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Advancing impact evaluation in applied limnology

Avançando em avaliações de impacto na limnologia aplicada

Luiz Guilherme dos Santos Ribas[1]*, André Andrian Padial[2] and Luis Mauricio Bini[1]

[1]Pós-graduação em Ecologia e Evolução, Laboratório de Ecologia Teórica e Síntese, Universidade Federal de Goiás, Av. Esperança, s/n, Campus Samambaia, CEP 74690-900, Goiânia, GO, Brasil

[2]Universidade Federal do Paraná, Laboratório de Análise e Síntese em Biodiversidade, Pós-graduação em Ecologia e Conservação, Av. Coronel Francisco H. dos Santos, 100, Jardim das Américas, CEP 81531-990, Curitiba, PR, Brasil

*email: lg_ribas@hotmail.com

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Abstract: Accurate impact evaluations of different interventions are paramount in environmental sciences. In this context, the main challenge is to identify causal relationships to understand how different interventions affect the systems of interest. For this task, the counterfactual thinking can be used to estimate the impacts of interventions on the real scale of the problem using observational data. By definition, counterfactuals are states contrary to facts. In the context of interventions, they are the states of the units of analysis in the absence of intervention. This approach allows one to estimate the impact more accurately by comparing the differences between factual and counterfactual states. In this essay, we present some basic elements of the counterfactual thinking and discuss how it, based on experiences in other areas (e.g., medicine and economics), may be useful for the research of complex problems in aquatic ecology.

Keywords: applied limnology; causality; counterfactual; impact evaluation; intervention.

Resumo: Avaliações de impacto acuradas de diferentes intervenções são necessidades na área ambiental. Nesse contexto, o principal desafio é identificar relações causais com o objetivo de compreender como diferentes intervenções afetam os sistemas de interesse. Para tal, a lógica contrafactual pode ser usada para estimar impactos de intervenções na escala real do problema utilizando dados observacionais. Contrafactuais são estados contrários aos fatos. No contexto de intervenções, seriam os estados das unidades intervindas na ausência da intervenção. Essa abordagem permite estimar o impacto de maneira mais acurada ao comparar as diferenças entre os estados factuais e contrafactuais. Nesse ensaio, apresentamos alguns elementos básicos da lógica contrafactual e discutimos como essa lógica, considerando o que ocorre em outras áreas (e.g., medicina e economia), pode ser útil para a pesquisa de problemas complexos em ecologia aquática.

Palavras-chave: avaliação de impacto; causalidade; contrafactual; limnologia aplicada; intervenção.

1. Introduction

Suppose a conservation program aiming to restore riparian forests and improve the water quality in a watershed. In this scenario, the need for an impact evaluation analysis would be paramount to assess whether this intervention reached the expected goals (Frondel & Schmidt, 2005; Ferraro & Pattanayak, 2006; Ferraro, 2009). The results of this analysis could justify (or not) the application of such intervention in other watersheds. However, even though most ecologists would agree about the need for good programs to evaluate the impact of interventions, they are rare in applied ecology (Ferraro & Pattanayak, 2006), especially in applied limnology. Indeed, several papers have emphasized the need for more rigorous evaluations of the effectiveness of conservationist interventions (e.g., Kleiman et al., 2000; Pullin & Knight, 2001; Salafsky et al., 2002; Salafsky & Margoluis, 2003). Also, Ferraro & Pattanayak (2006) highlighted that effectiveness of interventions are frequently assumed without convincing evidence.

However, designing good evaluation programs is far from being trivial. To rigorously evaluate the effect of an intervention it is necessary to think how it could potentially change causal relationships, which in turn would change the outcomes of interest (Pearl & Mackenzie, 2018). And, to establish a causal relationship, it is necessary that the factors involved interact in a way that the change in the state of one factor (i.e. cause factor) results in change in the state of other factor (i.e. effect factor; Pearl, 2009). More specifically, a causal relationship is one that *X* causes *Y*, in which *Y* would not exist if *X* did not exist (i.e., attribution) or one that *X* contributes, together with other factors, to change the state of *Y* (i.e., contribution; White, 2010). Such causal relationship cannot be studied by simply using models that relate 'predictive' and 'response' variables. Therefore, to study causal relationships, such as the relationship between a certain intervention and its potential outcomes in an impact evaluation study, it is necessary to manipulate cause variables in the system of interest to estimate how such manipulation alters subsequent causal relationships and results in changes in the distributions of effect variables (Holland, 1986; Pearl & Mackenzie, 2018).

