionario.

Il secondo gruppo include variabili legate alla governance aziendale e alle politiche ambientali:

- *Board Gender Diversity* (BDIV): percentuale di donne sul totale dei membri del board, è espressione della diversità di genere nel Consiglio di amministrazione. Una maggiore presenza femminile è spesso associata a una maggiore sensibilità alle tematiche ESG.
- *Board Size* (BSIZ): Numero di membri del Consiglio di amministrazione alla chiusura dell'anno fiscale. Riflette la dimensione dell'organo di governance, potenzialmente rilevante per la qualità delle decisioni strategiche, anche in ambito ambientale.
- *CSR Sustainability Committee* (CSR): variabile dicotomica (1/0) che segnala la presenza di un comitato per la responsabilità sociale d'impresa (CSR) e/o la so-

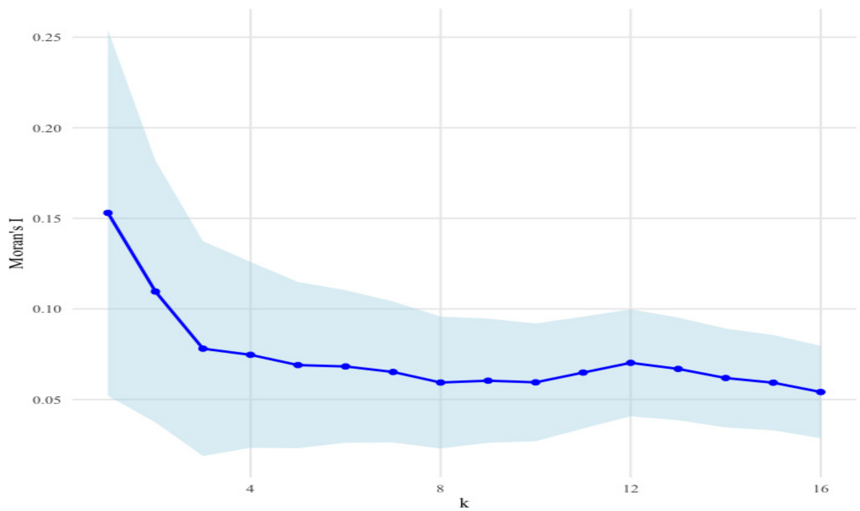
stenibilità. Il comitato, essere istituito a livello di board o di alta dirigenza, è responsabile delle decisioni strategiche in materia di sostenibilità.
– *Policy Emissions Reduction* (EPOL): variabile dicotomica (1/0) che rileva se l'impresa dispone di una politica strutturata per la riduzione delle emissioni. Comprende: i) emissioni verso aria, acqua e suolo derivanti dalle attività core dell'impresa; ii) presenza di processi, meccanismi e/o programmi specifici di contenimento delle emissioni; iii) adozione di sistemi formalizzati e documentati di gestione ambientale orientati al miglioramento continuo.

4. Risultati

La presenza e l'intensità dell'autocorrelazione spaziale a livello globale nella performance ambientale delle imprese europee sono analizzate mediante l'indice I di Moran, calcolato sulla variabile *Environmental Pillar Score*. Data la natura puntuale delle osservazioni, la matrice dei pesi spaziali (W) è stata costruita secondo il criterio dei *k-nearest neighbours* (KNN), che assegna a ciascuna unità un numero fisso *k* di vicini, ovvero le *k* aziende più prossime in termini di distanza euclidea.

La Figura 1 mostra l'andamento dell'indice *I* di Moran al variare di *k*. Si osserva una tendenza decrescente dell'autocorrelazione spaziale all'aumentare del numero di vicini considerati. Escludendo i primi tre valori (*k*=1, 2, 3), il massimo relativo dell'indice *I* si registra rispetto a *k*=12, ragion per cui questo valore è stato adottato per la costruzione della matrice dei pesi spaziali utilizzata nell'analisi. La matrice KNN adottata è stata, infine, standardizzata per riga.

