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Spatial Economic Impacts of the TEN-T Network Extension in the Adriatic and Ionian Region

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Abstract: Investments in transportation infrastructure have been identified as one of the main factors to promote territorial economic growth. However, appraisal methods currently used in the planning practice do not consider spatial economic distributional effects, ignoring who within a given region would receive greater economic benefits from an investment than others (and eventually who might receive worse). In this paper, a modelling framework is proposed to assess the spatial economic impacts of transportation infrastructure investments; the method combines spatial regressions with transportation accessibility analysis, assuming Gross Domestic Product per Capita variation as a proxy of the economic growth. The application to the case study is related to the Adriatic and Ionian region, which includes both some EU (Italy, Slovenia, Croatia, and Greece) and non-EU countries (Bosnia-Herzegovina, Montenegro, Albania, North Macedonia, and Kosovo) and is characterized by huge disparities in terms of infrastructural assets. The models allow us to both statistically prove the importance of spatial modelling specifications and to forecast economic impacts that would be generated by ongoing infrastructure investment plans for the reconstruction of the road and railway networks in the region; this highlighted where current economic disparities tend to be bridged up, i.e., mainly along the foreseen extensions of the Trans-European Transport Network (TEN-T) corridors, and where not.

Keywords: accessibility analysis; spatial regressions; transportation infrastructure; gross domestic product; Western Balkans

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1. Introduction

Transportation networks play a key role in supporting transportation-based economic activities [1]; they ease the movement of individuals and goods, stimulating both the economic and mobility demand growth [2], maintaining fair life quality standards [3], and facilitating the interaction among groups living in different areas or among economic activities spatially distributed over different territories. In the era of a globalized economy, having efficient transportation connections provides a competitive advantage, for instance, regions with better accessibility to market locations will be generally more productive than areas with lower accessibility levels [4]. However, in the scientific literature, transportation accessibility has been only recognized as one of the necessary components for territorial economic progress [5]; positive economic externalities (such as agglomeration, labor market economies, high-quality labor force) and favorable policy environments are among the other ingredients that favor substantial economic growth [6].

Despite the importance of transportation infrastructure and its key role in regional economic development, appraisal methods used in current practice usually fail in assessing its impact from a holistic perspective. For instance, traditional cost–benefit analysis [7] focuses only on efficiency as a single policy objective, ignoring a wider economic estimation. Moreover, it usually evaluates the overall impact of a given project on a given region, without considering the evaluation of the distributional effects. Who would receive greater benefits within a region following the completion of a given infrastructure? Are there any areas that could be worsened by higher impacts on potentially competing ones?

To answer these questions, this paper proposes a method based on spatial regressions, including both transportation and socioeconomic-context-related variables, for the estimation of the economic impact of transportation infrastructure. The contribution of this study to the existing literature is twofold:

- testing spatial modelling specifications, proving the statistical significance of the spatially lagged terms in predicting Gross Domestic Product per Capita (GDPC) variation intended as a proxy of the economic growth;
- forecasting the extent to which the Trans-European Transport Network (TEN-T) extension in the Adriatic–Ionian (AI) region can contribute to its regional economic growth.

The case study of the AI region is still underexplored in the scientific literature, despite being characterized by several peculiarities. The region includes both some EU (Italy, Slovenia, Croatia, and Greece) and non-EU countries (Bosnia-Herzegovina, Montenegro, Albania, North Macedonia, and Kosovo) and is characterized by huge disparities in terms of infrastructural assets.

The remainder of this paper is organized as follows. The next section (i.e., Section 2) provides a literature review on methodologies to assess the economic impact of transportation infrastructure. Section 3 describes the proposed methodology, which is subsequently applied to the case study in Section 4. Results are then discussed in Section 5, while concluding remarks, limitations of the study, and future research directions are finally reported in Section 6.

2. State of the Art

In the literature, studies dealing with economic impact assessment due to new transportation infrastructure and services use different approaches. These can be clustered in three groups, according to the method they follow [8,9]: cost–benefit analysis (CBA), computable general equilibrium (CGE) models, or econometric analysis.

CBA is a tool usually adopted in transportation planning practice to assess whether a new transportation infrastructure is economically efficient or not. It is based on a comparison between costs (e.g., investment, operation, and maintenance) and benefits (e.g., travel time savings, tolls and fares savings, greenhouse gases, and local pollutant emission reductions), all expressed in monetary terms through monetization coefficients where needed [10]. Even if widely used (e.g., [10–13]), and also due to the fact that it is proposed and standardized in many national and supranational guidelines (e.g., [6]), CBA still lacks the ability to properly estimate the wider economic impact of a given project, since it mainly focuses on the comparison of different projects. Moreover, traditional applications are not sensitive to distributional effects, evaluating an investment in its entirety, even if better-off population groups or territories are benefitted at the expense of worse-off ones [14,15].

CGE models are instead commonly used to quantify the economic impacts of transportation infrastructure; these are characterized by a set of simultaneous equations simulating the interactions between the transportation system and the economic one, considering they are based on the microeconomic consumer and production theory [16]. CGE models allow for the extraction of welfare and any other economic metric, since all the relations and agents' behavior can be simulated (e.g., [17,18]); however, at the same time, they are data-demanding and also demanding in terms of spatial and transportation network characterization.

