Spatial Causality: A Systematic Review on Spatial Causal Inference

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Abstract

The growing interest in causal inference in recent years has led to new causal inference methodologies and their applications across disciplines and research domains. Yet, studies on *spatial* causal inference are still rare. Causal inference on spatial processes is faced with additional challenges, such as spatial dependency, spatial heterogeneity, and spatial effects. These challenges can lead to spurious results and subsequently, incorrect interpretations of the outcomes of causal analyses. Recognising the growing importance of causal inference in the spatial domain, we conduct a systematic literature review on spatial causal inference based on a formal concept mapping. To identify how to assess and control for the adverse effects of spatial influences, we assess publications relevant to spatial causal inference based on criteria relating to application discipline, methods used, and techniques applied for managing issues related to spatial processes. We thus present a snapshot of the state of the art in spatial causal inference and identify

methodological gaps, weaknesses and challenges of current spatial inference studies, along with opportunities for future research.

1 Introduction

Causal inference is the procedure of extracting knowledge about a causal relationship based on the occurrence of an effect. Causal inference analyses the situation of the outcome variable when the cause is changed (Pearl 2009). Analytical techniques for causal inference have been developed in recent decades across different domains, e.g., health, economy, ecology, and most prominently epidemiology (Aldrich 1995; Handa et al. 2020; Nguyen and Gouno 2020; Ohlsson and Kendler 2019; Pearl 1988; Pearl 2000; Pearl 2009; Rubin 2005; Saddiki and Balzer 2018; Solvang and Subbey 2019; J. Zhao et al. 2020), and are increasingly finding their ways into analyses with a spatial component (Kolak 2017; Kolak and Anselin 2020). In most current spatial analyses, the typical goal is identifying correlation between variables. Yet, causation cannot be simply implied when a significant and robust association or correlation are found (Aldrich 1995; Altman and Krzywinski 2015; Ter Braak 2017).

The nature of spatial and non-spatial processes is different because of the unique nature of spatial effects, e.g., spatial dependence and spatial heterogeneity (O'Sullivan and Unwin 2014). These characteristics can affect the results of a causal analysis on data capturing spatial processes, chiefly by inaccurate estimation of the causal effects. These causal effects may be both under- or over-estimated. For example, Ning et al. (2019) reported a challenge in detecting the effect of an advertising campaign on store sales because of the spatially correlated effects of proximal stores.

The mentioned characteristics of spatial processes thus violate fundamental assumptions of existing methodological frameworks for causal inference. These assumptions depend on the selected structure for causal analysis. For instance, the "Stable Unit Treatment Value Assumption" (SUTVA) is a base assumption in Rubin's causal model (Rubin 1974; Rubin 1986; Rubin 2005). SUTVA is one of the best known assumptions in non-spatial causal inference (Rubin 1986), emphasizing:

1. The independence of every unit; refers to no interactions among units[1]. For example, the assumption that one patient's result will not affect other patients' results; and

2. The assumption of a single, well-defined version for each treatment. In the above example, under the SUTVA assumption, administering drug A with a lower dosage is considered a *different* treatment to the administration of the identical drug A but with a higher dosage (Yao et al. 2020).

In spatial analyses, SUTVA is violated because of spatial dependence and heterogeneity. First, spatial interactions between proximal units (i.e., spatial dependence) violate the independence of units assumption. Second, because of the typical spatial variation in the spatial distribution of a phenomenon in a geographical area (i.e., measured intensity), the phenomenon must be considered location by location as a different version of treatment. Such spatial heterogeneity violates the single version of the treatment assumption.

Violation of SUTVA is among the main challenges to spatial causal inference, at least Rubin's causal model. The direct applicability of causal inference methods developed for non-spatial data on data about spatial processes is challenging. Despite an increased interest in using causal inference methods in the spatial domain, a systematic literature review on this topic is rare. There is only one recent literature review paper (B. J. Reich et al. 2020) on the spatial causal inference methods focused on the epidemiological and environmental domains.

It is the aim of our systematic literature review to not only assess and identify the different challenges of spatial causal inference for researchers broadly, but also assist these researchers with the application of spatial causal inference to their work, both through a deepened understanding of causal analysis and through pointers to the available methods and their applicability in spatial analysis.

In this study we contribute:

[1] A unit is the primary object of a study. Units can be persons or spatial regions (Holland 1986; Rubin 1974)

1. An overview of applications of causal inference analysis in spatial processes;
2. Extract and systematise methods applied in recent case studies;
3. Identify challenges experienced in these studies;
4. Identify opportunities for future works to do logical and theoretical developments in spatial causal inference.

2 Theoretical Development of Causal Inference

Most of the motivational research questions in science are causal, rather than associational (Pearl 2009). For example, *What is the effect of industry growth on the urban environment?*, *What are the effects of increasing the tax on house price?*, or *What is the effect of climate change on bushfires?* are causal questions that cannot be answered without knowledge about the data generating process and be answered based on the data alone and the distribution functions. Associational questions can be investigated by statistical analysis, but causal questions cannot be answered only by standard statistical methods and tools (Pearl 2009).

Causal analysis looks beyond association and infers not only the relationships under static conditions, but also the dynamic relationships, with changes in associations affected by external interventions or treatments (Pearl 2009). Despite these fundamental differences, the terms *association*, *correlation* and *causation* are often incorrectly used synonymously. Association (or dependence) indicates a general relationship between two variables, where one of them provides some information about another. Meanwhile, correlation refers to a specific kind of association and captures information about the increasing or decreasing trends (whether linear or non-linear) of associated variables (Altman and Krzywinski 2015). Causation refers to a stronger relationship between two associated variables, where the *cause variable "is partly responsible for the effect, and the effect is partly dependent on the* *cause"* (Yao et al. 2020, p. 1).

Requirements of using untested assumptions (such as independency of covariates and treatment to control confounding bias) and new notations for explaining causal relationships are two main differences between causation and association (Pearl 2009). Notations of probability alone cannot encode causal relationships. The ability to analyse the response of the effect variable by changing the cause variable can be a significant difference between "causal inference" and "inference of correlation" (Pearl 2009). For example, suppose a policymaker who only examines the correlational relationship between variables of the degree of respect to the rules and the number of infected people during the COVID-19 pandemic in a low-income country. This correlational view can lead to the wrong inferences and unsuitable policies, while a deeper analysis of the causal factors beyond correlational relationships may identify the country's economic situation as the leading cause for the high infection rate. This example illustrates how policy- and decision-makers should evaluate deeper causal relationships beyond mere correlations to understand society better and improve governance.

2.1 Experimental and Quasi-experimental Studies

While the identification of causal relationships appears trivial, this is not so in most situations and, we usually can not directly manipulate the magnitude of causal variables to explore their effects. Experimental randomised control trials (RCTs) are the most effective way to provide consistent and unbiased controls of causes to isolate their effects. Unfortunately, well-designed RCTs are costly in time, resources, and effort (Farmer et al. 2018; Sorensen et al. 2006; Yao et al. 2020). RCTs have significant limitations, such as enabling the assessment of only a limited number of subjects per experiment, focusing on the average of samples rather than individualised effects on subjects, and ethical limitations to many trials (e.g., assessing the effects of physical ment on students' learning skills) (Yao et al. 2020). These restrictions limit the applications of RCTs. Alternative methods are needed to compensate for these constraints.

Currently, causal inference on large observational data instead of RCTs has become an area of interest, motivated by the growing amounts of available data (i.e., the lower budget requirements). Such observational studies are assumed to be faster, cheaper, and with less limitations on the number of evaluated treatments (Hernán et al. 2013; Sorensen et al. 2006; Yao et al. 2020). Causal inference in observational data is, however, challenging because we cannot expose units to treatments randomly (Shadish et al. 2002; Stuart and Rubin 2008). The quasi-experimental study design is a suitable method for causal inference analysis in observational data without randomisation (Bärnighausen et al. 2017; Kim and Steiner 2016), in particular when randomisation is impractical or unethical. For example, we cannot use RCTs to measure the effect of building a shopping centre or a metro station on people's quality of life at a specific time and location, because the treatment assignments (the building site presence) are not randomised and controlled in these studies. This means that we cannot randomly assign the regions to a group that is exposed to the effect and another that is not. Analysing such observational data with quasi-experimental methods is the best available alternative. While quasi-experimental frameworks are applicable in the absence of randomisation, the estimation of causal impacts on effect variables may be contaminated by confounders (Atwater and Babaria 2001; Dinardo 2010; Shadish et al. 2002). Various causal effect estimation methods for observational data based on machine learning methods are now rapidly emerging. While there are a few attempts to apply these techniques to geographical analyses (Delgado and Florax 2015; Dubé et al. 2014; Freni-Sterrantino et al. 2019), the methodological foundations for spatial causal inference are only in their infancy.

2.2 Conceptual Perspective on Spatial Causal Inference

2.2.1 Spatial Processes

Spatial causal inference improves our insights into spatial processes by supporting better understanding of the resulting data generation processes. The explanations of the cause of environmental spatial patterns are descriptions of spatial processes (Anselin et al. 2008), i.e., processes that are dependent on location in the space (Hofer and Frank 2008). Mathematically, a spatial process is a set of random variables $\{X\}_{i\in S}$ over S as a subset of locations in the d-dimensional Euclidean space R_d. X_i is then a random variable measured at location i (Kroese and Botev 2015). For each space S, we define a multivariate causal inference process that is a collection of processes for effective variables. For example, we can imagine $\{MSP\}_{i\in S}$ as a multivariate spatial process in S (Figure 1) that is made of four processes including $\{T\}_{i\in S}$, $\{X\}_{i\in S}$, $\{\epsilon\}_{i\in S}$, $\{Y\}_{i\in S}$ as treatment variable, covariates, error term, and outcomes, respectively. Each of these processes can be spatial or non-spatial.