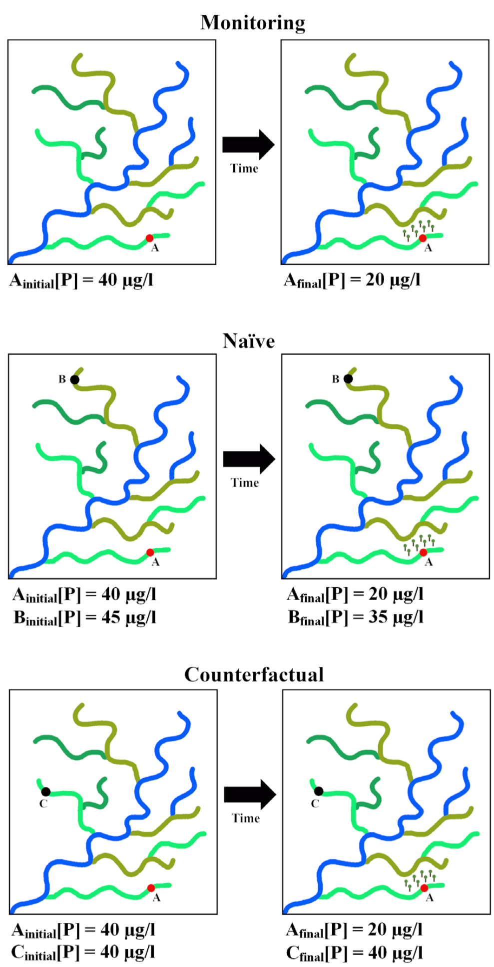
2. Traditional Impact Evaluations in Environmental Sciences

Disregarding causal relationships in the approaches used to evaluate the impact of interventions is still common in environmental sciences (Ferraro & Pattanayak, 2006). In general, the efficiency of interventions in environmental sciences is commonly studied by monitoring a set of indicator variables (see Chart 1). According to Ferraro (2009): "Environmental scientists and practitioners often assume that evaluation is simply an act of taking a careful look at the monitoring data. If the indicator improves, a program is deemed to be **working**. If the indicator worsens, one infers the program is **failing**." Even considering the importance of monitoring to understand and track how interventions are working, this approach has little to do with impact evaluations (Perrin, 2012).

Another common strategy in the environmental sciences is the comparison of intervened units and different non-intervened units, for example, in a Before-After-Control-Impact (BACI) framework (Smith, 2002; Chevalier et al., 2018). However, these units are not necessarily similar considering features that could affect both the selection of units that could receive the intervention and the causal relationships that could result in changes in the outcome variables (see Chart 1). And, by disregarding the importance of these differences, a study could under or overestimate the impacts of interventions (as shown by Andam et al., 2008). For example, suppose that a protected area is created on a steep terrain with low agricultural potential. In order to evaluate the impact of this protected area, also suppose that the deforestation rates of the protected area are compared to the deforestation rates of unprotected areas, however, these unprotected areas are in flat regions with high agricultural potential. The evaluation of the protected area's impact in avoiding deforestation would probably be overestimated because deforestation rates in the protected area would be low compared to unprotected areas, even without legal protection. In addition, in this hypothetical example, we could not state that the intervention (i.e., the creation of the protected area) caused the reduction in deforestation rates as the area was already prompted to have low deforestation rates due to its low economic potential to human use.

Chart 1. Different approaches to analyze the impact of a hypothetical restoration program in watersheds.

Assume an intervention in a watershed planned to restore riparian forests of a stream (red circle, A). This intervention is focused on improving stream water quality and its effectiveness can be measured by an impact evaluation that compares the outcome variable (total phosphorus concentration) in the periods before (initial) and after (final) the intervention. Also, consider that the waterbodies in the watershed have different environmental features that could change the causal relationship between the intervention and the outcome variable (represented by different colors of the streams). The first pair of panels from top to bottom (Monitoring) represents the approach of monitoring the outcome variable in the site under the intervention (red circle, A). In this approach, changes in the outcome variable could be erroneously related to the impact of the intervention, for we cannot be sure that only the presence of the intervention resulted in the observed state of the outcome variable. The second pair of panels (Naïve) represents an approach that compares control areas (black circle, B) with the area under intervention (red circle, A) to estimate the impact of the intervention. We consider this approach naïve because the selection of control areas disregards the features (represented by the different colors of the streams) that could influence the outcome variable, making the units (with and without intervention) incomparable. In the naïve approach, any difference in the outcome variable cannot be related to the presence of the intervention because the initial difference between the waterbodies could be the cause of the (final) differences. The third pair of panels (Counterfactual) represents the approach based on counterfactual thinking. This approach aims to estimate the impact of an intervention comparing the area under intervention (red circle, A) with a similar control area (black circle, C) considering features (represented by the different colors of the streams) that could influence the outcome variable. This control area estimates the state of the outcome variable if the intervention had never existed (i.e. counterfactual state). If the selection of the control unit considers the features that could influence the causal relationship between intervention and the outcome variable, it is possible to estimate the impact of the intervention similarly to a controlled experiment. This is so because the main difference between the waterbodies (with and without the intervention) is the presence of the intervention itself. Thus, differences in the outcome variable could be explained by the presence of the intervention and not due to differences in other features.