Lastly, econometric analysis is often used to quantify the overall economic impact brought by new transportation infrastructure. In this case, there is no need to specify and explain the economic interdependences between the considered variables; transportation- and territorial-context-related variables can be considered as an input to obtain measures such as the Gross Domestic Product per Capita (GDPC) variation as a proxy of the economic growth. Multiple linear regression models are the basic tool for this kind of analysis (e.g., [9,19,20]), but with the aim of capturing complex inter-relationships between variables, some authors proposed a Structural Equation Model (SEM)-based approach to deal with the economic impact estimation issue (e.g., [21,22]).

However, these methods are mainly criticized both for not considering spatial interactions among different geographical areas and for assuming a priori that variables included in the model specification are spatially independent [23]. Spatial econometric theory is therefore introduced to account for spatial effects (spatial heterogeneity or interdependency) that usually characterize problems involving territorial analysis and problems in relation to transportation services and infrastructure [24]. Several authors (e.g., [25–30]) have provided examples of spatial regressions in transportation planning studies and in general it has been proved that spatial models fit better than non-spatial ones [31], mainly due to the fact that transportation infrastructure is usually characterized by spatial spillover effects, affecting not only the region in which it is located, but also neighboring regions (e.g., [32–36]).

Therefore, to assess the economic impacts of transportation infrastructure investments, this paper uses a method combining spatial regressions with transportation accessibility analysis, having the advantages of considering spatially lagged effects between neighboring areas, being easily specified, and, at same time, not being too burdensome with respect to data needed.

3. Methodology

The methodological approach schematically depicted in Figure 1 is proposed. Starting from network performances and territorial attributes, zonal transportation accessibility is computed and considered as input (together with socioeconomic and political variables) in spatial regression models to estimate zonal Gross Domestic Product per Capita (GDPC). GDPC variation, intended as a proxy of economic growth, is indirectly calculated by simulating zonal transportation accessibility variation that would be generated by transportation infrastructure investments in a project scenario.

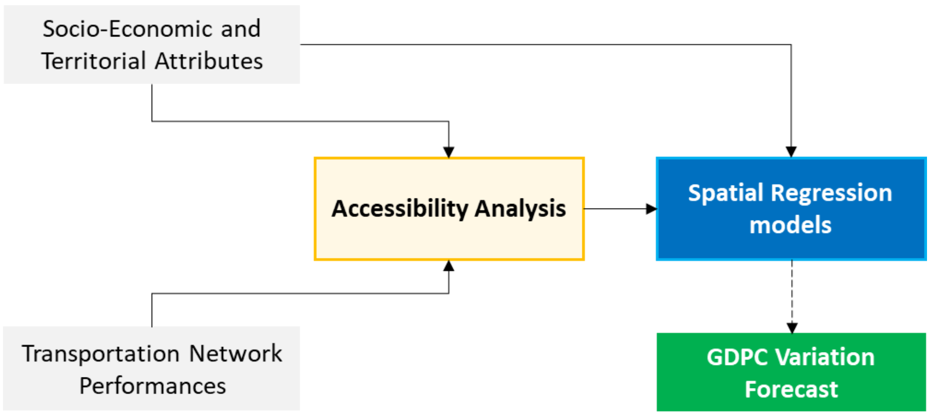

Figure 1. Simplified depiction of the proposed methodological approach.

3.1. Accessibility Analysis

Among the accessibility indicators proposed in the literature (see [37,38] for a taxonomy of them), the potential accessibility indicator is one of the most commonly used in transportation planning studies at the regional scale [39–41]. The accessibility indicator formulation used in this study is the one reported in Equation (1):

$$ACC_o = \sum_d Pop_d^{\alpha} * e^{-\beta \cdot C_{w,od}} \quad (1)$$

where:

- ACC_o is the accessibility of the origin zone o to destinations d;
- Pop_d is the population of the destination zone d;

- $C_{w,od}$ is the weighted average of the generalized travel cost $C_{od,m}$ on the different considered transportation modes m from the origin zone o to destinations d;
- α and β are two parameters, the output from the estimation of a descriptive trip distribu-tion model having as its denominator the same wording of the accessibility indi-cator previously introduced (see [42] for further details).

The generalized travel cost for the generic origin–destination pair (*od*) on the specific mode m is calculated using Equation (2):

$$C_{od,m} = T_{od,m} + \beta_{cm} \cdot cm_{od,m} \tag{2}$$

where:

- T_{od} is the travel time on the specific mode m;
- $cm_{od,m}$ is the monetary cost on the specific mode m as expressed in Equation (3).

$$cm_{od,m} = cm_{C,od,m} + cm_{Km,m} \cdot Km_{od,m} \tag{3}$$

- in which $cm_{C,od,m}$ is a constant depending on both the *od* pair and the mode m; $Km_{od,m}$ is the distance through the mode m, in kilometers, between the origin zone o and destination zone d, and $cm_{Km,m}$ is the average unitary cost per kilometer €/km referred to in the mode m;
- β_{cm} is an estimated coefficient.