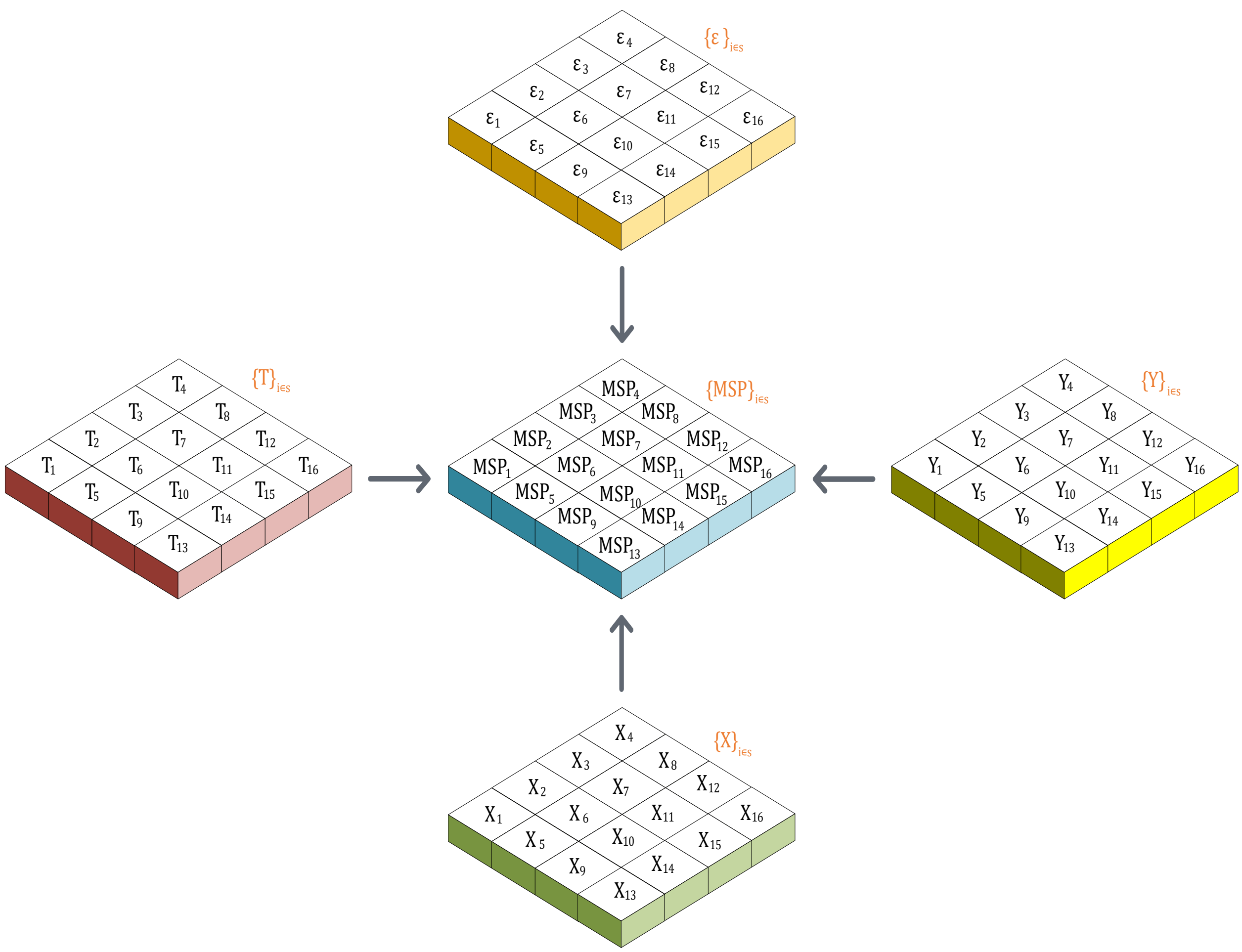

Figure 1: Multivariate Spatial Processes.

2.2.2 Spatial Causal Inference

In spatial causal inference, we study spatially located units affected by a defined treatment. These units can be any spatial objects, e.g., individual people (Nakano et al. 2018), pixels, cities or countries (Bardaka et al. 2018; Comber and Arribas-Bel 2017; Tranos 2012). Figure 2 shows three spatial units (i, j and k) with spatial interactions. T indicates whether a unit was treated ($T = 1$) or untreated ($T = 0$). Based on the 'First law of geography', "everything is related to everything else, but near things are more related than distant things"(Tobler 1970), these spatial units are likely interacting, with the interaction being lower the further apart they are. The nature of these interactions is contingent on the spatial dependence structure (Figure 3). Spatial interactions can have influences on the observed outcomes for each unit, because of the individual spatial lag or spatial error effects, or potentially because of the coexistence of both effects. In causal inference, one of the main goals is quantifying the treatment effects on the treated units. In spatial processes, untreated neighbour units will be indirectly affected by the treatment because of spatial spillover effects (see the violation of SUTVA noted earlier). To capture the portion of pure effects, these indirect effects must be assessed and, if possible, filtered. These indirect effects are the major difference between causal inference in non-spatial and spatial settings.

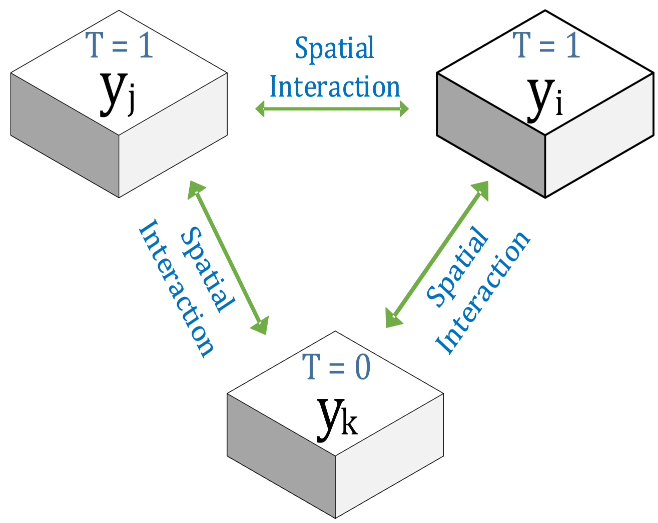

Figure 2: Spatial interactions among treated and untreated spatial units.

2.2.3 Spatial Dependence Structures

Figure 3 depicts the common dependence structures in spatial processes, including Spatial Lag (1), Spatial Error (2), Spatially-Lagged X Model (3) and Spatial Durbin Model (4). When causal inference is implemented on a spatial process, the structure of the spatial process should be considered because of these distinct indirect effects in the processes that can affect the results of the treatment effect analysis.

Spatial Lag is a type of spatial dependence structures (Figure 3(1)) (Anselin 1988), which includes interactions among the value of outcomes, where the value of a unit's outcome is spatially dependent on the neighbour units. In addition to direct causal effects, indirect effects of neighbours from both treated and control groups must be considered in this type of spatial dependence.

Spatial error models include interactions among units with spatial dependence in the error terms that can be caused by an omitted variable (Anselin 1988). This type of interactions can impact the outcomes of neighbouring units and lead to a biased effect measurement. As shown in Figure 3(2), there is an interaction among error terms of treated and untreated units (ϵ_i, ϵ_j, ϵ_k), and because of their roles in measuring the outcomes (y_i, y_j, y_k), these errors can have impacts on the measuring of the effect of a treatment.

Spatially-Lagged X Model (SLX) (Golgher and Voss 2016) is the third type of spatial dependence structures (Figure 3(3)). It includes spatial interactions in covariates without any spatial interactions among errors or outcomes. In this spatial dependence structure, one or more covariates (X_i, X_j, X_k) of the treated and control groups' units are spatially correlated and impact on outcomes (y_i, y_j, y_k).

The last type of common spatial dependence structures is the Spatial Durbin Model (SDM) (Anselin 1988; Elhorst 2010; Golgher and Voss 2016). This structure (Figure 3(4)) is the most complicated, with spatial interactions between covariates (X_i, X_j, X_k) and outcomes (y_i, y_j, y_k). The outcome for each unit is affected by the two types of spatial interactions and may lead to wrong effect measurements and incorrect causal inferences. In addition, there are some other spatial models such as Spatial Durbin Error Model (SDEM) and Kelejian-Prucha model (SAC) (Elhorst 2010; Golgher and Voss 2016) which are combinations of some of the above mentioned spatial models.

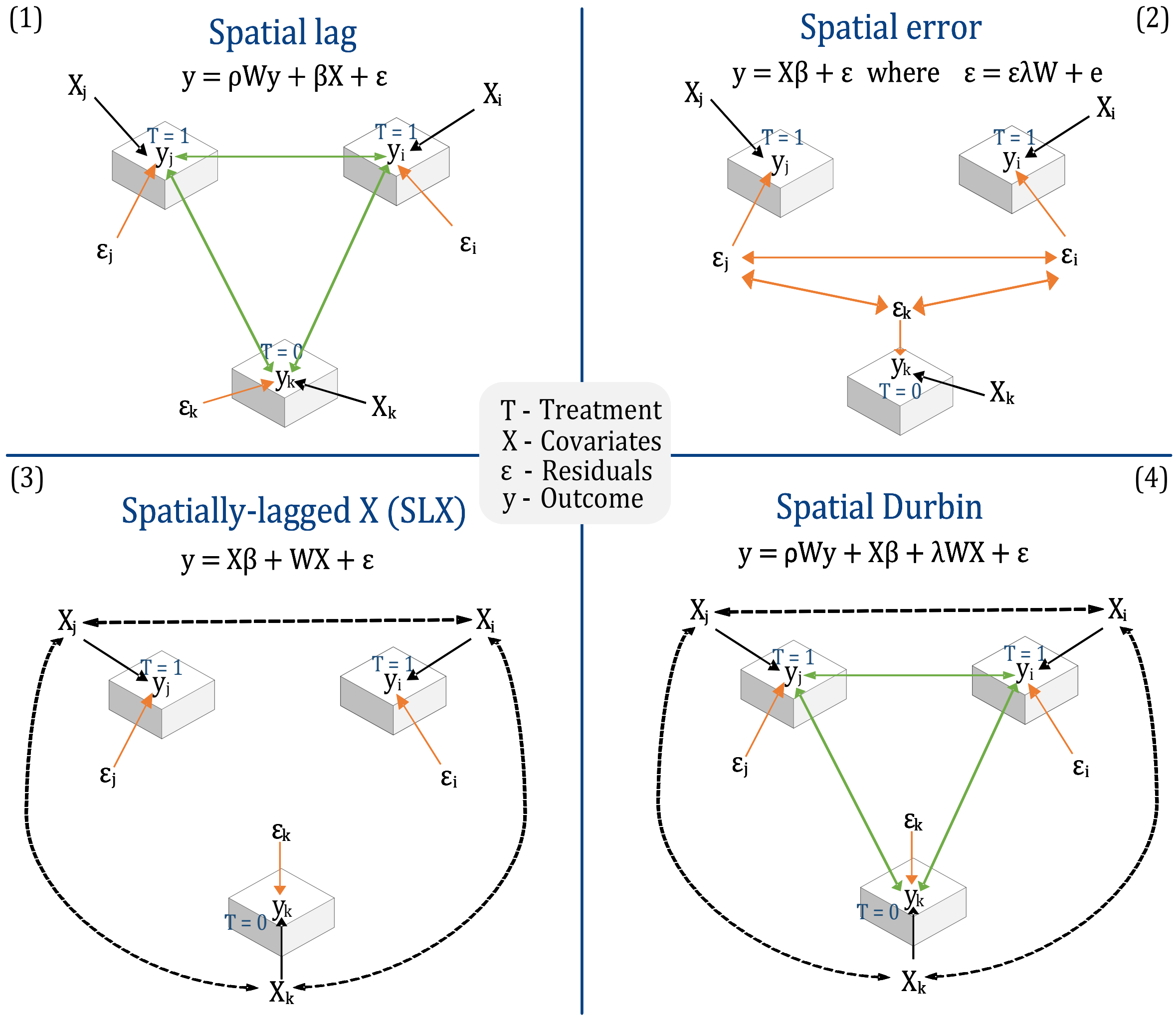

Figure 3: Various types of spatial dependence structures adapted from (Elhorst 2010; Golgher and Voss 2016); T - treatment, ϵ - error term, x - covariates, y - outcome variable, e - random error term.