Figura 1. Indice I di Moran al variare del numero di vicini k



La Tabella 1 riporta le principali statistiche descrittive. Tra le imprese analizzate si riscontra un'elevata eterogeneità sia in termini di performance ambientale sia di caratteristiche economico-finanziarie. L'*Environmental Pillar Score* (EPS) presenta una variabilità non trascurabile (DS=19,8), con una mediana (72,5) superiore alla media (68,7) a indicare una concentrazione relativamente maggiore di imprese su valori medio-alti di impegno ambientale. Tra le variabili finanziarie, il ROA mostra una forte dispersione (CV > 1), con valori minimi che suggeriscono la presenza di imprese con redditività negativa. Anche il *Leverage* (D/E) presenta una distribuzione asimmetrica e una marcata eterogeneità nella struttura del capitale. Le variabili dimensionali (TASS e MCAP) mostrano, invece, una distribuzione più regolare e risultano meno influenzate da outliers. Le variabili relative alla governance e alla sostenibilità indicano una diffusa formalizzazione delle pratiche ESG. In particolare, il 91% delle imprese dispone di un comitato CSR (CCSR), mentre il 96% adotta una politica strutturata per la riduzione delle emissioni (EPOL), in linea con quanto previsto dalla Direttiva 2014/95/UE (*Non-Financial Reporting Directive*, NFRD), che richiede alle imprese soggette all'obbligo di rendicontazione non finanziaria di fornire informazioni dettagliate su vari aspetti ambientali, tra cui le emissioni di gas a effetto serra. La diversità di genere nei consigli di amministrazione (BDIV) si attesta in media al 38%, un valore superiore alla soglia del 30% indicata in letteratura come livello minimo per garantire un impatto significativo sui processi decisionali (Joecks *et al*., 2013; Terjesen *et al*., 2015). Tuttavia, tale percentuale resta inferiore rispetto agli obiettivi normativi europei più recenti. La Direttiva 2022/2381/UE prevede, infatti, che, entro il 2026, le società quotate garantiscano almeno il 40% di membri del genere sottorappresentato nei board non esecutivi, oppure il 33% sul totale dei membri del board (Sghaier, 2025; García-Sánchez *et al*., 2024; Campbell & Bohdanowicz, 2018). Infine, la dimensione media dei board (BSIZ) è pari a 11 membri, in linea con le raccomandazioni europee in materia di governance efficiente e con la prassi delle imprese quotate nei mercati regolamentati (Pérez Troya, 2021).

Tabella 1. Statistiche descrittive

Variables	Min	Max	Media	Mediana	DS	CV
EPS	0.00	98.42	68.71	72.45	19.79	0.29
TASS	11.52	22.62	16.97	16.84	1.78	0.10
ROA	-63.72	190.43	6.37	5.45	11.08	1.74
D/E	-3713.84	1428.46	110.02	67.50	223.59	2.03
MCAP	13.87	21.47	16.48	16.26	1.33	0.08
BDIV	0.00	66.67	38.33	38.46	9.93	0.26
BSIZ	4.00	28.00	11.11	11.00	3.62	0.33
CCSR	0.00	1.00	0.91	1.00	0.28	0.31
EPOL	0.00	1.00	0.96	1.00	0.19	0.20

DS: Deviazione standard; CV: Coefficiente di variazione

Per verificare la natura della dipendenza spaziale, sono stati eseguiti i test Lagrange Multiplier (LM) nella versione standard e robusta. Il test LM-lag risulta significativo ($\chi^2 = 14{,}631^{***}$, $p < 0{,}001$), segnalando la presenza di autocorrelazione spaziale nella variabile dipendente ($\rho \neq 0$). Anche il test LM-error è significativo ($\chi^2 = 11{,}680^{***}$, $p < 0{,}001$) e indica autocorrelazione spaziale nei termini di errore ($\lambda \neq 0$). Tuttavia, i risultati delle versioni robuste dei test consentono di distinguere la fonte prevalente della dipendenza spaziale. Il test RLM-lag è significativo al 10% ($\chi^2 = 3{,}011^{*}$, $p = 0{,}0827$), mentre il test RLM-error risulta non significativo ($\chi^2 = 0{,}060$, $p = 0{,}8055$). Queste evidenze suggeriscono che la componente spaziale sia riconducibile principalmente a un'interazione endogena, ovvero a una correlazione spaziale tra i livelli di performance ambientale di imprese "vicine". In linea con l'approccio proposto da Elhorst (2010), si è pertanto optato per il modello SAR, che consente di modellare esplicitamente tale forma di dipendenza spaziale.