3.2. Spatial Regression Models

To justify the use of spatial regression models, testing for the presence of significant spatial autocorrelation in the dependent variable (GDPC, in this study) is needed. To this end, the Moran's Index (*MI*) is used; it stems from Pearson's correlation coefficient and ranges between −1 and +1, where a larger absolute value indicates higher spatial autocorrelation in data [43]. It is defined according to the formula in Equation (4):

$$MI = \frac{N\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(y_i - y)(y_j - y)}{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\sum_{i=1}^{N}(y_i - y)^2} \tag{4}$$

in which:

- N is the number of zones;
- w_{ij} represents the elements of the spatial weight matrix W, escribing the spatial relationship between zone i and zone j;
- y_i is the dependent variable, i.e., GDPC, related to zone i;
- y is the average of the dependent variable among all the observations.

To test the complexity of spatial relationships between the considered variables, four different spatial model specifications are tested. The Spatial Durbin Model (SDM) (Equation (5)) allows us to capture spatial effects in an unrestricted way, including the spatial contribution of both the dependent and independent variables. The Spatial Autoregressive Model (SAR) (Equation (6)) instead includes only the spatial effect of the dependent variable, nullifying the spatial effects of the independent ones, unlike the SDM. On the contrary, the Spatially Lagged X Model (SLX) (Equation (7)) considers only the spatial effect of the independent variables, without including the spatial effect of the independent one in the model specification. Finally, the Spatial Error Model (SEM) (Equation (8)) considers the spatial contribution only in the error term, which therefore has a spatial specification. Starting from considerations in [6], socioeconomic-, political-, and transportation-context-related independent variables are considered; these are the same in all the modelling specifications in order to provide a final nested comparison.

$$\begin{aligned}\ln(GDPC_i) = \alpha_i \quad & +\rho \sum_{j=1}^{N} w_{ij} ln(GDPC_j) + \theta_1 \sum_{j=1}^{N} w_{ij} ln\left(EMP_{RATEj}\right) \\ & +\theta_2 \sum_{j=1}^{N} w_{ij} EQI_j + \theta_3 \sum_{j=1}^{N} w_{ij} ACC_j + \beta_1 lnEMP_{RATEi} + \beta_2 EQI_i \\ & +\beta_3 ACC_i + \varepsilon_i\end{aligned} \tag{5}$$

$$\begin{aligned}\ln(GDPC_i) = \alpha_i \quad & +\rho \sum_{j=1}^{N} w_{ij} ln(GDPC_j) + \beta_1 lnEMP_{RATEi} + \beta_2 EQI_i + \beta_3 ACC_i \\ & +\varepsilon_i\end{aligned} \tag{6}$$

$$\begin{aligned}\ln(GDPC_i) = \alpha_i \quad & +\theta_1 \sum_{j=1}^{N} w_{ij} ln\left(EMP_{RATEj}\right) + \theta_2 \sum_{j=1}^{N} w_{ij} EQI_j + \theta_3 \sum_{j=1}^{N} w_{ij} ACC_j \\ & +\beta_1 lnEMP_{RATEi} + \beta_2 EQI_i + \beta_3 ACC_i + \varepsilon_i\end{aligned} \tag{7}$$

$$\begin{gathered}\ln(GDPC_i) = \alpha_i + \beta_1 lnEMP_{RATEi} + \beta_2 EQI_i + \beta_3 ACC_i + u_i \\ u_i = \lambda \sum_{j=1}^{N} w_{ij} u_j + \varepsilon_i\end{gathered} \tag{8}$$

where:

- $\ln(GDPC)$ is the N size vector of the natural logarithm of the GDPC, in which N is the sample size; $h \in \{i; j\}$, in which i refers to the considered zone and j to the neighboring ones;
- $\ln(EMP_{RATE})$ is the N size vector of the natural logarithm of the employment rate;
- EQI is the N size vector of the European Quality of Government Index (see [44]);
- ACC is the N size vector of the potential accessibility indicator calculated through Equation (1);
- w_{ij} represents the elements of the spatial weight matrix W;
- α is the N size vector of the intercept;
- ε is the N size vector of the independent normally distributed error terms, with 0 mean and constant variance σ^2;
- u is the N size vector of the spatially dependent error terms;
- ρ, λ, β_k, θ_k are estimated regression coefficients; $k \in \{1; 2; 3\}$.

Among the above specifications, the spatial model that best fits is then subsequently used for GDPC variation forecast with reference to one or more project scenarios.

4. Application to the Adriatic and Ionian Region Case Study

The application is related to the Adriatic and Ionian (AI) region (Figure 2); it is currently characterized by a high level of disparities between countries from the economic, political, and social perspectives, but also from point of view of infrastructural assets. Moreover, it includes both some EU countries (Italy, Slovenia, Croatia, and Greece) and non-EU ones (Bosnia-Herzegovina, Montenegro, Albania, North Macedonia, and Kosovo). The application is limited to road, rail, and maritime transportation, identified as the most relevant transportation modes for the purpose of our analysis and in relation to the considered case study. This section is organized as follows. Data sources used are briefly described in Section 4.1, accessibility analysis related to the current scenario is reported in Section 4.2, while spatial regression model estimation results are shown in Section 4.3. Gross Domestic Product per Capita (GDPC) forecast due to the TEN-T network extension in the AI region is finally reported in Section 4.4.

Figure 2. Adriatic and Ionian region location map.