2.2.4 Structure of Spatial Causal Inference Problems

We categorize causal inference processes into sixteen types by studying the combinations of the fundamental spatial or non-spatial characteristic of the treatment, covariates, error terms, and outcomes (Table 1). The adjectives *spatial* and *non-spatial* can here be interpreted as a short-hand for *spatially varying or not*. In non-spatial treatment, the process of treatment assignment acts as an independent random process (IRP) or complete spatial randomness (CSR) (O'Sullivan and Unwin 2014). The IRP or CSR process of treatment assignment assumes two main conditions: the equal probability of being treated for each unit and independence of event of treatment for each unit from occurring treatment in other units. A non-spatial treatment does not mean that it does not have a spatial footprint, but merely it is allocated to units as a CSR and there is no clustering in spatial distribution of treated units. The same applies to covariates, errors, and outcomes.

In causal inference, we assess the effects of treatment variables ($\{T\}_{i \in S}$) on the outcome variables, where treatments should be assigned randomly to the units of analysis. However, when treatments impact spatially proximal units in a spatial process, these effects may not be apparent directly when measuring causal effects (Geisler and Nichols 2016; Gobillon and Magnac 2016). If treatments are assigned spatially, we end up with causal inference processes such as SSSS, SSSN, SNNN, SSNN, SSNS, SNSS, SNNS, and SNSN, and obtain biased results in our multivariate spatial process (Table 1). Figure 4 shows a spatially correlated treatment assignment.

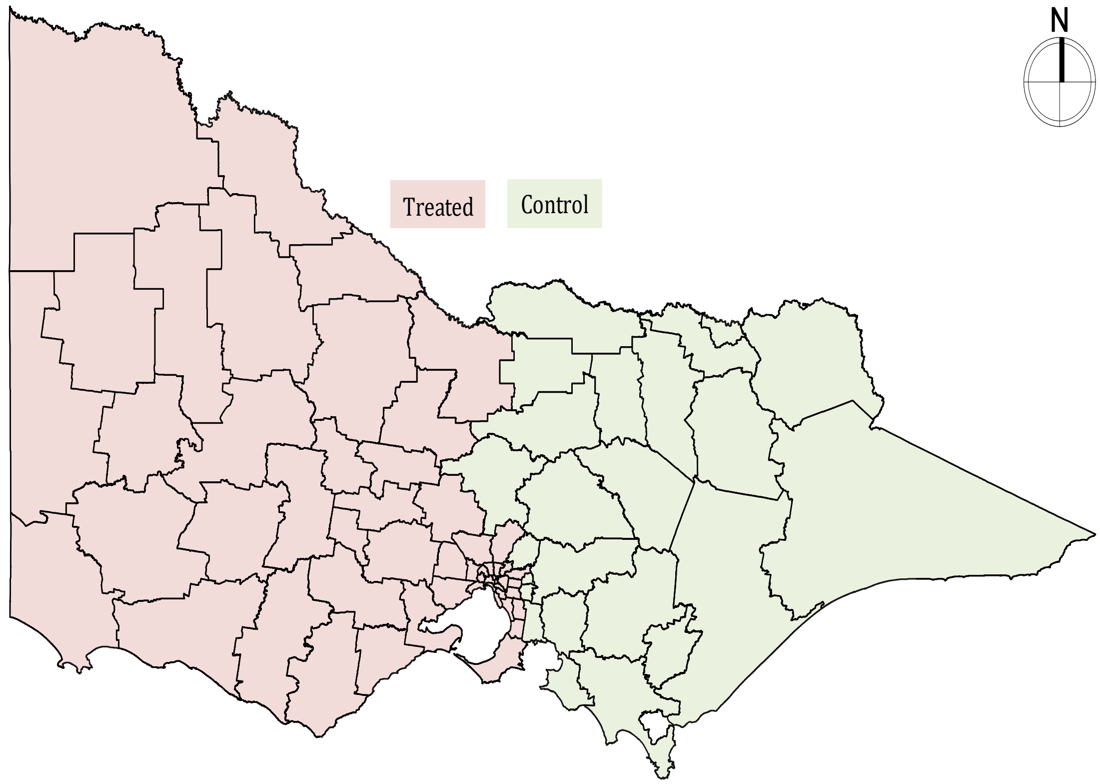

Figure 4: Spatially assigned treatment.

In a spatial process, treatments can be spatially lagged and affect outcomes, i.e., as in the SLX model (Halleck Vega and Elhorst 2015; Kolak and Anselin 2020). This type of spatial dependence between the treatment variables, covariates, error terms and outcomes can act as indirect treatment for control units, and thus can be the source of indirect effects (Y. Chen et al. 2016; Delgado and Florax 2015; Geisler and Nichols 2016; Maas and Watson 2018; Nakano et al. 2018). Consider Figure 5, with two groups of spatial regions (control and treated). Some of the control regions, such as region k, have neighbours from the treated group, and are affected by these neighbours because of a spatial dependence structure. Conversely, some controlled regions may not have such treated neighbours (e.g., region v). These may be affected indirectly (second-order influence), by other neighbours that have been in turn directly affected by treated neighbours. Indirect effects are challenging to handle in causal inference analysis of spatial processes because they complicate the isolation and measurement of real effects of treatments on the processes.

On the other side, in causal inference processes where the treatment assignment is non-spatial (NSSS, NSSN, NNNN, NSNN, NSNS, NNSS, NNNS, and NNSN) (Table 1), spatial influence entailed by the spatial dependence structure will be removed. Researchers studied two types of treatments in their studies. For example, planned cross-rail terminals (Comber and Arribas-Bel 2017), bus rapid transit (D'Elia et al. 2020), and a policy of alcohol drinking age are spatially assigned treatments (Kolak and Anselin 2020), while riverboat casino gambling is assumed as a randomly and non-spatially assigned treatment (Geisler and Nichols 2016). To have an unbiased analysis, they assumed the treated and control groups' members were assigned randomly, and the results of Moran's I (approximately 0) confirmed this assumption. Similarly to treatments, the outcome variables, covariates, and error terms can all be spatially dependent, and each of them can influence the quantification of causal effects of treatment in a spatial process (Bardaka et al. 2018; Geisler and Nichols 2016; Maas and Watson 2018; Tan et al. 2019).

Outcomes of a multivariate spatial process $\{MSP\}_{i \in S}$ can also be spatially varied and thus be modelled by Spatial Lag, Spatial Error, SLX or SDM, based on their spatial dependence structures. For example, Bardaka et al. (2018) assessed the effects of urban rail investments on the level of gentrification in Denver's neighbourhood. They employed a panel data estimator with spatial error components for accounting for heterogeneity and spatial dependence. In addition to the spatial dependence among treatment and outcome variables of units in cross-sectional data, causal inference may target processes of type NSNN with spatially varied explanatory variables and with impacts on measured treatment's effects (Geisler and Nichols 2016; Graham et al. 2016). Finding examples for all the probable causal inference processes is difficult. We hypothesize that the noted combinations of qualities of processes on which causal inference may be undertaken (Table 1) all exist in the real world, thus providing a full picture of possible combinations that need to be methodologically addressed. We thus consider the resulting spatial dependence structures from these processes in our discussion.

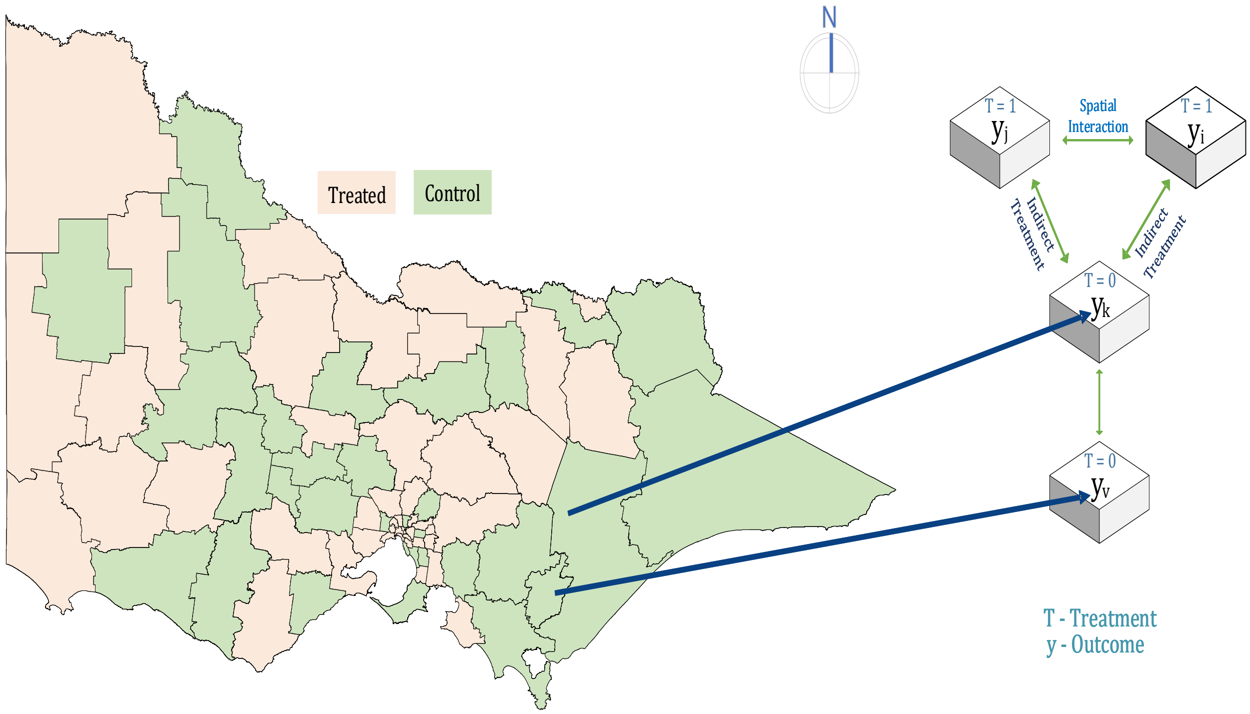

Figure 5: Schema of indirect effects: T - treatment, y - outcome variable.

