Chapter 9
Data and Modelling for the Territorial Impact Assessment (TIA) of Policies

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Abstract Territorial Impact Assessment (TIA) is still a 'new kid on the block' on the panorama of policy evaluation methodologies. In synthesis, TIA methodologies are thematically holistic and multi-dimensional and require the analysis of a wide pool of data, not only of economic character but also related with social, environmental, governance and planning processes, in all territorial scales. For that, TIA requires a wealth of comparable and updated territorialised data. Here, data availability is often scarce in many of the selected analytic dimensions and respective components, to assess territorial impacts in a given territory, in particular in the domains of governance, planning and environment. In this context, this chapter presents a list of non-traditional potential indicators which can be used in existing TIA methodologies. Moreover, the analysis was able to show how important can be the use of non-traditional data, to complement mainstream statistical indicators associated with socioeconomic development trends. However, for the interested scientist, the dispersal of existing non-traditional data per a multitude of sources can pose a huge challenge. Hence the need of an online platform which centralises and updates non-traditional data for the use of all interested in implementing TIA methodologies.

9.1 Introduction

Academia and public and private entities are being flooded with 'tsunamis' of traditional and non-traditional data for their research. This data is collected via multichannel business environments (Baesens, 2014) and via, for instance, 'sensors, smartphones, internet, social media, and administrative systems'.[1] The central

[1] https://ec.europa.eu/jrc/en/research/centre-advanced-studies/css4p

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question for this chapter is how and which available non-traditional data can increase the effectiveness of the Territorial Impact Assessment (TIA) (see Medeiros, 2020b, 2020d) of projects, programmes and policies, via existing or novel TIA methodologies. This chapter is written in a necessary condensed and focused way and is guided by the following three policy questions raised by European Commission (EC) Joint Research Centre (JRC) (Bertoni et al., 2022):

1. How can CSS help evaluate the measure and its territorial impacts, either in an ex ante way (using simulation methods) or in an ex post one (using data science ones)?
2. Which sources of data could be used to better consider EU territorial heterogeneity?
3. What are the challenges of this approach, for example, how can we establish the correct level of spatial granularity, trading off the optimality of the targeted policy measure with the costs/timeliness of the decision?

All these questions are, in our view, relevant and reflect emerging axioms on the importance of considering the territorial dimension in analysing and assessing the implementation of policies, at different policy phases (ex ante, mid-term, and ex post), that have begun to permeate the policy evaluation discourse over the past decades. The first question provides an insightful emphasis to debate the potential positive and complementary contribution of non-traditional data to analyse all policy phases of TIA, in order to improve its effectiveness. The second aims to identify concrete sources of non-traditional data which can complement mainstream traditional data when implementing a TIA methodology. This is particularly relevant for TIAs since they should consider a broad and comprehensive set of indicators covering all dimensions and components of territorial development (Medeiros, 2014a). Finally, the third question touches a critical foundation of the implementation of TIAs: how to identify the appropriate territorial level for the TIA analysis and the dimensions and components for the analysed policy, in order to increase the efficiency and effectiveness of TIA evaluations. All these questions will be further scrutinised in Sect. 9.3. In this regard, and based on past TIA evaluations (Medeiros, 2014b, 2016a, 2017b), non-traditional data can provide crucial inputs on components related to the territorial governance and spatial planning dimensions of territorial development, which are difficult to obtain via traditional data sources.

9.2 TIA: A Literature Review

What is and why TIAs? These fundamental questions are answered in existing literature in various manners, from the first known report which unveiled the first TIA model (TEQUILA—see ESPON 3.2, 2006), through to a recent book which explains each one of the existing TIA methodologies (Medeiros, 2020d). From the first to the last, no more than 15 years have passed. This formally makes TIA methodologies ‘new kids on the block’ of policy evaluation (Medeiros, 2020c).