4.1. Data Source

The analysis focuses on a sample consisting of 225 NUTS-3 zones included in the AI region. For each zone, and neighboring zones where needed, several socioeconomic data have been collected. Particularly, zonal population (Pop), employment rate (EMP_{RATE}), and Gross Domestic Product per Capita ($GDPC$) come from worldwide [45], European [46,47], and National Statistical Offices [48–50] publicly available databases. The European Quality of Government Index (EQI) has been directly taken by [44] for the European countries, while it has been estimated starting from World Bank data [51] for non-European ones. Transportation-related variables come from ad hoc macro-simulation transportation models related to road, rail, and maritime transportation developed for the AI region within the PTV VISUM software; the modelled multimodal network consists of about 60,000 nodes and 200,000 links, a quarter of which are related to rail transportation. Even though the focus is on the AI region, the model also includes 136 EU and non-EU zones to simulate the interaction with the former. All the data used for spatial modelling estimation refer to the base year of the analysis, i.e., 2017.

4.2. Current Scenario Accessibility Analysis

With reference to the current scenario, multimodal accessibility analysis results are shown in Figure 3. The map highlights an east–west accessibility pattern; the western part of the AI region (i.e., the one mainly composed by the Italian provinces) has an average accessibility level greater than the Balkan countries. This is mainly due to the greater performances of the existing Italian transportation infrastructural asset in relation to the Balkan one; high capillarity together with high multimodal network performances guarantee lower generalized travel costs and, subsequently, more opportunities for interaction for those living in this area. Moreover, with reference to Italy, it is worth noting a north–south accessibility pattern: the northern regions benefit from greater accessibility due to both a greater transportation network density and to their structural geographical location, i.e., geometrically more central in relation to the distribution of the European population than peripheral southern Italian areas.

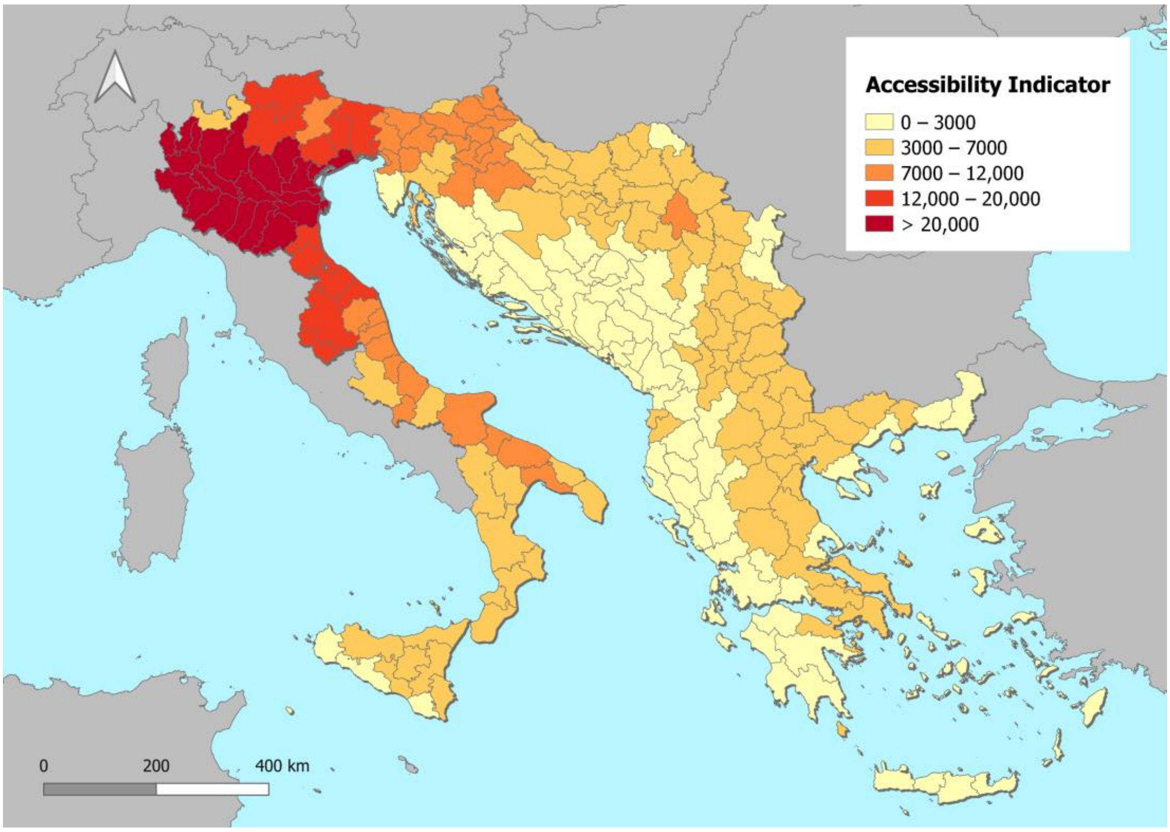

Figure 3. Accessibility indicator [*10,000] map related to the current scenario.

4.3. Spatial Regression Model Estimations

As a preliminary step, the presence of spatial autocorrelation of the dependent variable (i.e., GDPC) has been probed, and the resulting Moran's Index (MI) is equal to 0.92; this has been then tested against the one obtained by randomizing the sample through a Monte Carlo simulation (i.e., the one referring to a dataset with no spatial structure). The hypothesis that two MIs are statistically equal has been rejected (p-value < 0.001).

Results from the spatial regression model estimations using year 2017 cross-sectional data are reported in Table 1. A queen-based contiguity binary matrix W has been used, having a row-normalized weight and elements $w_{ij} \neq 0$ if zone i and zone j are neighbors, and $w_{ij} = 0$ if vice versa. Moreover, a k-Nearest Neighbors criterion has been used to account for the presence of islands, which rely on maritime connection toward the land zones.