As discussed, those four types of spatial interdependence in treatment, explanatory variables, error terms, and outcome variables lead to systematic spatial biases, inaccurate measurements of causal effects and finally wrong inferences in studies applying causal inference on spatial processes.

Table 1: Types of processes for causal inference analysis.

Treatment	**Covariates**	**Error terms**	**Outcome**	**Causal Inference Process**
Spatial	Spatial	Spatial	Spatial	SSSS(S4)
Spatial	Spatial	Spatial	Non-Spatial	SSSN(S3N)
Spatial	Non-Spatial	Spatial	Spatial	SNSS
Spatial	Non-Spatial	Spatial	Non-Spatial	SNSN
Spatial	Spatial	Non-Spatial	Spatial	SSNS
Spatial	Spatial	Non-Spatial	Non-Spatial	SSNN
Spatial	Non-Spatial	Non-Spatial	Spatial	SNNS
Spatial	Non-Spatial	Non-Spatial	Non-Spatial	SNNN(SN3)
Non-Spatial	Spatial	Spatial	Spatial	NSSS(NS3)
Non-Spatial	Spatial	Spatial	Non-Spatial	NSSN
Non-Spatial	Non-Spatial	Spatial	Spatial	NNSS
Non-Spatial	Non-Spatial	Spatial	Non-Spatial	NNSN
Non-Spatial	Spatial	Non-Spatial	Spatial	NSNS
Non-Spatial	Spatial	Non-Spatial	Non-Spatial	NSNN
Non-Spatial	Non-Spatial	Non-Spatial	Spatial	NNNS(N3S)
Non-Spatial	Non-Spatial	Non-Spatial	Non-Spatial	NNNN(N4)

3 Material and Method

This research follows the method by Okoli and Schabram (2010) for a systematic literature review, structured along four main methodological steps: Planning, Selection, Extraction, and Execution. Figure 6 shows the structure of this study.

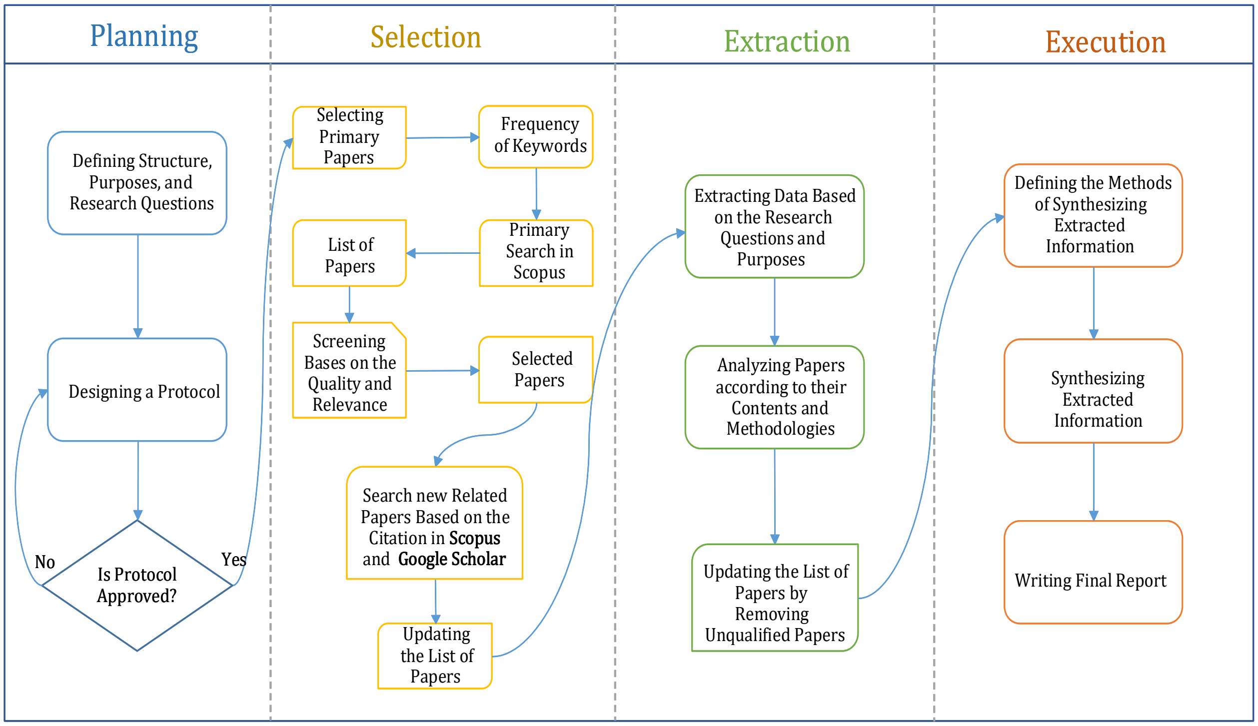

Figure 6: Methodology of study.

Twenty-three seed papers were selected at the beginning of the planning phase based on their relevance to the causal inference in spatial processes. Based on the 23 primary documents, a text mining process was used to extract the most frequent sets of monograms and bigrams from the whole parts of papers. We then manually selected a combination of monogram and bigram keywords (Table 2) to search for relevant papers in the Scopus database. This led to the identification of 490 papers, which were then screened by assessing the title, abstract and contents (in this order) to recognise related investigations for in-depth review. This checking resulted in 159 papers subjected to a detailed eligibility analysis. This detailed check examined if the papers meet the following criteria: (1) the paper used causal inference in a spatially related context; (2) the paper investigated the challenges and solutions for causal inference analysis in the spatial domain; and (3) the paper applied models/techniques to investigate the causal relationships and effects among spatio-temporal factors. The detailed assessment resulted in 66 eligible papers for final review.

Table 2: Criteria applied to choose publications for analysis in this study.

Search Query	("spatial correlation" OR "spatial effects" OR "spatial dependence" OR "spatial autocorrelation" OR "spatial observational data") AND ("causal inference" OR "causal effect" OR "causal impact")
Document Type	Journal articles, Conference proceeding paper
Language	English
Publication Date Range	January 2000-27 September 2020

4 Results

4.1 Application Disciplines Covered by the Selected Studies

The literature review captures a broad range of application disciplines. As shown in Figure 7, almost 34 % of studies focused on economic issues, followed by ecological investigations with 23 %. Moreover, these two categories make up more than half of all papers. In stark contrast, the least represented studies were those from the disciplines of political science and energy (both 2 %). Furthermore, transportation, environmental, health and criminology are the other categories with 18 %, 13 %, 5 %, and 3 % respectively.

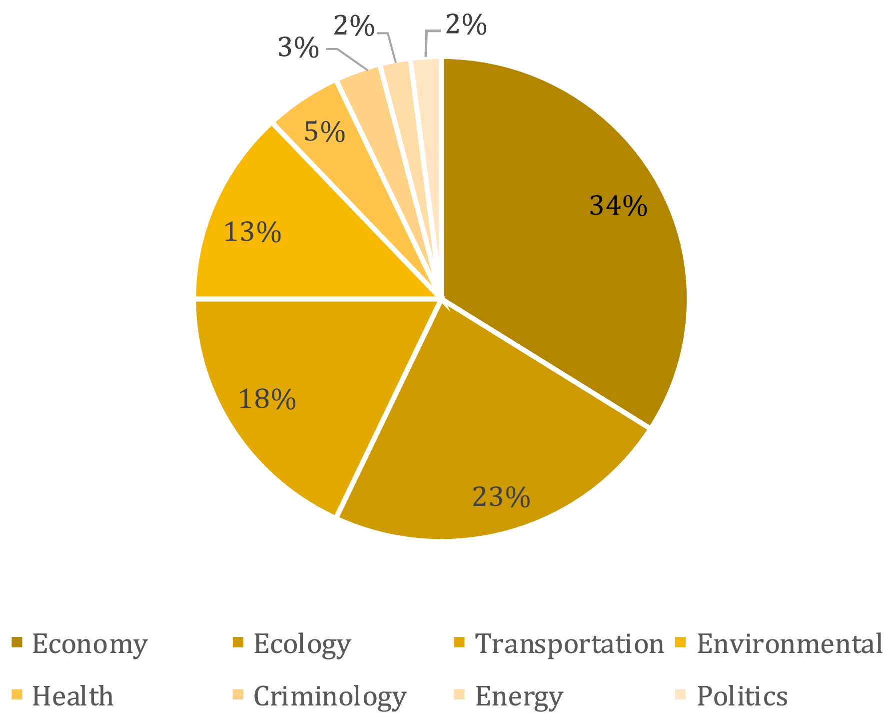

Figure 7: General information of selected documents.

4.2 Causal Inference Models used for Spatial Observational Data

We have identified four main causal models used to analyse the observational data captured by the systematic literature review process. These are the Potential Outcome Framework (Rubin Causal Model) (Rubin 1974; Splawa-Neyman et al. 1990), the Structural Causal Model (Pearl 1995; Pearl 2009; Pearl 2014), Granger Causality (C. W. J. Granger 1969; C. W. Granger 1980), and the Empirical Dynamic Modelling framework (Chang et al. 2017; Deyle, Maher, et al. 2016; Grziwotz et al. 2018; Ye et al. 2015). Table 3 maps the different causal frameworks used to assess causal relationships to the respective papers in this literature review. The Potential Outcome Framework was the main type of causal models in the selected studies (Table 3), used in about 56 % of the reviewed studies, followed by the Structural Causal Model (27 %) and Granger Causality (6 %). The portions do not sum to 100 % because each research may apply various causal inference models or because some papers do not uniquely identify the used causal model(e.g., review papers).

Table 3: Reviewed literature categorised by type of causal model used.