3. Counterfactual Alternatives

Surely, experimentation is one of the most powerful approaches to establish causal relationships. In this approach, casualization ensures the independence between observations and one can accurately estimate the impact of an intervention when comparing experimental (or "treated") units with control units (Raper, 2019). However, conducting controlled experiments is often infeasible due to several reasons such as resource limitation, ethical issues, practical and logistical difficulties (Underwood, 1992; Lan & Yin, 2017). Furthermore, extrapolating the results of a "classical" (small-scale) experiment to the scale of interest may result in flawed conclusions given that processes may be far different comparing experimental and real scenarios (Cook et al., 2008). This is the main reason for using observational data to estimate impact of interventions.

Counterfactual thinking can be used to overcome the problems associated with "classical" experimentation (Ferraro & Pattanayak, 2006; Pearl & Mackenzie, 2018) by comparing factual states with states that contradict factual situations (i.e. counterfactual states; Pearl & Mackenzie, 2018). In the example of the effect of riparian restoration on the water quality of streams (see Chart 1), we would have to evaluate the state of these same streams in situations where the restoration was not implemented. However, we have the *fundamental problem of causal inference*: a given unity (stream in our example; see Chart 1) cannot be in the same state, with and without the intervention, at the same time (Holland, 1986). Hence, counterfactual states do not exist and they should be estimated. After, to estimate the impact of interventions, counterfactual states are compared to factual states (e.g., Andam et al., 2008; McConnachie et al., 2015; Sonter et al., 2017). But how to apply the counterfactual thinking to evaluate the impact of interventions? One possibility consists in estimating counterfactual states similarly to situations of controlled experiments, but with observational data (e.g., Andam et al., 2008; McConnachie et al., 2015; Sonter et al., 2017).

Understanding how different features influence the causal relationship between the intervention and the outcome of interest is crucial to estimate counterfactual states (Imbens & Rubin, 2015). In our hypothetical example, we could envisage the following counterfactual state: "how would water quality be without the intervention?" In this example, we know that water quality is influenced by nutrient inputs from terrestrial ecosystems and this kind of knowledge should be taken into account to estimate adequate counterfactual states. After considering which features are important (e.g., limnological characteristics, nutrient inputs and type of soil), different methods (e.g., matching; see Stuart, 2010) can be applied to select control areas comparable, according to these features, to impacted areas. Hence, it is possible to estimate more accurate counterfactual states to compare with the factual states (i.e., units under the intervention) and, finally, estimate the impact of an intervention with the required rigor (see Chart 1). Many methods can be used to estimate counterfactual states, however, a detailed description of these methods is out of the scope of this paper (interested readers should consult Stuart (2010), Imbens & Rubin (2015) and Pearl & Mackenzie (2018) for a practical and theoretical introduction to the topic).

Counterfactual thinking has been applied in environmental sciences to estimate, for example, the effects of legislations focused on endangered species (Ferraro et al., 2007), the effectiveness of protected areas (Andam et al., 2008), programs to control invasive species (McConnachie et al., 2015) and ecosystem services payments (Pattanayak et al., 2010). Nonetheless, similar studies in different ecosystems and with the goal of evaluating different interventions are still rare. For example, as far as we know, there is no study based on counterfactual thinking that estimated the effect of interventions on continental aquatic ecosystems. However, we believe that limnology and related fields will greatly benefit from adopting counterfactual thinking. Furthermore, it is urgent to estimate the impact of interventions in continental waters if we want to influence public policies and future conservation actions. In summary, we need to multiply the example of the classical study of Schindler & Fee (1974), which was essential for the formulation of laws to restrict phosphorus content in effluents.

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