As expected, β_1, β_2, and β_3 coefficients measuring the direct impacts (i.e., not spatially lagged) of the independent variables on the dependent one are positive in all model specifications; an increase in the employment rate or in the quality of government or in the transportation accessibility of zone i generates an increase in the GDPC of the same zone. θ_2 and θ_3 coefficients measuring the spatially lagged impacts of EQI and ACC, respectively, are highly statistically significant (p-value < 0.001) only in the SDM specification. They both have negative signs, highlighting the presence of a "spatial competition" effect between neighboring areas, for instance, an increase in the transportation accessibility in nearby zone j will negatively affect the GDPC of zone i due to both a potential greater attractiveness and a more competitive accessibility advantage of the former (zone j). The SEM model has the λ coefficient, the one associated with the spatially lagged error, with a high statistical significance (p-value < 0.001), highlighting the presence of spatial effects not explicitly considered in this model specification, except in the error term. Furthermore, both the SEM and the SLX have higher intercepts with respect to the other estimated models and these are also highly statistically significant, indicating how both exclude important variables in their specification (for instance, the spatially lagged GDPC).

Table 1. Results from spatial regression model (SDM, SAR, SLX, SEM) estimations.

	SDM	SAR	SLX	SEM
$\ln(EMP_{RATE})$ (β_1)	0.161 ***	0.126 **	0.115	0.150 **
EQI (β_2)	0.402 ***	0.226 ***	0.414 ***	0.468 ***
ACC (β_3)	0.262 ***	0.044	0.263 *	0.292 ***
$W \cdot \ln(EMP_{RATE})$ (θ_1)	−0.131		0.139	
$W \cdot EQI$ (θ_2)	−0.241 ***		0.244 *	
$W \cdot ACC$ (θ_3)	−0.231 ***		−0.009	
α_i	2.040 ***	2.497 ***	9.102 ***	9.206 ***
ρ	0.800 ***	0.711 ***		
λ				0.808 ***
Observations	225	225	225	225
Pseudo-R^2	0.904	0.891		0.901
Multiple R^2			0.730	
Log Likelihood	−0.45	−13.93	−116.1	−3.84
Akaike Inf. Crit.	18.91	39.86	248.1	19.69
LR Test	231.2 ***	211.4 ***		231.6 ***

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

With the aim of identifying the model that fits best, a comparison through the Akaike Information Criterion (AIC) has been performed; the Spatial Durbin Model proved to be preferrable (i.e., lower AIC value) and it has been used for GDPC forecasting reported in Section 4.4. This is also proof of how spatial relationships between variables play a fundamental role in the economic impact assessment of transportation infrastructure; among all the estimated models, the SDM is the only one that considers the spatial effect of both the dependent ($GDPC$) and independent variables (EMP_{RATE}, EQI, ACC), capturing the most complex spatial relationships between nearby areas, unlike the other model specifications.

4.4. GDPC Variation Forecast Due to the TEN-T Network Extension in the AI Region

The simulated project scenario includes all the road and rail projects as per [52], extending the TEN-T network in the AI region, as reported in Figure 4.

Results from the project scenario accessibility calculation are reported in Figure 5; the map shows how the greatest percentage variations are related to the Balkan area. This is in line with what might be expected, considering that most of the investments are located in the Western Balkans.

Considering the whole AI region, the average accessibility increase was found to be equal to +14% (see Table 2). It is worth noting that the coastal area of Bar (Montenegro), together with the surrounding ones, presents the highest benefit in terms of relative accessibility variation (+93.1%); this is due to important road (the Blu Highway, included in the Mediterranean TEN T Corridor) and railway projects located in the same area. The same goes for Bosnia-Herzegovina; this benefit was found to be on average a +37.8% accessibility increase, touching higher percentages where road and rail projects included both in the South East Europe Transport Observatory (SEETO) Corridor Vc or Route 2 are located. Serbia also benefits from a significant increase in accessibility (up to +62% variation), mainly due to the reconstruction and modernization of the railway line that is part of the Orient-Est/Med TEN-T corridor.