Causal Model	Literature	Proportion
Potential Outcome Framework (Rubin Causal Model)	Aliaga et al. (2011), Arpino, Mattei, et al. (2016), Bardaka et al. (2018), Bardaka et al. (2019), Brachert et al. (2019), Cai et al. (2020), Y. Chen et al. (2016), Comber and Arribas-Bel (2017), Dai et al. (2020), D'Arcangelo and Percoco (2015), Delgado and Florax (2015), D'Elia et al. (2020), Deng et al. (2011), Donner and Loh (2019), Eum et al. (2019), Geisler and Nichols (2016), Giudice et al. (2019), Gobillon and Magnac (2016), Hüttel et al. (2014), Karamba and Winters (2015), Kolak and Anselin (2020), H. Li, Graham, et al. (2019), H. Li, Zhu, et al. (2020), Linke et al. (2015), Maas and Watson (2018), Marcos-Martinez et al. (2019), Meldrum (2016), Mueller et al. (2018), Nakano et al. (2018), Ning et al. (2019), Oakley and Tsao (2007), Paiva et al. (2015), Pirani et al. (2020), Ramboer and Reynaerts (2020), Schleicher et al. (2020), Tan et al. (2019), Wolff et al. (2014), Yadavalli and Landers (2017), Zhang et al. (2019), and L. Zhao et al. (2020)	56.06 %
Structural Causal Model (Pearl Causal model, Structural equation models, Path analysis)	Becker et al. (2012), Betz et al. (2018), Bilgel (2019), Biswas et al. (2015), Bovendorp et al. (2019), Cho et al. (2012), Craven et al. (2020), Duarte et al. (2009), Gouveia et al. (2014), Hatami (2018), Hohberg et al. (2020), Houle (2005), Kırdar and Saracoğlu (2008), Knick et al. (2017), L. Li et al. (2015), Olivier and Van Aarde (2017), Qian et al. (2009), Rompré et al. (2007), and Toranza and Arim (2010)	27.28 %
Granger Causality	Adedoyin and Bekun (2020), Cattaneo et al. (2016), Graham et al. (2013), L. Li et al. (2015), and Tranos (2012)	06.06 %
Empirical Dynamic Modelling	Z. Chen et al. (2018)	01.51 %

4.2.1 Potential Outcome Framework (Rubin Causal Model)

The Rubin Causal Model (RCM) was developed based on a series of studies by Neyman (Splawa-Neyman et al. 1990), Rubin (Rubin 1974; Rubin 1977; Rubin 1978; Rubin 2006), and Holland (Holland 1986; Holland and Rubin 1987). Therefore, RCM is sometimes called the Neyman-Rubin causal model or the Neyman-Rubin-Holland model. In this model, each individual unit has two potential states: whether it is *under treatment*, or with *no treatment* (Holland 1986; Rubin 1974; Rubin 2006). In RCM, the degree of a causal effect is the difference between the value of outcomes in two states: under treatment, and without treatment.

RCM has two essential parts: the *potential outcomes*, for defining causal effects, and the *assignment mechanism* for assigning a treatment to a unit. We can imagine a population of n units (e.g., individuals), each belonging to one of the *treatment* or *control* (i.e., *no treatment*) groups. If T_i is a random variable of treatment, T_i=1 and T_i=0 are the states assignable to the ith individual, defining their membership in the treatment or control groups. Each unit then has two potential outcomes, $Y_i(T_i)$ ($Y_i(1)$ or $Y_i(0)$). $Y_i(1)$ refers to the outcome when an individual is assigned to the treatment group, and $Y_i(0)$ refers the outcome when an unit is assigned to the control group. The observed data for the ith unit are a pair of (T_i, Y_i) values. Equation 1 captures the potential outcome for each unit:

$$Y_i^{obs} = T_i Y_i(1) + (1 - T_i) Y_i(0) = \begin{cases} Y_i^{obs}(0), & \text{if } T_i = 0 \\ Y_i^{obs}(1), & \text{if } T_i = 1 \end{cases} \tag{1}$$

The degree of effect of a treatment on a unit is therefore equal to $Y_i(1)$ - $Y_i(0)$. Each unit can, generally, belong to only one group at a time, and we can only observe one of the possible outcomes, $Y_i(1)$ or $Y_i(0)$. Thus we cannot measure the treatment effect on unit i directly. This issue is called the fundamental problem of causal inference by Holland (Holland 1986). There are some solutions to overcome this fundamental problem of causal inference, either estimating the average treatment effect on a unit (ATE, Equation 2, E is expected value).

$$ATE = E\{Y_i(1)\} - E\{Y_i(0)\}; \tag{2}$$

Or by defining fundamental assumptions such as SUTVA, Ignorability, and Positivity.

Integration of the Ignorability and the Positivity assumptions is known as Strong Ignorability or Strongly Ignorable Treatment Assignment (Imbens and Rubin 2015; Rosenbaum and Rubin 1983; Rubin 1978). Based on a Positivity assumption each unit has a positive probability for getting the treatment. Ignorability refers to the no unmeasured confounder and no selection bias. For example, suppose the government choose regions with a strong economic situation as a treated group to assess the effects of a tax reduction policy on the improving economic situation and other regions as a control group. In that case, this analysis will have selection bias, and the Ignorability assumption will be violated. In this case, the treatment assignment (tax policy) will lead to better outcomes because tax reduction policy will cause improvements in the economic situation of treated regions. Then treatment assignment will not be independent of outcomes. This assumption can be explained as below:

$Y_i(1)$, $Y_i(0) \perp\!\!\!\perp T \mid C$, where T and C refer to treatment and observed confounder variables respectively.

In RCM for spatial processes, the most critical challenge stems from the violation of SUTVA because of spatial spillover effects. If unaccounted for, this violation can lead to biased estimates. To mitigate the impact of such indirect effects, researchers utilised a number of strategies. For example, Arpino, Mattei, et al. (2016) conducted the analysis at the minimum aggregate level where there is no interference between units, thus achieving that SUTVA was plausible. This solution requires a transformation of observational data to a suitable aggregated level and a subsequent estimation of the treatment effects at a coarser (macro) level (Kolak and Anselin 2020). In other studies, researchers managed SUTVA by measuring direct and indirect effects separately (Bardaka et al. 2019; Delgado and Florax 2015; Zhang et al. 2019). When applying RCM, researchers should explicitly consider indirect causal effects in spatial processes because of the effects of treated neighbour units on the untreated units.

4.2.2 Structural Causal Model

Structural Causal Models (SCMs) (e.g., Pearl Causal Model, Structural Equation Model (SEM), and Path Analysis) (Table 3) are based on explicit causal graphs and structural equations capturing causal relationships in a process (Yao et al. 2020). Path analysis assesses the processes with effect on an outcome and uses multiple-regression analysis to measure the strength of causal relationships in such a causal system (Lleras 2004; Scheiner et al. 2000). For example, Olivier and Van Aarde (2017) used path analysis to recognise the direct and indirect influences of characteristics of a forest on species diversity. Also, path analysis and SEM were used by researchers for assessing the causal relationships in spatial processes (Betz et al. 2018; Biswas et al. 2015; Duarte et al. 2009; Gouveia et al. 2014; Houle 2005; Toranza and Arim 2010). The Pearl Causal Model is based on his work on Directed Acyclic Graphs (DAGs). DAG analysis is similar to path analysis where path analysis is the antecedent of the DAG (Imbens 2020; P. Wright 1928; S. Wright 1934); DAG can be a powerful approach of demonstrating causal relationships (Imbens 2020). Bilgel (2019) used DAGs for causal reasoning between gun policy and crime rate in different counties of the United States. Cho et al. (2012) showed that DAG analysis is a suitable method for variable selection and improving the performance of a hedonic model when multicollinearity arise amongst numerous explanatory variables. SCMs are suitable models for exploring causal relationships and help researchers get a clear insight into data generation processes in their analyses; these models also are applicable for extracting direct and indirect effects in the causal processes.

4.2.3 Granger Causality

Granger Causality (GC) has been developed for analysing the flow of information and causal effects between two variables in a time series (C. W. J. Granger 1969; Stokes and Purdon 2017), and was developed specifically for econometric time series analysis. In this model of causality, the first time series (X_i, t) is called the cause of the effect time series (Y_i, t), if (1) (X_i, t) happens *before* the effect time series and (2) the knowledge of the cause time series improves the prediction of the values in the effect time series. In this situation, using the history of (X_i, t) in addition to the history of (Y_i, t) helps to predict the value of (Y_i, t) better than predictions based on the history of (Y_i, t) alone. This then proves that (X_i, t) causes (Y_i, t), and any knowledge about (X_i, t) can help to predict some knowledge about (Y_i, t) (C. W. J. Granger 1969; C. W. Granger 1980). The mathematical structure of Granger causality is based on two equations (Equation 3 and 4):

$$y_t = \sum_{t=1}^{L} \alpha_i y_{t-i} + \epsilon_{t,1} \tag{3}$$

$$y_t = \sum_{t=1}^{L} \alpha_i y_{t-i} + \sum_{t=1}^{L} b_i x_{t-i} + \epsilon_{t,2} \tag{4}$$

Where L is the maximal lag for x_t and y_t; $\epsilon_{t,1}$ and $\epsilon_{t,2}$ are the error terms of two mentioned regressions of (Y_i, t) on (X_i, t) at time t; α_i and b_i are the regression coefficients for y and x respectively. To assess the magnitude of influence of the cause x on the prediction of effect y, a number of tests have been proposed, such as the Granger-Wald test (L. Li et al. 2015) and the Dumitrescu–Hurlin test (Dumitrescu and Hurlin 2012). While GC is a powerful method for assessing the direction of causal relationships, its most important challenge is the limitation restricting the application to the analysis of a causal relationship only between two variables (Tranos 2012). Cattaneo et al. (2016) used a GC test for panel data to explore the direction of the causal relationship between the flow of students (dependent variable) and air transport services as an independent variable. Another application of GC in spatial processes is the identification of causal relationships between variables for better prediction of dependent variables. L. Li et al. (2015) used Granger causality to find the most relevant dimensions for having better prediction of traffic flow.

4.2.4 Empirical Dynamic Modelling

Empirical Dynamic Modelling (EDM) is an emerging paradigm that can differentiate between correlation and causality, and can be useful for decision-makers in distinct fields, thus far primarily explored in environmental assessment and epidemiology. EDM is a causal model for nonlinear processes that Granger Causality cannot assess. It is well possible that a number of studies led to spurious results due to the application of linear correlation analyses. Yet, either a non-linear dependence that can not be revealed by correlation may exist between causes and effects, or, vice-versa, correlations that are not due to causal factors may be detected. This is the case of nonlinear and dynamic intrinsic processes. The later case, *mirage correlation*, is a challenging issue when linear methods are applied in time series that are generated from such nonlinear processes, which may lead to wrong inferences (Deyle, Fogarty, et al. 2013; Deyle, Maher, et al. 2016; Sugihara et al. 2012). This is the case addressed by EDM. Mirage correlation is a result of state dependency as a feature of nonlinear dynamical systems (Sugihara et al. 2012; Ye et al. 2015). State dependency refers to the change in the relationships among interacting variables in the various states of a dynamical process (Chang et al. 2017; Grziwotz et al. 2018; Sugihara et al. 2012). Nonlinear statistical methods have been developed for mitigating the state dependency in dynamical systems, which are based on the state space reconstruction. EDM has various applications including (1) assessing the complexity of systems, (2) discerning nonlinear dynamical systems form linear stochastic systems, (3) exploring causal variables, (4) predicting of outcomes, (5) depicting the robustness and sign of a relationship, (6) investigating the scene of the external disorder (Chang et al. 2017). EDM is useful in assessing dynamic systems with weak causal connections, in contrast to the Granger Causality paradigm (Sugihara et al. 2012). For example, Z. Chen et al. (2018) used EDM to discover causal relationships between different meteorological factors and avoid biased nonlinear and complicated interactions between individual factors.