Table 9.1 TIA methodologies and main pros and cons

Name	Pros	Cons
TEQUILA	First TIA. Robust from a methodological standpoint	Does not apply counterfactual evaluation analysis
STEMA	Very complete set of indicators	Relatively simplistic and difficult to spatialise
EATIA	Goes beyond the use of negative/positive impacts	Weak from a methodological rationale–pain free
TARGET_TIA	Flexible, robust, sound and applies counterfactual analysis	Is not to be used quickly if robust impact scores are needed
QUICK_TIA	Presents online attractive cartography at several spatial scales	Does not really produce reliable and sound impact scores
TERRITORIAL FORESIGHT	Based on a wide participatory engagement—future trends	Largely dependent on the knowledge of participants
LUISA TERRITORIAL MODELING	Produce various scenarios of regional development	Largely dependent on the statistical data

Source: Own elaboration

Mostly driven by the ESPON programme, the TIAs are now entering a more mature phase, which is testified by several methodological upgrades from some of the ESPON TIA methodologies (TEQUILA, STEMA, etc.—see Tables 9.1 and 9.2). Even so, current ESPON TIAs are profoundly preconditioned by their erroneous rationale which means it is possible to obtain a valid and sound TIA score in a quick manner (Medeiros, 2016c).

Inevitably, any state-of-the-art literature review of TIA methodologies must start with the first one: the pioneering quantitative TIA model known as TEQUILA. This multi-criteria model is supported by a quantitative database on EU NUTS 3, to assess ex ante impacts of EU directives. According to the authors of this methodology, the criteria to select the TEQULA data refers to the main dimensions of territorial cohesion, territorial efficiency, territorial quality and territorial identity, and their sub-dimensions, measurable by multiple indicators (Camagni, 2020), particularly economic-related ones (Table 9.2). Also devised within the first ESPON programme, the STEMA TIA model is based on an original qualitative-quantitative methodological approach, returning ex ante and ex post impact scores. Just like the TEQUILA model, the STEMA uses traditional sources of data, mostly related to the economic dimension of development (Prezioso, 2020). The same goes for the ESPON EATIA (Marot et al., 2020) and the simplified QUICK_TIA (Ferreira & Verschelde, 2020). Crucially, all these four ESPON TIA models are supported by existing sources of quantitative databases at the EU level (mostly NUTS 2 and 3), collected from several sources and organised in the ESPON database, which has data related to agriculture and fisheries, economy, education, environment and energy, governance, health and safety, information society, labour market, population

Table 9.2 TIA methodologies. Evaluation phases, type of data, sources of data, computational methods and dimensions of territorial development

Name	Evaluation phase		Type of data		Sources of data			Computational method			Dimensions of territorial development				
	Ex Ante	Ex Post	Qualitative	Quantitative	Classical	Mix	Novel	Webgis	Excel	Other	Eco	Soc	Env	Gov	Pla
TEQUILA	X			X	X			X	XX	XX	XX	XX	XX	X	X
STEMA	X	X	X	X	X			X	XXX	X	XXX	XX	XX		
EATIA	X		X	X	X			X	XX	XX	XXX	XX	X	X	
TARGET_TIA	X	X	X	X	X			X	XXX	X	XX	XX	XX	XX	XX
QUICK_TIA	X		X	X	X			XXX	X	X	XXX	XX	X	X	
T. FORESIGHT	X		X		X			X	X	XXX	XXX	XX	XX	X	X
LUISA T. M.	X			X	X	X		XXX	X	X	XXX	XX	XX		X

Source: Own elaboration

Note: *ECO* economic competitiveness, *SOC* social cohesion, *ENV* environmental sustainability, *GOV* territorial governance, *PLA* spatial planning, *XXX* strong, *XX* average, *X* weak, *WEBGIS* use of online geographical information system platform to present the impact scores, *EXCEL* use of Microsoft excel or alike, to obtain the impact scores and living conditions, science and technology, territorial structure, transport and accessibility.