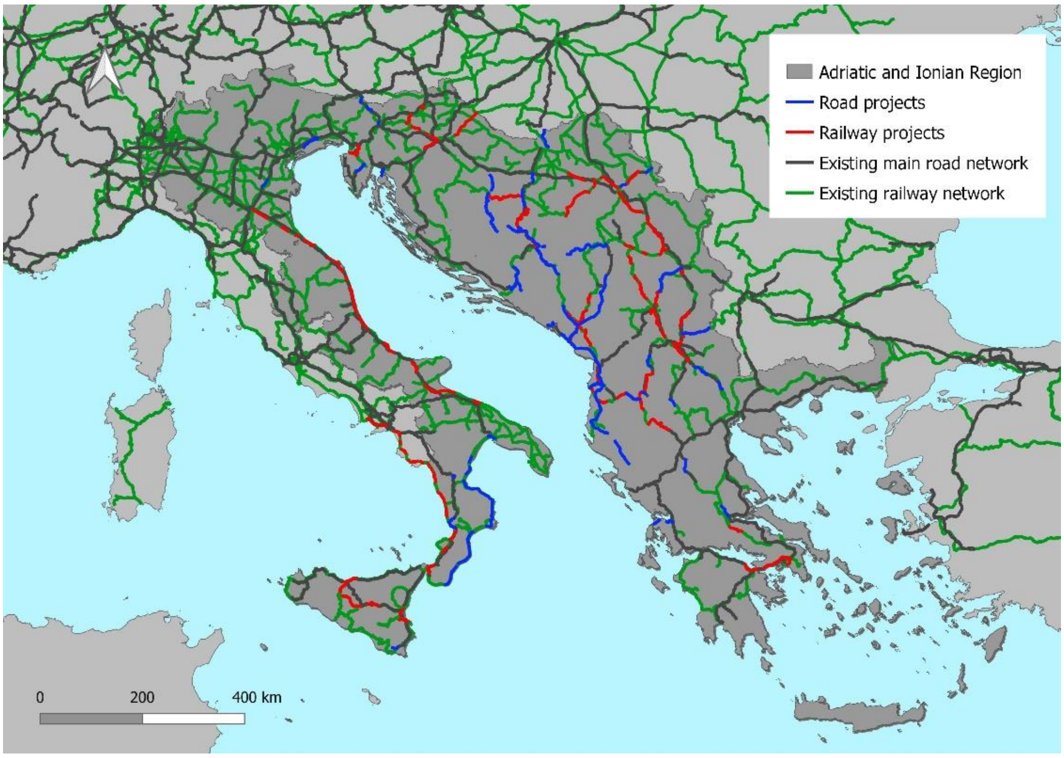

Figure 4. Existing main road and railway networks, together with main road and railway projects in the Adriatic and Ionian region, as per [52].

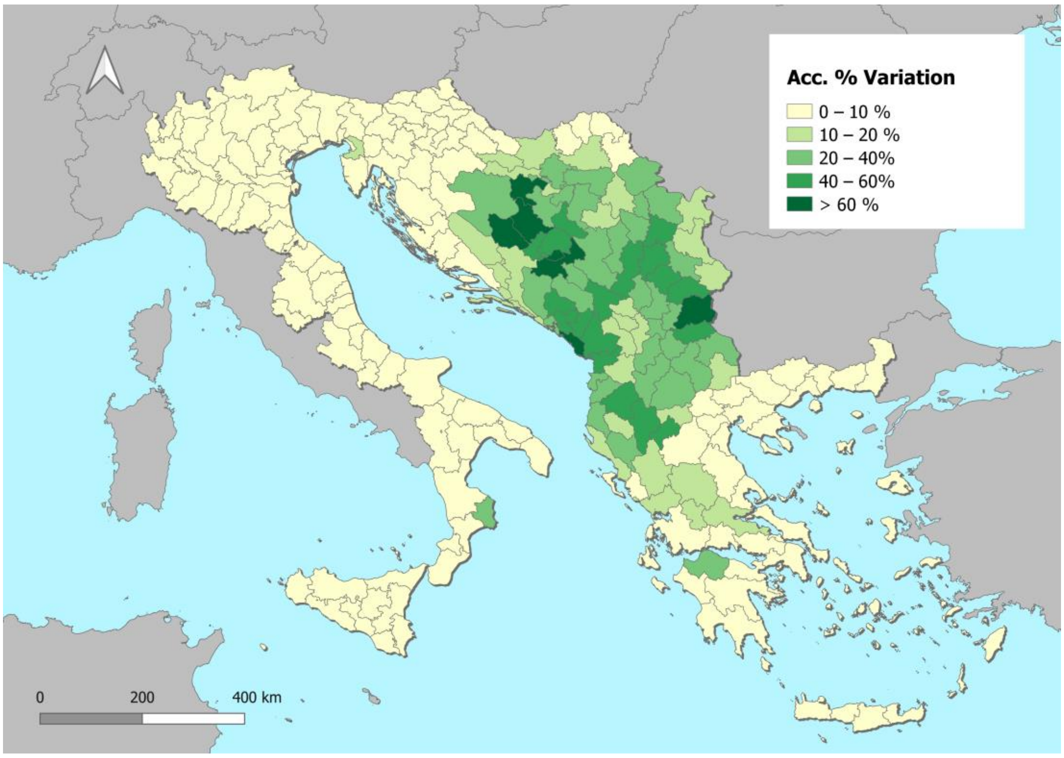

Figure 5. Accessibility indicator percentage variation between current and project scenario.

Table 2. Accessibility values [*10,000] and absolute/relative changes between current and project scenario.

Country	Accessibility Values (*10,000)		Accessibility Changes		
	Current Scenario	Project Scenario	Absolute	Relative	Relative NUTS 3 Range [Min–Max]
Albania	2138	2771	634	29.6%	[12.4–54.7%]
Bosnia-Herzegovina	2428	3344	916	37.8%	[4.5–93.0%]
Croatia	5333	5709	376	7.1%	[1.0–20.9%]
Greece	2460	2634	175	7.1%	[0.0–42.0%]
Italy	13,671	13,865	194	1.4%	[0.1–30.2%]
Kosovo	3920	4972	1052	26.8%	[13.7–39.8%]
Montenegro	1580	2321	741	46.9%	[21.5–93.1%]
North Macedonia	4255	5540	1285	30.2%	[15.6–45.6%]
Serbia	4180	5264	1084	25.9%	[2.6–62.1%]
Slovenia	9391	9748	356	3.8%	[0.8–15.7%]
Adriatic–Ionian Average	**6735**	**7216**	**481**	**14.0%**	**[0.0–93.1%]**

Taking these new zonal accessibility values as input, the estimated Spatial Durbin Model (see Section 4.3) has been used for GDPC forecasting. Results in terms of zonal GDPC percentage variations are reported in Figure 6; the map highlights how some areas experience a GDPC increase (blue-colored zones on which the darker is the blue, the higher is the GDPC % increase), while it decreases in some others (light red-colored areas).