4.3 Challenges for Causal Inference in Spatial Processes

In this section, we investigate how the reviewed papers mitigated the particular spatial data challenges impacting on the applicability of the causal inference frameworks reviewed earlier.

4.3.1 Spatial Spillover Effect

The spatial spillover effect (indirect effect) is one of the most important challenges in spatial causal inference because of interference between units and the violation of fundamental assumptions of causal frameworks, e.g., SUTVA (Bardaka et al. 2018; Kolak and Anselin 2020). Spatial models (Figure 3) such as Spatial Lag, SLX, and SDM cannot be interpreted as simple regression (Equation 5) because of spatial dependence between dependent variables or other covariates (Golgher and Voss 2016). In a simple regression, we have only a simple relationship between y and X.

$$y = \beta X + \epsilon \tag{5}$$

While the respective equations for the Spatial Lag (Equation 6), SLX (Equation 7), and SDM (Equation 8) models are:

$$y = \rho W y + \beta X + \epsilon \tag{6}$$

$$y = \gamma W X + \beta X + \epsilon \tag{7}$$

$$y = \rho W y + \gamma W X + \beta X + \epsilon \tag{8}$$

In these equations of spatial models, we can see some weighted elements as spillover effects sources (blue parts of equations). For the Spatial Lag, the spillover is caused by the dependent variable, while in the SLX, the spatially dependent covariates are the source of the spillover effect. Also, there are two sources of spillover effects, the dependent variable and the spatially dependent covariates, for SDM simultaneously.

In some studies, units are assumed fully mutually independent, without any interference between them. This assumption simplifies analyses significantly and makes it easier to estimate causal effects (Imbens 2020). Yet, spatial spillover effects violate SUTVA because of spatial interactions and interferences between units in a spatial process. Therefore, the results of such causal analyses under the violation of SUTVA will be biased, inconsistent, and depending on the strengths of the spillover effects, wrong.

The existence of spatial interactions and interferences therefore requires new strategies to account for direct and indirect spillover effects. Increasingly, studies investigate means to relax some of the strong assumptions of casual inference, such as SUTVA. For instance, Delgado and Florax (2015) provided a method for quantifying causal effects under spatial interactions between spatial units. The proposed method could measure direct and indirect causal effects under relaxed SUTVA by explicitly modelling indirect effects. They considered the effects of treated units as indirect effects on the control units and measured the ATE based on the spatial lag model.

Giffin, B. Reich, et al. (2020) proposed a method based on a generalized propensity score for dealing with direct and indirect (spillover) effects for the spatial processes. They applied a Bayesian spline-based regression to reduce the problem's dimensions and provide enough variables for the generalized propensity score. This method is dependent on both the well-defined propensity score and the potential outcomes model. Transforming observational data from a fine-grained level to the minimum aggregation where SUTVA will be relaxed is a common strategy to avoid spillover effects (Arpino, Mattei, et al. 2016; Gangl 2010; Imbens and Rubin 2015; Kolak and Anselin 2020; Moffitt 2005; Morgan and Winship 2015; Smith 2003). However, with this strategy, parts of information related to the actual effect will be lost because of measuring treatment effects at an integrated level only, which may reduce the utility of the findings to policy and decision-makers (Kolak and Anselin 2020).

4.3.2 Spatial Heterogeneity

A significant issue with the application of standard causal inference methods is related to the spatial variance in the strength of casual relationships in the area of interest analysed. Such spatial variance – heterogeneity – signals structural instability. This instability can be because of heteroskedasticity (the non-constant error variance), or due to the structure of variable coefficients in a regression model (Anselin 2001; Brunsdon et al. 1996; Fotheringham et al. 1996). In that case, SUTVA is violated by spatial heterogeneity of treatment among units at individual or group levels (Kolak and Anselin 2020). Spatial variation of the treatment variable would, under conditions of ordinary causal inference, be interpreted as different versions of the treatment, thus violating SUTVA and leading to biased or inconsistent estimates, or even spurious inferences about the causal process (Corrado and Fingleton 2012).

Generally, researchers have assumed (1) the same coefficient for the whole study area and only referred to the spatial heterogeneity indirectly (Hartwig 2010; Shiu and Lam 2008), or (2) employed panel data estimators with spatial error components accounting for unobserved spatial heterogeneity (Bardaka et al. 2018; Rompré et al. 2007). Bilgel (2019) recently proposed a multiscale geographically weighted instrumental variables regression (MGWIVR) to manage spatial heterogeneity. This method manages spatial heterogeneity by estimating a unique regression with locally varying coefficients for each county.

4.3.3 MAUP and Ecological Fallacy

The modifiable area unit problem (MAUP) refers to the dependency of results of statistical analysis on the spatial scale (Openshaw 1984). Based on the MAUP, a variable can manifest different behaviours at different spatial scales, often due to aggregation over areas of vastly different sizes. The capability of aggregated data to describe individual observations is reversely dependent on the MAUP effects. MAUP is known as the ecological fallacy in social science, that refers to the inaccurate inferences about individuals because of aggregated data (Wong 2009). In some cases, researchers use aggregation to manage spatial dependency and relax SUTVA, but they are, conversely, faced with challenges of information loss and ecological fallacy (Cerqua and Pellegrini 2017; Deng et al. 2011; Eum et al. 2019; Giudice et al. 2019; Sexton et al. 2002). Therefore, while aggregation is a straightforward approach to relax SUTVA, it is not effective and suffers from inherent spatial issues.

4.3.4 Selection Bias

Selection bias related to the selection of treatment and control groups' members in quasi-experimental methods is another potential concern noted by researchers (Butsic et al. 2017; D'Elia et al. 2020; Deng et al. 2011; H. Li, Graham, et al. 2019; Nakano et al. 2018). Selection bias can manifest in two manners: (1) in the selection of units, and (2) in the selection of variables (Schleicher et al. 2020). For example, when assessing causal effects of a tax reduction policy on people's lives in different regions of a state, it is important to select balanced treated and control groups. Selection of similar control and treated units based on their characteristics helps to measure the effect of a policy without bias. Matching methods such as Propensity Score can manage this type of bias in causal inference. Selection bias also appears because of omitted variables, if an omitted variable is correlated with treatment and outcome variables (Butsic et al. 2017).

Researchers thus far managed selection bias with diverse, ad-hoc strategies: Cerqua and Pellegrini (2017) employed a quasi-experimental matching difference-in-differences estimator to minimising selection bias, while Giudice et al. (2019) used matching techniques by using spatial features of units of study such as size, distance and, slope in the selection of treated and control groups' members for managing selection bias. Alternatively, D'Elia et al. (2020) provided a framework for managing selection bias by propensity score matching method (the nearest-neighbour matching) and spatial hedonic models. Spatial models included the spatial lag to account for the spatial dependence between neighbours and spatial error for the effect of unobservable variables on the outcome variable.

4.3.5 Confounding Bias

Confounders are unobservable variables that depend on both treatment and outcome variables and are an important consideration when analysing observational data (Freedman 2005). Measuring average spillover effect on a unit is challenging because of confounding variables (Cerqua and Pellegrini 2017). There are direct and indirect methods for managing confounding bias by unobservable variables. Direct methods for controlling confounding include restriction (limitation of the study by removing probable confounders of the study) (Grimes and Schulz 2002; Hennekens, Mayrent, et al. 1987), matching (finding pairwise treated and control units based on the confounding variables) and stratification (a post-hoc analysis for stratifying results based on the levels of confounding variable). Quasi-experimental methods are an alternative for managing confounders indirectly (Campbell et al. 1963; Hatami 2019).

In addition to help with assessing a causal system for potential confounders, causal diagrams can help select the most important confounders that should be observed (i.e., data should be collected), thus controlling for the bias, including prior to data collection (Pearl 2009). Propensity score matching can help to manage omitted and confounding variables (Rosenbaum and Rubin 1983). Graham et al. (2013) provided spatial longitudinal generalised linear mixed models for managing confounding and spatial interferences among units. Hatami (2018) proposed a protocol to manage spatial and temporal confounders. They applied an integration of Bayesian networks (BNs) and structural equation modelling (SEM) to model causal effects of environment when confounding bias is controlled. Hatami (2019) provided a review of the controls for confounding bias in environmental studies with causal models.

4.3.6 Omitted Variables

Omitted variables are a subset of confounding variables. These variables are significant covariates which are wrongly eliminated from the model – either because of unavailability or due to misspecification of the analysis. Omitted variable bias is challenging in spatial causal inference because it directly affects the estimators of a causal model (Wooldridge

2013). Omitted variable bias can be caused only when the omitted variable is correlated with both the exposure (treatment) and outcome variables (Gunasekara et al. 2008). Omitted variable bias is one of the primary sources of endogeneity and spatial errors that can be managed by using the Instrumental Variables method (Becker et al. 2012; Betz et al. 2018; Mueller et al. 2018). When using cross-sectional data[2], the omitted variable bias increases. Kırdar and Saracoğlu (2008) proposed a method for transforming the structure of data to a panel structure by dividing the total time span into shorter periods. With this structure, they could use regional fixed effects for managing omitted variable bias.

4.3.7 Direction of Causal Relationships and Reverse Causality

Finally, a challenge in spatial causal inference is related to correctly determining the direction of causal relationships. Extracting causal relationships without checking for the direction of causality may lead to spurious causal inference. Granger causality and EDM are both suitable frameworks for extracting the direction of causality. Tranos (2012) used Granger causality to examine the direction of causality between internet infrastructure and the economic development of city-regions in Europe. The Granger causal model can also be useful for assessing the direction of causal relationships in panel data (Cattaneo et al. 2016). Aliaga et al. (2011) applied a strategy similar to Granger causality for extracting causal relationships and their directions. The method was based on the Lagrange Multipliers test (Anselin et al. 2008) with two steps: in the first step, dependency between variables were assessed, and in the second step, causal relationships and their directions were extracted.

4.4 Common Methods in Spatial Causal Inference

Table 4 presents the distribution of causal inference methods applied in the reviewed spatial causal inference literature. As noted in Table 4, the most frequent method employed to quantify causal effects is the Matching Method (36.3 %), followed by Difference-in-Difference

[2] "Cross-sectional data are data that are collected from participants at one point in time" (Lavrakas 2008)

(30.3 %), and Structural Equation Models and Path Analysis (21.2 %). Presenting the technical knowledge of extracted methods is not in the scope of this paper, beyond the brief overview above.

Table 4: Common Methods of Causal Inference in reviewed literature.