Soon after the creation of the first ESPON TIAs, other TIAs or similar policy assessment methodologies were designed to assess territorial impacts. The first was the TARGET_TIA which, unlike the ESPON TIAs, was specifically designed to assess the ex post impacts of EU Cohesion Policy. Just like the TEQUILA, however, the TARGET_TIA selected the quantitative indicators based on the concept of Territorial Cohesion, but with different analytic dimensions (socioeconomic cohesion, territorial governance and cooperation, polycentricity and environmental sustainability). It uses mainly traditional sources of data for socioeconomic and environmental dimensions. This data is complemented with non-traditional statistical sources of data collected for the dimensions of cooperation/governance and polycentrism, in databases like the INTERACT KEEP database and other sources available in different national and EU entities. In the meantime, the TARGET_TIA was already tested in specific EU programmes like the EU INTERREG-A (Medeiros, 2017a). For this case, the selected quantitative data referred to the two main dimensions of cross-border cooperation (territorial development and reduction of border barriers) and respective components. In this regard, it goes without saying that the collection of data on persisting border barriers required the access to non-mainstream sources of data, which are available in distinct regional and national entities.

Finally, the two remaining types of TIA methodologies mentioned in this chapter are designed for specific policy evaluation contexts. The first, known as Territorial Foresight, is used when the analysis of long-term developments is required. For this, qualitative data is collected via questionnaires, comprising three elements: content, geography and time (Böhme et al., 2020). Conversely the LUISA model ‘is based on the concept of ‘land function’ for cross-sector integration and for the representation of complex system dynamics’ (Lavalle et al., 2020). It is fundamentally supported by territorial indicators collected from several external models and presented via an online tool: the Urban Data Platform. This means that it explores higher spatial granularities than other TIA tools, since it provides information at the urban level.

9.3 Computational Guidelines on TIA

9.3.1 The Main Contribution of Computational Social Science for Territorial Impact Assessment

As seen in the previous section, existing TIA methodologies are supported by traditional sources of quantitative data. These are retrieved from EU national and sometimes regional statistical entities such as the Eurostat, ESPON and JRC databases. In some cases, specific data is obtained directly from non-mainstream data sources, especially for measuring components associated with governance and spatial planning dimensions of territorial development. In this context, there is a wide scope for incorporating non-traditional sources of data (see McQueen, 2017) in the implementation of TIA methodologies, in the following domains.

9.3.1.1 Complementarity

Territorial impact assessment analysis is generally related to analysing policy impacts on territorial development or territorial cohesion trends. It can, of course, also tackle other policy arenas, such as territorial cooperation or territorial integration (on territoriality, see Medeiros, 2020a). The problem here is that, as a holistic concept, territory encompasses basically all aspects related to the concept of development (Potter, 2008). This scenario implies a constant struggle to find, in traditional sources of data, a balanced set of indicators for all the analytical dimensions of, for instance, territorial development (Medeiros, 2019), hence, the potential benefits of usage of non-traditional data (e.g. digital footprint, digital tracking data, etc.) to complement largely incomplete traditional sources of data in implementing a TIA methodology. Here, besides the economic-related pool of statistics, which are normally relatively abundant at several territorial levels, the remaining policy dimensions of development can be enriched by non-traditional sources of data. These include social statistics, like 'quality of life' indicators, which often depend on an individual perception, which can be acquired via enquiries made with mobile phones. Furthermore, environmental-related data, such as the potential 'carbon footprint' of each individual in a given territory, can be acquired by means of online questionnaires via mobile phones or even by data on road congestion and public transport data. In the latter case, online applications such as the Flightradar24 (flightradar24.com) or the UCL Energy Institute portal to visualise the world's shipping routes can be used to estimate a carbon footprint impact score for each intended territorial scale. These are just a few examples that can also be applied in other dimensions of territorial development, such as territorial governance (e.g. to identify social engagement and participation in a given domain via the analysis of social network geo-tagged information) and spatial planning (e.g. to determine the compacity of urban areas via the visualisation of Google Maps).

9.3.1.2 Real-Time Information

One of the main advantages of non-traditional sources of data is the possibility to analyse territorial flows of data in real time. One aforementioned example is Flightradar24, which presents the current location of all commercial airplanes at any given time. The same goes for data which can be collected from some public transport operators and mobile phone companies tracking the exact location of individuals in a real-time context. This data, once aggregated and anonymised, can be particularly useful, for instance, to assess cross-border flows, which are a crucial element to understanding the territorial impacts of cross-border cooperation (Medeiros, 2018), or urban mobility processes (Pucci et al., 2015).