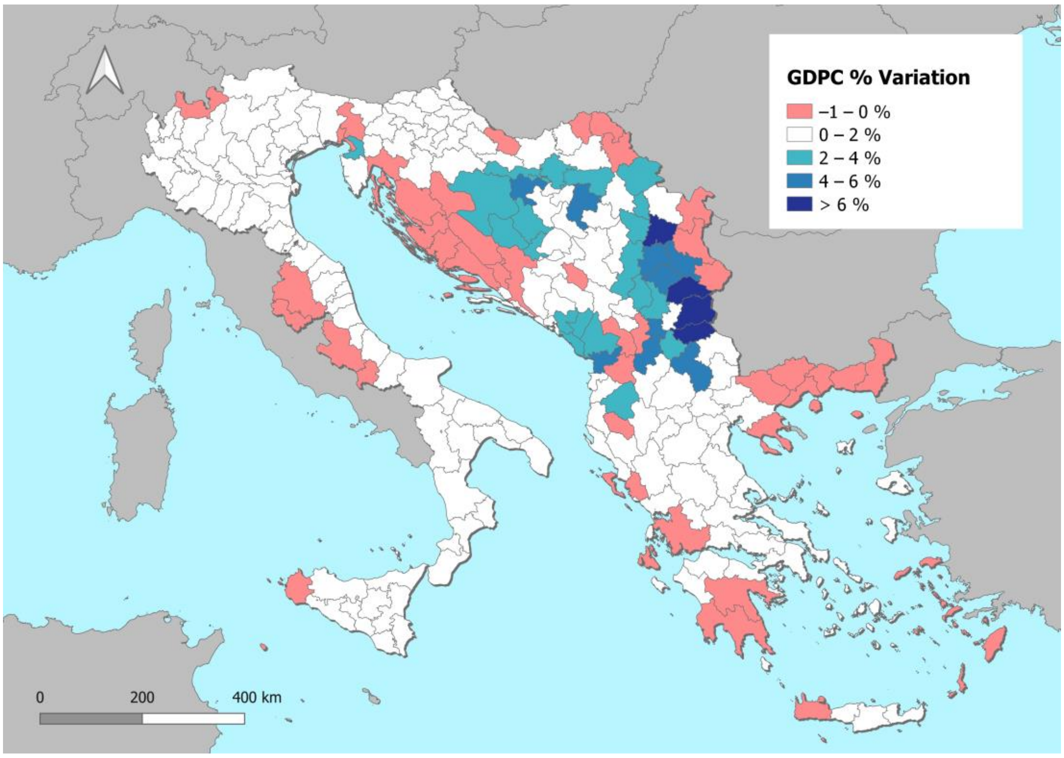

Figure 6. GDPC percentage variation between current and project scenario.

5. Discussion

The estimated Gross Domestic Product per Capita (GDPC) percentage variation due to road and railway projects extending the TEN-T network in the Adriatic and Ionian (AI) region was found to be equal to +0.9% on average at the NUTS-3 level. Even though it is not directly comparable since it is context-specific, it is worth noting that the estimated value is in line with those previously obtained by other authors, for instance, [19], using a Spatial Durbin Model specification, stated that the Eastern European countries (including Estonia, Latvia, Lithuania, Poland, the Czech Republic, Slovakia, Hungary, Slovenia, Croatia, Romania, Bulgaria, and Greece) could benefit from the TEN-T core road corridors' completion with a GDPC increase ranging from +0.9% to +1.3%. Apart from the average value, the GDPC percentage variation estimated in this study ranges between −0.8% and +10.2% at the NUTS-3 level for the AI region, where higher percentages are related to non-EU countries characterized by underdeveloped transportation networks (e.g., North Macedonia or Serbia). In fact, average National GDPC increases reported in Table 3 show that Western Balkans countries benefit from a +1.8% GDPC increase on average, unlike the EU countries, where the economic impacts are lower (+0.2% on average).

Table 3. GDPC values [€] and absolute/relative changes between current and project scenario.