I risultati del modello SAR (Tabella 2) evidenziano un coefficiente di autocorrelazione spaziale (ϱ) pari a 0,2655, significativo all'1%. Questo valore conferma la presenza di una chiara dipendenza spaziale endogena nelle performance ambientali delle imprese: le performance ambientali di ciascuna impresa sono influenzate positivamente da quelle delle imprese "vicine". Questo effetto favorisce l'innovazione e può ridurre i vincoli finanziari, migliorando la performance ambientale complessiva delle aziende in un'area o settore (Ren *et al.*, 2023; Peng *et al.*, 2021). Per quanto riguarda gli effetti diretti, che rappresentano l'impatto delle covariate sulla performance ambientale dell'impresa stessa, i risultati evidenziano che la dimensione aziendale (TASS) esercita un effetto positivo, in linea con l'ipotesi secondo cui imprese più grandi tendono ad adottare strategie ambientali più strutturate, anche grazie a economie di scala e maggiore pressione reputazionale (Hanjani & Kusumadewi, 2023; Zheng *et al.*, 2020). Anche la redditività (ROA) dimostra come una migliore performance economica e una maggiore efficienza nell'impiegare le risorse per generare profitto siano associate a una maggiore capacità di investimento in pratiche sostenibili (Nguyen *et al.*, 2021). La struttura finanziaria (leverage) non mostra una relazione significativa per cui il livello di indebitamento non costituisce un vincolo diretto all'impegno ambientale. Analogamente, la capitalizzazione di mercato (MCAP) non risulta statisticamente significativa e non si traduce necessariamente in un migliore profilo ambientale.

Gli indicatori di governance evidenziano un ruolo rilevante nella determinazione della sostenibilità ambientale. La presenza di una maggiore diversità di genere nei consigli di amministrazione (BDIV) risulta positivamente associata alla performance ambientale, a sostegno dell'ipotesi secondo cui una maggiore rappresentanza femminile contribuisce a sensibilizzare l'organo di governance sulle tematiche ESG (Guin *et al.*, 2024). Anche la dimensione del board (BSIZ) ha un effetto positivo a indicare che consigli di amministrazione più ampi offrono una maggiore capacità di affrontare la complessità delle decisioni strategiche in ambito ambientale (Aguilera *et al*., 2021). Infine, sia la presenza di un comitato CSR (CCSR) sia l'adozione di una politica formale di riduzione delle emissioni (EPOL) risultano associate a un miglioramento delle performance ambientali. I coefficienti elevati e significativi confermano l'efficacia delle strutture di governance formali nel promuovere comportamenti sostenibili (Massuga *et al*., 2024; Azimi *et al*., 2023). Per quanto riguarda gli effetti indiretti (*spillover*), ossia l'impatto che una variazione nelle caratteristiche di un'impresa esercita sulle imprese "vicine", i risultati sono coerenti con quelli diretti. Gli effetti *spillover* di TASS, ROA, BDIV, BSIZ, CCSR e EPOL risultano tutti positivi e significativi, sebbene di magnitudo inferiore rispetto agli effetti diretti. Ciò indica che l'impegno ambientale delle imprese può essere in parte trainato dal comportamento delle imprese circostanti, secondo una logica di emulazione strategica o di adeguamento competitivo territoriale. Al contrario, gli effetti indiretti associati a leverage (D/E) e MCAP non risultano significativi. Questo rafforza l'idea che né la struttura del capitale né il valore di mercato esercitino un impatto sulle scelte ambientali delle imprese (Baum-Snow *et al*., 2024; Matray, 2021; Siedschlag & Yan, 2021).