9.3.1.3 Spatial Accuracy

Another advantage related to digital tracking is the collection of highly accurate spatial data (Christl & Spiekermann, 2016) which is normally absent in traditional sources of data. However, this data collection should comply with the right of citizens to minimise their digital footprint (Bronskill & McKie, 2016). One domain in which spatial accuracy for TIA is particularly relevant is the analysis of all sorts of flows, especially in urban areas. As Cao (2018) puts it: 'data science can also fundamentally change the way political policies are made, evaluated, reviewed and adjusted by providing evidence-based informed policy making, evaluation, and governance'.

9.3.2 Sources of Data Towards an Analysis of EU Territorial Heterogeneity

I still remember the wise words of a former university professor on research methodologies stating that 'before you think you will not find the data you need, try hard and you will be amazed on what data is out there'. Indeed, data of all kinds and sources is waiting to be found in a myriad of places, to be treated and used in various studies. In the case of TIAs, it would appear reasonable to surmise how important it is to have access to a wide pool of updated and georeferenced data at several territorial levels and at several policy domains. In this regard, the writing of this particular chapter confirmed the premise that it is possible to access a wider pool of data to be used in TIA methodologies, to complement the ones commonly available in traditional data sources (regional, national and EU statistical entities and databases).

What is more striking, as seen in Table 9.3, is that it was possible to find alternative non-traditional sources of data that have already been explored and presented in scientific literature. These data covers basically all dimensions and respective components of a central concept for elaborating TIA analysis: territorial cohesion. Here, the economic-related indicators were basically the exception as regards the availability of relevant non-traditional data which can be used to assess territorial cohesion trends in a given territory. Also, it goes without saying that what this research found does not necessarily equate precisely to all potential non-traditional indicators which can eventually be found and applied in assessing each of the territorial cohesion analytic components. Moreover, many other non-traditional data sources can be found and used to analyse other topics which can be assessed via TIA methodologies, such as cross-border cooperation programmes, and urban, rural or regional development policies, among several other policy domains.

The selection of the territorial cohesion concept (Medeiros, 2016b) serves as a concrete and optimal example to explain the potential selection of sources of non-traditional data towards an analysis of EU territorial heterogeneity. Firstly, territorial cohesion is a multi-dimensional concept which encompasses a wide array of policy arenas, which can, in its own right, be also subject to a stand-alone TIA analysis, as is the case of environmental sustainability-related policies. Secondly, territorial cohesion can be analysed at different territorial levels, and some of them, especially at the urban and local levels, can greatly benefit from the new spatial granularity provided by some of the already available non-traditional sources of data.

In detail, Table 9.3 provides at least one example of a potential indicator and respective data source which can be used to assess most of the identified territorial cohesion components. This is particularly valid for analysing social cohesion, environmental sustainability, territorial governance and cooperation and trends in morphological polycentricity. A large part of these novel and non-traditional data, which can be used as complementary to existing traditional data, is linked to mobile technologies (i.e. phones). Due to the large amount of presented examples, a more detailed explanation of each one of these sources of alternative data can be found on the presented literature references. One can, however, highlight the tremendous possibilities provided by mobile technologies to study commuter flows using public transport in a given territory, which can deliver a very precise location at different times of the day, and even real-time information. Another example is the collection of data from certain operators on the production and use of renewable sources of energy at any given time, in different locations. This data can be particularly useful since traditional sources of statistics do not yet provide detailed information, per territorial sub-national unit, on the production and use of renewable energy. Most instructive in the polycentricity analytic domain of territorial cohesion is the possibility to use geospatial data sources to assess the degree of urban compactness, which is otherwise difficult to analyse by means of traditional sources of data. Finally, it is interesting to see the number of digital sources of information which can be used to analyse and measure governance and cooperation-related analytic components such as social participation and interaction. How far and how this data is spatially detailed and how it can be updated is, however, a discussion topic for subsequent analysis.