Country	**GDPC Values (€)**		**GDPC Changes**		
	Current Scenario	**Project Scenario**	**Absolute**	**Relative**	**Relative NUTS 3 Range [Min–Max]**
Albania	3495	3540	45	1.3%	[−0.5–4.1%]
Bosnia-Herzegovina	4574	4635	61	1.3%	[−0.3–4.5%]
Croatia	9940	9993	53	0.5%	[−0.4–3.0%]
Greece	13,516	13,539	23	0.2%	[−0.3–2.0%]
Italy	26,338	26,378	40	0.2%	[−0.1–0.8%]
Kosovo	3482	3543	60	1.7%	[−0.1–4.2%]
Montenegro	6908	6998	90	1.3%	[−0.4–3.2%]
North Macedonia	4497	4645	149	3.3%	[0.9–10.1%]
Serbia	4390	4479	90	2.0%	[−0.8–10.2%]
Slovenia	18,229	18,386	157	0.9%	[−0.2–3.2%]
Adriatic–Ionian Average	**14,177**	**14,235**	**58**	**0.9%**	**[−0.8–10.2%]**
EU Countries inside the AI Region average	**19,321**	**19,367**	**46**	**0.2%**	**[−0.4–3.2%]**
non-EU Countries inside the AI Region average	**4482**	**4562**	**80**	**1.8%**	**[−0.8–10.2%]**

As was found from the modelling estimation, the spatially lagged effect on GDPC, i.e., the influence of the neighboring areas, is negative and can sometimes be predominant. The positive effect on GDPC given by (direct or indirect, i.e., through network effects) accessibility increases in the whole study area is sometimes overbalanced by negative spatially lagged effects, resulting in a GDPC positive variation polarization, mainly where interventions are located, to the detriment of the nearby zones.

For instance, Italy has an infrastructural enhancement on the Adriatic and Tyrrhenian corridors, resulting both in a positive GDPC variation on coastal areas (up to to +0.8%) and a slight GDPC decrease in the nearby Apennine hinterland regions (up to −0.1%). Another example is related to inland areas of Bosnia-Herzegovina and Croatian coastal areas; while the former benefit from a +2.7% GDPC increase on average, the latter have a decrease of up to −0.3% and −0.4%, respectively. In addition, some Albanian areas experience negative economic impacts since they are geographically located in an "investment shadow area"; they are surrounded by important infrastructural enhancements, but they do not benefit from them, as their rail and road network is not well-integrated and connected.

The potential conflict between direct and spatial spillover effects has also been highlighted by [53]; as in this study, they confirm the possibility of having negative spillover effects caused by increased territorial competition exceeding direct positive ones, therefore suggesting to policymakers that these impacts should always be taken into account in transportation project appraisal [54]. However, there are other studies (for instance, [55]) finding neither positive direct nor negative spillover effects of transportation investment on the regional growth, arguing that other factors such as investment in research and development or regional migration rates are far more important than transportation-related variables in explaining regional economic welfare.

In this study, the statistical significance of both socioeconomic (i.e., the employment rate EMP_{RATE}) and political-context-related variables (i.e., the quality of government index EQI) in estimating GDPC has been proven, suggesting how policies and decisions affecting contexts other than real-world transportation could positively impact regional economies. In particular, a positive impact on GDPC can be achieved by acting on different systems (for example, the socioeconomic, the political, or the transportation systems), and different policies, not limited to transportation, should be evaluated in a comparative way, especially with reference to those areas where investments in transportation infrastructure are not cost-efficient due to the topography of the territory in which they would be located.

6. Conclusions

In this paper, a modelling framework is proposed to assess the spatial economic impacts of transportation infrastructure investments; it combines spatial econometric techniques with transportation accessibility analysis to estimate the variation of zonal Gross Domestic Product per Capita (GDPC), assumed as a proxy of the economic growth. The application to the Adriatic and Ionian (AI) region case study is presented; among its peculiarities, the area includes both EU (Italy, Slovenia, Croatia, and Greece) and non-EU countries (Bosnia-Herzegovina, Montenegro, Albania, North Macedonia, and Kosovo) and is characterized by high disparities in terms of infrastructural assets.

The estimated models allowed us to prove the importance of considering the spatial relationship between variables in transportation infrastructure economic impact evaluation. The Spatial Durbin Model specification was found to be the one that best fits; among those tested, it is the only model specification able to capture complex spatial relationships between nearby areas, considering spatially lagged effects generated from both the dependent ($GDPC$) and independent variables (i.e., the employment rate EMP_{RATE}, the quality of government index EQI, and the transportation accessibility indicator ACC).

Finally, the estimated SDM model has been used to forecast GDPC variation due to road and rail investments foreseen in the AI region by supranational strategies, as per [52]. It allows us to first quantitatively measure the zonal GDPC variation due to an increased multimodal transportation accessibility, and second it allows us to outline where current economic disparities tend to be bridged up (i.e., mainly along the foreseen extensions of the TEN-T corridors) and where not, suggesting the need of new policies to fill these gaps.

Among the limitations of this research, it is worth mentioning the modelling estimation using cross-sectional data. The use of panel data would have given more robust estimates; however, to the best of our knowledge, longitudinal data related to variables considered in this study are not publicly available for Western Balkan countries. Moreover, spatial modelling estimations have been performed using data related to 2017, i.e., a few years before disruptive crises such as the COVID-19 pandemic and the Ukraine war happened; these had and will have impacts on regional economies that the model fails to capture by its very nature.

Another limitation is that the simulated project scenario considers only road and railway projects in the AI region, ignoring those located in neighboring countries; results for the edge zones must be therefore carefully evaluated. Future research should address these limitations in order to obtain, on the one hand, more accurate estimates, and on the other, more reliable results for the bordering areas to draw up wider considerations. Moreover, a possible follow-up to this study could evaluate the impact on regional economies of investments in transportation nodes that are not considered in this study. This would be possible by adapting the proposed methodology by introducing a service frequency variable in the accessibility indicator formulation, consequently simulating the impact that would be generated by increases in service frequencies allowed by nodal (such as ports or airports) capacity enhancements.

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