Method	**Literature**	**Proportion**
Matching Methods	Arpino, Mattei, et al. (2016), Butsic et al. (2017), Y. Chen et al. (2016), D'Elia et al. (2020), Donner and Loh (2019), Giffin, B. Reich, et al. (2020), Giudice et al. (2019), Gobillon and Magnac (2016), Hüttel et al. (2014), Karamba and Winters (2015), Keeler and H. M. Stephens (2020), Kolak and Anselin (2020), H. Li, Graham, et al. (2019), H. Li, Zhu, et al. (2020), Marcos-Martinez et al. (2019), Meldrum (2016), Mueller et al. (2018), Nakano et al. (2018), Oakley and Tsao (2007), Olivier and Van Aarde (2017), Paiva et al. (2015), Papadogeorgou et al. (2019), Ramboer and Reynaerts (2020), Schleicher et al. (2020), Wolff et al. (2014), Yadavalli and Landers (2017), and Zhang et al. (2019)	36.3 %
Difference in Difference (DiD)	Bardaka et al. (2018), Bardaka et al. (2019), Butsic et al. (2017), Cerqua and Pellegrini (2017), Y. Chen et al. (2016), Comber and Arribas-Bel (2017), D'Arcangelo and Percoco (2015), Delgado and Florax (2015), D'Elia et al. (2020), Eum et al. (2019), Geisler and Nichols (2016), Gobillon and Magnac (2016), Hohberg et al. (2020), Kolak and Anselin (2020), Maas and Watson (2018), Nakano et al. (2018), Oakley and Tsao (2007), Ramboer and Reynaerts (2020), Tan et al. (2019), and Zhang et al. (2019)	30.3 %
Structural Equation Models (SEM) or Path Analysis	Aliaga et al. (2011), Betz et al. (2018), Biswas et al. (2015), Bovendorp et al. (2019), Duarte et al. (2009), Gouveia et al. (2014), Hatami (2018), Hatami (2019), Houle (2005), Knick et al. (2017), L. Li et al. (2015), Olivier and Van Aarde (2017), Qian et al. (2009), Rompré et al. (2007), Thaden and Kneib (2018), and Toranza and Arim (2010)	21.2 %
Instrumental Variables (IV)	Becker et al. (2012), Betz et al. (2018), Bilgel (2019), Butsic et al. (2017), Giffin, B. J. Reich, et al. (2021), Graham et al. (2013), Hohberg et al. (2020), Kırdar and Saracoğlu (2008), Marcos-Martinez et al. (2019), and L. Zhao et al. (2020)	13.6 %
Regression Discontinuity Design (RDD)	Brachert et al. (2019), Butsic et al. (2017), D'Arcangelo and Percoco (2015), and Hohberg et al. (2020)	06.0 %
Directed Acyclic Graphs (DAGs)	Bilgel (2019) and Cho et al. (2012)	03.0 %
Convergence Cross Mapping	Z. Chen et al. (2018)	01.5 %

4.4.1 Matching Methods

Matching methods balance the treated and control groups based on the distribution of their covariates, in order to enable robust causal inference established on the fundamental assumptions such as SUTVA (Stuart 2010; Stuart, King, et al. 2011). The main objective of matching methods is managing selection bias and achieving balanced treated and control groups (Bardaka et al. 2019; Cerqua and Pellegrini 2017; D'Elia et al. 2020; Deng et al. 2011; Oakley and Tsao 2007; Paiva et al. 2015). Matching methods can be used in two stages, before as well as after intervention. Matching before intervention is a procedure of matching during the study design and during data collection stages, while the state of after intervention refers to the reduction of differences between treated and control units for measuring effects of an existing intervention. These methods can be based on the Mahalanobis Distance, propensity score, genetic, and full matching techniques (Diamond and Sekhon 2013; Iacus et al. 2012; Stuart 2010). Advantages of matching methods are less dependency on the amount of data and their capabilities to integrate with other approaches, while ignoring unobserved confounders is their drawback (Scheiner et al. 2000).

Matching is the dominant method among the reviewed studies (36 %), often applied in combination with other quasi-experimental methods for better results. For example, Y. Chen et al. (2016) showed that integrating matching with fixed effects estimation can help manage sources of bias and lead to robust results. Nakano et al. (2018) used integration of fixed effects Difference-in-Difference (FE-DID) with propensity score matching difference-in-differences (PSM-DID) to evaluate effects of a training policy on farmers' productivity. Marcos-Martinez et al. (2019) used a combination of spatial econometric methods, genetic matching algorithms and regressions with instrumental variables to manage the effective variables on regional economic for quantifying the impact of a policy on local income and employment. A combination of matching methods with a traditional spatial hedonic model and weighted regression was explored by D'Elia et al. (2020). They used propensity score matching for weighting, to prevent sample size loss that is common when applying matching methods. To account for spatial effects, Giudice et al. (2019) used a spatial matching method based on the one-to-one nearest neighbour matching to manage selection bias. They then used postmatching regression analyses to remove unobserved time-invariant heterogeneity.

Indeed, determining the contribution of a treatment based on the unobserved covariates that cannot be used in matching, the problem of finding optimum matches, and sample size reduction (because of keeping only matched cases) are three main limitations of matching methods (D'Elia et al. 2020). Matching estimators can provide an accurate estimation for matched units; however, treatment effects for whole units may differ from estimated effects for only matched units (Butsic et al. 2017).

4.4.2 Difference-In-Difference

Difference-In-Difference (DID) is a method where data of a process are collected before and after a treatment for well defined treated and control units. DID is the most suitable method for policy evaluations, and variation in coefficient of the trend for the treated group in comparison to the expected trend based on the counterfactual outcomes (Table 3) are evaluated as a treatment effect (Bardaka et al. 2018; Delgado and Florax 2015; Pynegar et al. 2018). In the quasi-experimental methods, all treatment, effect and confounder variables, plus treated and control groups' members, can be determined based on the research questions and hypotheses of the study. 30 % of the reviewed studies have employed the Difference-In-Difference (DID) analysis.

The violation of SUTVA in spatial processes makes quasi-experimental methods biased and inconsistent, which is the main challenge for standard DID. Therefore, Delgado and Florax (2015) proposed a spatial Difference-In-Difference (SDID) that accounted for spatial dependency in treatments and outcomes and managed spatial effects through the inclusion of spatial autoregressive parameters and accounting for the neighbourhood effects in standard DID. They further proposed XSDID as a Spatial Difference-In-Difference for evaluating the spatial effects in the situations that covariates (X) are spatially correlated. Other researchers used DID integrated with fixed effects and propensity score matching for estimating the causal effects in spatial processes (Cerqua and Pellegrini 2017; D'Elia et al. 2020; Nakano et al. 2018; Oakley and Tsao 2007). Others extended methods based on the DID to measure the causal effects in spatial processes. Bardaka et al. (2019) developed a spatial DID (SDID) model with possible sequential treatments over time with the capability of measuring the spillover effects within a spatial process as indirect causal effects. In addition, Maas and Watson (2018) used a difference-in-difference-in-differences approach (DDD) to estimate causal effects of residential parking policy on the values of homes in a specific region. They further used the inverse distance weighted matrix in their spatial models to account for spatial autocorrelation.

As noted previously, in spatial processes it is always possible for the units in the control group to be indirectly affected by treated units due to spatial spillover. Tan et al. (2019) used the DID model to evaluate the effects of new metro stations on local land use and housing prices. In a two-stage process, they first apply a standard DID model ignoring spatial dependence and compare the outcomes with those of a spatial DID model where they assessed the effects of spatial dependence by evaluating a spatial lag and spatial error model. If the differences between the two approaches showed small values, they propose to neglect spatial dependence and apply a standard DID model. However, this approach is complicated because it requires checking the spatial dependence by Moran's I and a subsequent methodological adjustment to spatial or nonspatial DID.

4.4.3 Structural Equation Models and Path Analysis

SEM and Path analysis can be used for evaluating direct and indirect causal effects in a process (Betz et al. 2018; Hatami 2018; Houle 2005; Kırdar and Saracoğlu 2008; Knick et al. 2017; Olivier and Van Aarde 2017; Toranza and Arim 2010). These methods are the third most common group of methods for spatial causal inference in the assessed literature (21.2 %) (Table 4) and have been used in the studies based on the Structural Causal Models (Table 3). Causal analysis of complex multivariate processes with non-trivial relationships between participating variables can be done by SEM (Bizzi et al. 2013). In a SEM, causal effects are summarized in a causal diagram based on the statistical analysis and the theory of causation, thus enabling researchers to explicitly identify confounding bias (Hatami 2019; Pearl 2009). Rompré et al. (2007) employed SEM to quantify the effects of environmental variables such as climate, topography and plant on bird species richness. Qian et al. (2009) compared SEM and spatial regression to assess the relationships of variables in their study for assessing effects of environmental variables on mammal species richness. To assess the differences between non-spatial SEMs and explicitly spatial models, they first used Moran's I to verify the spatial autocorrelation in residuals of nonspatial regression models, and subsequently applied linear spatial models and compared the results. Spatial models depicted better fit based on the analysis of R-square and AIC (Akaike Information Criterion). Gouveia et al. (2014) fitted SEM with bootstrap (a form of random sampling method) methods to manage the non-normality of variables and structural error. In an integrated approach, Bovendorp et al. (2019) combined Bayesian networks (BNs) with graphical structural equation modelling to quantify the environmental(such as forest size, forest cover) effect when confounding bias was controlled.

4.4.4 Directed Acyclic Graphs

DAGs have only been used in 3 % of studies reviewed. Causal relationships and confounders can be represented by DAGs. Nodes and directed edges are two primary components of a DAG, where nodes demonstrate random variables, while edges show causal relationships (Pearl 2009). DAGs are an expressive approach similar to Bayesian networks enabling the selection of appropriate variables in hedonic models. This method is conceptually related to the Structural Causal Model (Table 3) and can overcome the issue of multicollinearity in the processes with a high number of explanatory variables that participate in the hedonic models. Cho et al. (2012) used DAGs for selecting appropriate explanatory variables in their study. They showed that DAGs could be a complementary method for hedonic models to select appropriate explanatory variables with less level of multicollinearity. Still, the existence of spatial error autocorrelation was a common issue in the two specified hedonic models.

4.4.5 Instrumental Variables

In causal inference, instrumental variables (IV) can be used instead of the treatment variables. When there are endogenous explanatory variables in the structural model, IV presents a suitable approach to achieve consistent estimates. Thus, IVs are exogenous instruments independent of the error term (the unobservable characteristics) that have a high correlation with the treatment variable (Butsic et al. 2017; Owen 2017). They are particularly suitable when the analyst is uncertain whether a treatment is more likely to be the cause or effect. IVs present a means to account for the omitted variable bias problem and to remove the correlation between treatment and unobservable confounders (Angrist and Krueger 2001). While IV is an appropriate method to overcome endogeneity, finding suitable instruments remains problematic (Liscow 2013).