9.3.3 Main Challenges on Using Non-traditional Sources of Data on Implementing TIA Methodologies

The previous topic unveiled a wealth of non-traditional sources of information to implement TIA methodologies, mostly based on the use of territorial cohesion as a central concept for the TIA analysis, as would be the case in assessing the

Table 9.3 Non-traditional data for analysing territorial cohesion

Dimension	Component	Traditional indicators	Potential non-traditional indicator	Data and source
Socioeconomic cohesion	Productivity	Work productivity	–	–
	Income	GDP per capita	–	–
	Employment	Employment rate	–	–
	Innovation	Patents granted	Patents in ITC-related technology classes	EU ESSLait project Micro Moments Database (OECD, 2014)
	Infrastructure	Industrial parks	–	–
	Entrepreneurship	Startups	Number of Startups per university	University internet sites
	Education	Tertiary education (%)	Mobile phones for educational assessment	Mobile phone data (Şahin & Mentor, 2016)
	Health	Physicians per capita	Mobile phone data for informing public health actions	Mobile phone data (Oliver et al., 2020)
	Culture	Culture expenses (%)	Digital dimension of cultural capital	e.g. Reading IRT score (Paino & Renzulli, 2013)
	Exclusion/inclusion	Poverty rate	Digital poverty	e.g. digital interaction (Barrantes, 2007)
	Basic infrastructure	Public transports	Digital data for public transport	Mobile phone data and Smart card data (Zannat & Choudhury, 2019)

(continued)

Table 9.3 (continued)

Dimension	Component	Traditional indicators	Potential non-traditional indicator	Data and source
	Security	Criminality rate	Urban crime	Mobile Phone Data (Traunmueller et al., 2014)
Environmental sustainability	Climate change	CO_2 emissions	Environmental extremes and population	Mobile network data from MDEEP project (Lu et al., 2016)
	Energy	Renewable energy production	Renewable energy usage	Mobile Data via network operators using renewable energy (Syed et al., 2021)
	Nature and biodiversity	Protected areas (%)	Visitation in parks and protected areas	Mobile phone data (Monz et al., 2019)
	Environment and economy	Share of expenses with environment	Environmental quality	Client-server architecture of the WISE-MUSE mobile application for analysing environment (Akhmetov & Aitimov, 2015)
	Natural resources/garbage	Share of urban waste collected	Sustainability	Large-scale social data and machine-learning based on 12,720 electric vehicle (EV) charging stations (Asensio et al., 2020)
	Environment and health	Waste collection and treatment	Environmental health decision support	Sensors integrated into mobile devices (Bae et al., 2012)
Territorial cooperation and governance	Horizontal cooperation	Interreg-C programmes	Territorial ties	International call traffic (Blumenstock, 2011)
	Vertical cooperation	Territorial cooperation entities	–	–
	Participation	Elections participation rate	Social participation	Internet social participation (Anderberg et al., 2021)
	Involvement	NGOs + territorial partnerships	Social interactions.	Social network geo-tagged information (Keusch et al., 2019)

	Information	Public consultation processes	Measuring information skills	Navigation, evaluation and management (ITU, 2018)
Morphologic Polycentricity	Hierarchy/ranking	Urban dwellers (%) /City ranking	Urban commuting flows	Data from mobile phones (Yu et al., 2020)
	Density	Population density	Population density distribution	Network Topology data + MS Counters (Joint Research Centre et al., 2015)
	Connectivity	Apartments with cable per capita	Network measurement	Cellular data network measurement for mobile applications e.g. mobile commerce (Wittie et al., 2007)
	Distribution/shape	City compactness index	Urban compactness	Geospatial data sources (Lan et al., 2021)

Source: Own elaboration

territorial impacts of EU Cohesion Policy in a given territory. In almost every way, however, the use of these ‘novel and digital’ sources of data comes with known challenges, mainly related to the goal of establishing the necessary correct level of spatial granularity provided by spatial analysis, as is the case of a TIA. Alike and complementary challenges can be exposed when trying to find and use such sources of data.