Tabella 2. Stime del modello SAR

SAR	Effetti diretti		Effetti spillover	
Variabili	**Stime**	**Errore standard**	**Stime**	**Errore standard**
TASS	3,3716***	0,6594	1,1967**	0,5296
ROA	0,2141***	0,0685	0,0760*	0,0393
D/E	0,0030	0,0031	0,0011	0,0013
MCAP	0,0506	0,7601	0,0179	0,2874
BDIV	0,1659**	0,0719	0,0534*	0,0289
BSIZ	0,8259***	0,2129	0,2931**	0,1377
CCSR	15,8436***	2,4639	5,6238**	2,4383
EPOL	14,5315***	3,7176	5,1580**	2,4893
ρ	0,2655***	0,0765		
Log Likelihood	-2498,17			
R^2	0,2871			
LR test	14,7190*			

Il test di verosimiglianza (LR=14,719; $p < 0,1$) segnala l'opportunità di estendere il modello SAR includendo effetti spaziali esogeni tramite covariate spazialmente ritardate. Il miglioramento dell'adattamento conferma la maggiore adeguatezza del modello SDM, che consente di catturare simultaneamente gli effetti spaziali endogeni ed esogeni e restituire una rappresentazione accurata delle performance ambientali.

Le stime del modello SDM (Tabella 3) restituiscono un coefficiente di autocorrelazione spaziale (ρ) pari a 0,2304, positivo e significativo, seppur leggermente inferiore rispetto al corrispondente valore stimato nel modello SAR. Questo conferma che, anche con l'inclusione di effetti spaziali esogeni, persiste una relazione di interdipendenza spaziale diretta tra le performance ambientali delle imprese, accompagnata dall'influenza esercitata dalle caratteristiche delle imprese "vicine". Gli effetti diretti risultano coerenti con quelli ottenuti nel SAR. Le dimensioni aziendali (TASS) e la redditività (ROA) conservano un impatto positivo, a conferma che le imprese più grandi sono più strutturate per l'adozione di pratiche ambientali e che una solida posizione economico-finanziaria favorisca investimenti in sostenibilità. La diversità di genere nei board (BDIV) e la loro dimensione (BSIZ) conservano un effetto positivo, confermando il ruolo delle strutture di governance inclusive e di ampia composizione nella promozione di pratiche ambientali. Anche la presenza di un comitato CSR (CCSR) e l'adozione di politiche formalizzate di riduzione delle emissioni (EPOL) risultano associate a un miglioramento significativo delle performance ambientali, coerentemente con quanto osservato nel modello SAR.

Per quanto riguarda gli effetti spillover, la maggior parte delle variabili di governance (BSIZ, BDIV, EPOL) conserva effetti positivi anche sulle imprese "vicine", a differenza delle variabili finanziarie (TASS, ROA, D/E, MCAP), le quali non presentano relazioni significative con le performance ambientali delle imprese "vicine". Questi risultati indicano che gli spillover ambientali sono guidati da elementi di governance e, in misura ancora maggiore, da scelte di policy per la riduzione delle emissioni, piuttosto che da caratteristiche economico-finanziarie.