The IV method is derived from the Structural Causal Model (Table 3). About 13.6% of the reviewed studies employed Instrumental variables in their analyses. The conditions of an appropriate IV are violated with spatial instruments because of spatial spillover effects. Therefore, treatment variable will behave as an endogenous variable, and inferences become invalid (Betz et al. 2018). Based on the nature of spatial processes, researchers have employed different strategies to manage issues with the applicability of instrumental variables. For example, Marcos-Martinez et al. (2019) managed the spillover effects problem in their spatial process with instrumental variables. They integrated spatial econometric methods and genetic matching algorithms with instrumental variables to quantify causal effects in their study. Bilgel (2019) employed a multiscale geographically weighted instrumental variables regression (MGWIVR) approach to overcome spatial nonstationarity and endogeneity in a spatial analysis of effect of gun ownership on the crime rate. This method could manage two main challenges in this study, spatially varied effects (spatial heterogeneity) and endogeneity of gun ownership.

4.4.6 Regression Discontinuity Design

Regression Discontinuity Design (RDD) introduced by Thistlethwaite and Campbell (1960). In this approach, treated group members are selected based on a sharp threshold assignment rule or break in the data; for example, units within a certain distance (e.g., within a policy neighbourhood) can be selected for treatment. RDD leads to a robust causal inference, but enables to infer outcomes only for a small subgroup of units (Alix-Garcia et al. 2018). Only 6 % of the evaluated investigations have applied RDD for their analyses. D'Arcangelo and Percoco (2015) employed a spatial RDD and used the distance variable to manage spatial effects. Similarly, Brachert et al. (2019) used RDD to assess the causal effects of an investment place-based policy on West Germany related to the investment grants to structurally weak districts to reduce regional inequality. This model works based on the Potential Outcomes Causal Model (Table 3) and for measuring the effects of treatment operates based on comparing observed outcomes and counterfactual outcomes, similar to the DID method.

4.4.7 Convergent Cross-Mapping

Convergent Cross-Mapping (CCM) underpins the Empirical Dynamic Modelling causal model (Table 3) and as a relatively recent method, it is represented only by 1.5 % of articles in the reviewed literature. Second, this low proportion may be due to the keywords identified from seed papers. It is a method for extracting causal relationships from nonlinear dynamic systems. It can be used to assess the bi-directional relationships between two variables isolated from other variables, but it is distinct from Granger causality. CCM can eliminate mirage correlations and extract meaningful causal relationships between two variables. In nonlinear complex systems, the correlational analysis may lead to distinct biases because of complicated interactions between variables. Z. Chen et al. (2018) employed CCM to recognize the effects of meteorological factors on local PM2:5 among the cities of China.

4.5 Reproducibility

53 % of reviewed papers did not report what software was applied in their analyses. R is the most commonly used software in the reviewed papers, with 26 %. Also, Stata and ArcGIS were used, both with 11 %. However, ArcGIS generally was used only for preparing data for the analyses or visualisations. Only 12 % of reviews cited the code used in their analyses. This low rate of accessibility to code is a big challenge that not only limits reproducibility of the reviewed papers, but also affects the portability and translation of approaches to other case studies in spatial causal inference. Additionally, the validation of models and results was not a regular component of the analytical processes in these studies, present only in 14 % of papers. In sum, in most of the reviewed research, there are no clear procedures related to reproducibility and validation. We can trust more the results of papers with straightforward approaches with a sufficient level of details.

5 Conclusions and the Way Forward

Causal inference is a domain of science which has developed progressively in the last three decades, across different disciplines (Aldrich 1995; Handa et al. 2020; Nguyen and Gouno 2020; Ohlsson and Kendler 2019; Pearl 1988; Pearl 2000; Pearl 2009; Rubin 2005; Saddiki and Balzer 2018; J. Zhao et al. 2020). Causal inference is instrumental to generate knowledge about the effects of policies, events or actions on outcomes of a process. Methods of causal inference analysis are increasingly applied in policy analysis (Brachert et al. 2019; Cerqua and Pellegrini 2017; Gobillon and Magnac 2016; Kolak and Anselin 2020), infrastructure projects effects analysis (Bardaka et al. 2018; Bardaka et al. 2019; Comber and Arribas-Bel 2017; Zhang et al. 2019), and machine learning and big data analysis (Z. Chen et al. 2018; L. Li et al. 2015).

Applying causal inference to spatial processes should enable extracting causal relationships and effect analysis. The main issue with the application of standard causal inference to spatial problems is the specific nature of spatial processes. Based on Tobler's first law of geography, there is no independent random process (IRP) or complete spatial randomness (CSR) in the real world (Tobler 1970). This is because of unequal probability for events occurring (first-order effects, aka spatial heterogeneity), or the existence of dependency among events (second-order effects, aka spatial lag) in geographical environments (O'Sullivan and Unwin 2014). Spatial heterogeneity refers to the first-order effects, and spatial lag and spatial interactions refer to the second-order of effects. These types of effects make spatial processes different from nonspatial processes. These distinct manifestations of effects led to specific spatial dependence structures and the need for specialised spatial models to capture the real world, including considerations for spatial lag and spatial error. Current causal inference approaches attempt to port methods from nonspatial processes to the spatial domain, and do not systematically manage spatial effects. Thus, developing methods with explicit consideration for the characteristics of spatial processes is essential. Based on Table 1 we identified sixteen types of spatial processes, and each of them has specific characteristics of the dependence structures that should be explicitly addressed.

We have discussed how spatial heterogeneity and spatial interactions affect the measurement of a causal effect. To achieve accurate results from causal inference on spatial processes, we call for the development of new spatial causal inference methods. Such methods will enhance our ability to generate inferences about data stemming from spatial processes, notably data with manifest spatial heterogeneity and where spatial dependence affects the outcomes of causal inference.

Here, we have systematically reviewed existing knowledge about causal inference on spatial processes to recognise the current state of the art. We have thus obtained an overview of applied causal models in spatial causal inference analysis, identified challenges of causal inference on the spatial processes, highlighted analytical methods applied in the case studies, and identified opportunities for future studies. We hope that this systematic literature review will help researchers who are embarking on undertaking spatial analyses to achieve deeper insight into the application of spatial causal inference in their research. We identify the dominant types of causal models applied in causal inference analysis of observational data, including the Potential Outcome Framework or Rubin Causal Model (Rubin 1974; Splawa-Neyman et al. 1990), the Structural Causal Models (Pearl 1995; Pearl 2009; Pearl 2014), Granger Causality (C. W. J. Granger 1969; C. W. Granger 1980), and Empirical Dynamic Modelling (Chang et al. 2017; Deyle, Maher, et al. 2016; Grziwotz et al. 2018; Ye et al. 2015).

Our review also provides an in-depth understanding of the common challenges of causal inference in the spatial processes. Without accounting for these challenges in spatial causal inference, analysts obtain biased and inconsistent estimates, and wrong inferences about the causal process (Corrado and Fingleton 2012). The spatial spillover effect is the most common and important challenge in spatial causal inference analyses because of interference among units and thus violating the fundamental assumptions of causal frameworks, such as SUTVA (Bardaka et al. 2018; Kolak and Anselin 2020). Another significant issue is the spatial heterogeneity of casual relationships in different parts of a spatial area. The second component (well-defined treatment) of SUTVA can be violated by heterogeneity among units at individual or group levels (Kolak and Anselin 2020). MAUP is the next common challenge in the spatial causal inference that refers to the dependency of results of statistical analysis to the spatial scale (Openshaw 1984). MAUP is a straightforward approach to relax SUTVA, but it can produce other challenges such as loss of information and ecological fallacy (Cerqua and Pellegrini 2017; Deng et al. 2011; Eum et al. 2019; Giudice et al. 2019; Sexton et al. 2002). The mentioned three types of challenges are specially related to the spatial data and are not common in the nonspatial causal inference.

We identify four different types of common issues that impact on causal inference of both spatial and nonspatial processes. The first one is selection bias (Butsic et al. 2017;

D'Elia et al. 2020; Deng et al. 2011; H. Li, Graham, et al. 2019; Nakano et al. 2018) that refers to achieve a balance in the selection of treatment and control groups' members in quasi-experimental methods. Selection bias can happen in the selection of units and variables (Schleicher et al. 2020). To manage selection bias in spatial processes, new spatial matching techniques (D'Elia et al. 2020; Giudice et al. 2019) should be developed. Omitted variable bias is the next common challenge for spatial and nonspatial processes. This bias is one of the primary sources of endogeneity and spatial errors and can be managed by using different strategies such as the IV method (Becker et al. 2012; Betz et al. 2018; Mueller et al. 2018) and DID estimation(Butsic et al. 2017).

In addition to the omitted variables, confounder variables that depend on both treatment and outcome variables, are an important issues in analysing observational data (Yao et al. 2020). This type of bias can be managed by matching techniques, and Quasi-experimental methods in spatial and nonspatial causal inference analysis (Graham et al. 2013; Hatami 2018; Hatami 2019; Rosenbaum and Rubin 1983). The last common challenge in both spatial and nonspatial causal inference analysis is understanding the direction of causal relationships. Extracting causal relationships without assessing the direction of causality may lead to incorrect causal inference. Granger causality is a suitable framework for extracting the direction of causality (Aliaga et al. 2011; Cattaneo et al. 2016; Tranos 2012).

A critical part of our review is the assessment of the applied techniques in spatial causal inference. Our review shows that matching and Difference-In-Difference are dominant analytical methods. Path analysis and SEM can be used for evaluating direct and indirect causal effects in a process. IV will be a suitable approach when there are endogenous explanatory variables in a structural model, and can reduce omitted variable bias (Angrist and Krueger 2001). RDD, DAGs and CCM methods are currently more marginal methods. Most of the methods of spatial causal inference apply in a basic way to spatiotemporal data (spatial panel data). We assess the changes in the distribution of variables over time, before and after treatment. However, some methods such as IV, SEM, and DAG can be applied to cross-sectional spatial data.

In summary, we found that there are three main gaps related to the spatial causal inference. The first and most significant gap is the need for a comprehensive framework for causal inference in spatial processes. This framework can help the researchers working on the spatial and geographical issues better to understand potential procedures and solutions for their studies. The second one is a distinct lack of application of causal inference analysis in topics related to Spatial Cognition, such as the wayfinding process. Exploring causal relationships among the effective variables in the issues related to spatial cognition can help to have a better insight into the data generation process, optimized recommender systems and navigation systems for users. The last one is a lack of appropriate and convenient tools for spatial causal inference analysis. The assessments depict that existing techniques for causal inference are not adequate and appropriate to capture the complexity of the causal inference in spatial processes. These methods should be refined to measure real effects which are affected by spatial effects. This opens up opportunities for researchers studying spatial causal inference to design and develop methods based on the special characteristics of spatial data and processes.

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