9.3.3.1 The Relevance of the Sample

Collected data for TIA studies must be sound, reliable, comparable and georeferenced. As such, it is crucial that non-traditional data selected for TIA methodologies represent a relevant number (or sample) of the population (individuals, entities) on several territorial levels (from local to national if possible). Furthermore, existing data should be regularly updated, at least each year. For that, individuals and entities which are asked to provide their positions via mobile or non-mobile technological platforms should be convinced of the common benefits to change policies from transmitting the requested information on a regular basis.

9.3.3.2 Precise Location and Low Cost of Collected Data

Entities which use digital technological means to gather data should provide the produced data at distinct spatial granularities preferably via a free or low-cost online framework. This is, of course, challenging, particularly in establishing the correct level of spatial granularity and optimality of the targeted policy measure and costs/timeliness of the decision. These challenges depend on what policy is being assessed via a TIA methodology. In the case of assessing EU cross-border cooperation programmes, for instance, the level of spatial granularity would require the use of EU NUTS 3-related data. In this case, the cost and time associated with the acquisition of non-traditional data on cross-border commuting for each border NUTS 3, for instance, could be financially and timely viable in view of the analytic added value it would provide to the overall TIA analysis, based on our experience (Medeiros, 2017a). Indeed, one of the potential advantages of using data collected via the activation of the GPS location of mobile devices, or via digital questionnaires requesting the exact location of the individual, is the possibility to produce precise spatial analysis, which is vital for analysing certain territorial processes, such as metropolitan and cross-border commuting patterns.

9.3.3.3 Easy Access and Real-Time Data

One of the tantalising challenges associated with accessing non-traditional data sources is its dispersion by a myriad of different sources. In this regard, already existing statistical entities such as Eurostat and national statistic entities could centralise non-traditional data sources in their existing online platforms for data consulting. This would facilitate the access to data to all interested. Another possibility is to have an internet platform with links available to non-traditional sources of data divided by policy domains. Some of these sources are already provided on internet sites and a few demonstrate quite interesting real-time spatialised data (e.g. Flightradar24). To have a platform with the collection of all available real-time spatialised data sites would significantly reduce the time and, inevitably, costs associated with the search for non-traditional data to elaborate a TIA.

9.4 The Way Forward

In the context of policy evaluation, TIAs are relatively new. A cursory glance across existing TIAs also confirms their continuous modification and perfection process towards improved effectiveness in assessing the main ex ante (mostly) and ex post territorial impacts of projects, programmes and policies. In this evolving methodological context, the scientific relevance of using non-traditional data is particularly important for TIA, for several reasons. Firstly, by covering all dimensions of territorial development, TIAs require a wide set of comparable territorialised data which are often difficult to get via traditional data sources (regional, national and European statistic entities). In this regard, it is routinely contended that some dimensions and respective components of territorial development, such as territorial governance and spatial planning, have limited comparable and spatialised data, which can complement abundant data from socioeconomic development-related components. Secondly, non-traditional sets of data do not embrace real-time and spatial accuracy qualities, which can be of great value when assessing territorial impacts of certain policy areas, such as cross-border cooperation processes.

When contemplating the potential advantages of using non-traditional data in TIAs, which include their complementarity with traditional sources of data and the possibility of using real-time information and more detailed spatial accuracy, it is easy to demonstrate the potential advantages for existing TIA methods to not only provide more comprehensive and coherent TIA impact policy scores but to also improve overall policy forecast accuracy, both at ex ante and ex post evaluation phases. There are several open avenues for research on how to conciliate the use of traditional and non-traditional data to be used in TIA methodologies, which is still very much absent in current TIA related literature. There is a wealth of academic literature on the potential use of non-traditional data in many aspects of territorial development.