Tabella 3. Stime del modello SDM

SDM	Effetti diretti		Effetti spillover	
Variabili	**Stime**	**Errore standard**	**Stime**	**Errore standard**
TASS	3.3409***	0.6386	-2.7280	2.5958
ROA	0.1940***	0.0676	0.3902	0.3482
D/E	0.0031	0.0033	0.0218	0.0146
MCAP	1.4190*	0.7049	-0.0941	2.5266
BDIV	0.1875**	0.0744	0.1732*	0.0946
BSIZ	0.5803**	0.2468	1.6130**	0.6826
CCSR	14.6221***	2.5384	-0.6749	1.8207
EPOL	13.6482***	3.8189	12.3438**	5.2433
ρ	0.2304**	0.0907		
Log Likelihood	-2490.81			
R^2	0.3046			

5. Implicazioni e conclusioni

I risultati del lavoro evidenziano la necessità di integrare la dimensione territoriale nelle strategie di sostenibilità ambientale, superando visioni che si concentrano esclusivamente sulle caratteristiche individuali dell'impresa. La significativa presenza di *spillover* associati a caratteristiche di governance e policy indica che le buone pratiche ambientali non sono isolate, ma tendono a diffondersi sul territorio, soprattutto nei contesti ad alta densità relazionale e prossimità organizzativa. Questo fenomeno sottolinea come la sostenibilità aziendale non sia solo il risultato di scelte autonome, ma anche il prodotto di influenze reciproche e meccanismi di imitazione o pressione reputazionale tra imprese "vicine".

Tali evidenze suggeriscono un potenziale ruolo attivo delle reti territoriali nel promuovere l'adozione di comportamenti virtuosi anche da parte di imprese meno sensibili o con minori risorse dedicate alle tematiche ESG. In questa prospettiva, le politiche pubbliche dovrebbero non solo promuovere l'adozione di strumenti di governance ambientale a livello locale – favorendo, ad esempio, la diffusione di comitati CSR, l'adozione di politiche ambientali formalizzate o la composizione di board inclusivi – ma anche incentivare la cooperazione interaziendale su base territoriale. Misure come programmi di benchmark regionale, supporto a iniziative collaborative e regolazioni adattive possono potenziare l'efficacia degli interventi e stimolare un apprendimento collettivo orientato alla sostenibilità.

Dal lato manageriale, i risultati incoraggiano le imprese a considerare la propria strategia ambientale come parte di un ecosistema produttivo interconnesso. Le imprese che operano in ambienti territoriali dinamici possono trarre vantaggio dal posizionarsi come attori proattivi nella transizione ecologica, attivando sinergie locali, condividendo pratiche responsabili e rafforzando la propria legittimazione sociale. In quest'ottica, la sostenibilità aziendale non rappresenterebbe solo una leva competitiva individuale, ma anche una componente strutturale dello sviluppo territoriale integrato.

Un possibile sviluppo futuro riguarda l'adozione di modelli panel spaziali che permettono di osservare l'evoluzione degli spillover nel tempo, distinguendo tra effetti persistenti e shock transitori, e di valutare in che modo l'implementazione progressiva di politiche e regolamentazioni possa modificare la struttura delle interdipendenze territoriali. L'inclusione della dimensione longitudinale consentirebbe, inoltre, di mitigare alcune criticità legate alla causalità poiché specificazioni con effetti fissi spaziali e temporali contribuirebbero a controllare l'eterogeneità non osservata e a ridurre la distorsione da variabili omesse.

I modelli spaziali cross-section, pur efficaci nel rilevare la presenza di interdipendenze, non consentono di stabilire una relazione causale univoca. Gli effetti autoregressivi spaziali riflettono componenti simultanee difficilmente distinguibili da correlazioni dovute a fattori comuni per cui un'analisi di queste potenziali fonti di bias contribuirebbe a rafforzare l'interpretazione dei risultati e a definire con maggiore precisione l'ambito entro cui leggere gli spillover individuati.

Infine, il ricorso a una matrice *k*-nearest neighbours (*k*=12) ha trovato in questo studio una giustificazione empirica nell'andamento dell'indice di Moran. Potrebbe essere utile verificare la robustezza dei risultati rispetto a specificazioni alternative di matrici dei pesi spaziali. In tale ambito, matrici basate sulla distanza geografica e/o sulla prossimità settoriale potrebbero contribuire a chiarire se gli spillover osservati siano prevalentemente riconducibili alla vicinanza fisica e/o alla struttura produttiva delle imprese.

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