Amid this ever-growing body of literature discussing the potential use of non-traditional data for policy evaluation in specific policy areas, this chapter compiled, for the first time, a collection of potential non-traditional indicators, proposed in academic literature, which can be used in all existing TIA methodologies. There are, for sure, far more such indicators of this kind which can complement and complete the use of traditional datasets to be used in TIA analysis. What is striking are the tremendous possibilities to obtain non-traditional indicators for analysing the dimensions and components of territorial development as normally there are fewer options available with traditional data. It was indeed, a great surprise that it was possible to find a myriad of potential non-traditional indicators in components related to the analysis of, for instance, territorial governance, which imply wider possibilities to better understand social participation and involvement related processes. The same goes for increasing possibilities to better understand spatial planning trends via the analysis of specific components such as commuting flows, detailed analysis of demographic density and urban compactness. Likewise, the analysis of environmental sustainability trends on related components can be greatly improved using novel non-traditional data in areas such as renewable energy, environmental quality and sustainability. But even domains which are normally relatively robust in terms of data availability, such as the economic and social indicators, can be complemented by existing non-traditional sources of data in certain domains such as innovation, entrepreneurship, education, health, culture and security.

I have to admit that, prior to writing this chapter, I was not fully aware of the sea of possibilities offered by the potential use of non-traditional data indicators which can be used by TIA methodologies. Hence, what this chapter offers to the interested readers is a necessarily short and simplified introduction to the potential advantages of using non-traditional data when implementing TIA methodologies, as well as a wide number of potential non-traditional indicators and respective literature. Future analysis can detail even more the availability of such types of data to be used in assessing the territorial impacts of policies. Given the speed in which science evolves nowadays, I would not be surprised if 10 years from now, the number of non-traditional indicators that could potentially be used for TIA analysis has grown exponentially. But more importantly, in our opinion, existing and future sources of non-traditional data should be compiled on a regular basis and formatted in a sound, reliable, comparable and georeferenced manner, to be used in TIAs. By implication, these novel data should be easily accessible in online platforms and preferably free of charge, so they can be easily collected and used by all interested. In this regard, the EC can play a vital role in defining norms and regulations similar to the ones used for traditional data and use entities such as Eurostat and the JRC, as platforms to make it available to the general public in an organised manner, not only in datasets but also via Web Geographical Information Systems presenting real-time information.

To some extent, data science and technology are at the heart of an ongoing scientific and technological revolution and globalisation transformation. Even more starkly, the past decades saw a drastic change in data availability for policy evaluation. Indeed, around 30 years ago, the implementation of a TIA would be almost impossible since comparable spatialised data only existed for certain social and economic indicators. This means that it was only possible to assess socioeconomic impacts of a given policy. Instead, territorial impact analysis implies a balanced collection of not only socioeconomic but also environmental, governance and spatial planning related indicators. This context explains why TIA analyses are relatively recent. They gravely depend on data availability in several policy domains. For all involved in territorial analysis and specifically in implementing TIA methodologies, data availability is still a major challenge. This is particularly evident for ex post TIA analysis which require a crucial use of comparable quantitative data to verify territorial trends of the analysed territory using a wide set of indicators.

By proposing at least one potential non-traditional data indicator for almost all the components of territorial cohesion, to be used on TIA analysis, this chapter underlines a rosier foresight for TIA evaluations, no matter which methodology and selected time framework (ex ante, mid-term or ex post). This crucial positive implication of using non-traditional sources of data to implement TIAs in a more effective manner remains, however, to be seen in a practical manner, since there are still several challenges ahead to make them usable in scientific research, as previously mentioned. These challenges are also rooted in pre-conceptions related to the potential unreliability and incomparability of certain non-traditional data sources. Even so, the potential gains from using them for territorial analysis are evident. The idea, for instance, of using data from mobile phones and related mobile sources, to analyse metropolitan and cross-border commuting patterns is widely appealing for policy makers and evaluators. Similarly, data obtained from satellites can provide a very detailed spatial granularity, often absent from traditional sources of data. Hence, the use of programmes or software to automate the analysis of territorial impacts (programmatic scope), with a complementary use of non-traditional sources, heralds a battery of choices which are widely promising, but that are yet to be fully understood and tested. This is an appealing testing ground for future research for all involved in TIA implementation.

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