

Forum

Bridging parametric and nonparametric measures of species interactions unveils new insights of non-equilibrium dynamics



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A central theme in ecological research is to understand how species interactions contribute to community dynamics. Species interactions are the basis of parametric (model-driven) and nonparametric (model-free) approaches in theoretical and empirical work. However, despite their different interpretations across these approaches, these measures have occasionally been used interchangeably, limiting our opportunity to use their differences to gain new insights about ecological systems. Here, we revisit two of the most used measures across these approaches: species interactions measured as constant direct effects (typically used in parametric approaches) and local aggregated effects (typically used in nonparametric approaches). We show two fundamental properties of species interactions that cannot be revealed without bridging these definitions. First, we show that the local aggregated intraspecific effect summarizes all potential pathways through which one species impacts itself, which are likely to be negative even without any constant direct self-regulation mechanism. This property has implications for the long-held debate on how communities can be stabilized when little evidence of self-regulation has been found among higher-trophic species. Second, we show that a local aggregated interspecific effect between two species is correlated with the constant direct interspecific effect if and only if the population dynamics do not have any higher-order direct effects. This other property provides a rigorous methodology to detect direct higher-order effects in the field and experimental data. Overall, our findings illustrate a practical route to gain further insights about non-equilibrium ecological dynamics and species interactions.

Keywords: higher-order interactions, interaction matrix, Jacobian matrix, model-driven, model-free, non-equilibrium dynamics

Synthesis

Community ecology is built upon the concept of species interactions. Traditionally, parametric and nonparametric approaches to study community dynamics have considered different measures and interpretations of species interactions. That is, species interactions are measured as constant-direct and local-aggregated effects within the parametric and nonparametric approaches, respectively. It has remained unclear, however, under what conditions parametric and nonparametric views of species interactions tell a similar story, and what can be learned when they do not coincide. In this line, here we have provided a bridge between these two approaches (measures) and illustrated how to use their differences to gain new insights about nonequilibrium community dynamics.



Introduction

Community ecology are built upon the idea that species interact either directly or indirectly with other species (Abrams 1987, Thompson 2005, Morin 2009, Vellend 2016). Indeed, a central theme in ecological research is to understand how species interactions contribute to community dynamics (May 1972, Pimm 1982, Allesina and Tang 2012, Fukami 2015, Saavedra et al. 2017, Chesson 2018). Even macro-ecological studies that do not explicitly model species interactions are built upon the idea of an existing balance among species interactions (Hubbell 2005, Harte 2011, Staniczenko et al. 2017). Thus, ever since Odum (Odum and Barrett 2005), most ecologists classify species interactions not by their mechanisms, but according to the effects produced on the growth rate of populations (Abrams 1987 for an extended discussion on this topic). Yet, this simple definition has different measures and interpretations across theoretical and empirical studies (Case 2000), making necessary to understand how and when these measures can be linked.

In empirical and theoretical research, the effect of species interactions has been measured following parametric (model-driven) and nonparametric (model-free) approaches (Sugihara 1994, Turchin 2003). While the parametric approach has been the cornerstone of quantitative ecology (Kingsland 2015) the nonparametric approach has been increasingly adopted in empirical studies (Deyle et al. 2016, Ushio et al. 2018, Cenci and Saavedra 2019, Bray and Wang 2020, Karakoç et al. 2020, Ushio 2020, Yu et al. 2020). To explain the differences between the two approaches, we define them using the most general population dynamics of S interacting species in the form of continuous ordinary differential equations (the case for discrete difference equations is similar, Case 2000),

$$\frac{dN_i}{dt} = N_i f_i(N_1, \dots, N_S) \quad (1)$$

where N_i is the abundance (or biomass) of species i , and f_i is the per capita growth rate of species i .

The parametric approach typically measures species interactions as constant direct effects (mechanistic or phenomenological) between species (Case 2000, Song et al. 2020), and completely relies on knowledge about the governing population dynamics. The general formalism in the parametric approach partitions the general population dynamics (Eq. 1) as

$$\frac{dN_i}{dt} = N_i \left(\underbrace{\tilde{r}_i}_{\text{intrinsic growth}} + \underbrace{a_{ij}s_i(N_i)}_{\text{intraspecific}} + \underbrace{\sum_{j \neq i} a_{ij}g_{ij}(N_i, N_j)}_{\text{inter-specific}} + \underbrace{\sum_{j \neq k; j, k \neq i} b_{ijk}h_{ijk}(N_i, N_j, N_k)}_{\text{higherorder}} + \dots \right) \quad (2)$$

with both pairwise and higher-order terms. The pairwise formalism of population dynamics has been the basis of this approach. The pairwise formalism ignores the higher-order terms and focuses only on the pairwise terms, where r_i represents the intrinsic growth rate of species i (no density

dependency), a_{ij} represents the constant, direct, intraspecific (if $i=j$) and interspecific effect (if $i \neq j$), while $s_i(N_i)$ and $g_{ij}(N_i, N_j)$ represent the functional form of the intraspecific and interspecific direct effects, respectively. These constant direct effects a_{ij} can be the result of indirect mechanisms depending on the level of resolution of the model (MacArthur and Levins 1967, Abrams 1987), while the functional forms $g_{ij}(N_i, N_j)$ are not restricted to be linear and can incorporate non-additive effects (Tilman 1982, Billick and Case 1994, Letten and Stouffer 2019). A classic example of the pairwise formalism is the Lotka–Volterra (LV) dynamics (Lotka 1926, Volterra 1926), where $s_i(N_i) = N_i$, $g_{ij}(N_i, N_j) = N_j$. The matrix $\mathbf{A} = \{a_{ij}\}$ is called the interaction matrix, encoding the strength of pairwise, constant, direct effects (note these effects can be non-additive, Billick and Case 1994). Regardless of which form of functional responses is used, the sign pattern of the interaction matrix \mathbf{A} is usually fixed and interpreted as the type of pairwise direct effect, such as: mutualism, competition, predation or null (Abrams 1987, Callaway et al. 2002, Chamberlain et al. 2014, Song et al. 2020).

Despite the popularity of the pairwise formalism, the parametric approach can also be applied to a higher-order formalism of the general population dynamics (Eq. 2; Billick and Case 1994, Kleinhesselink et al. 2019). Higher-order effects correspond to constant direct effects among more than two species (which is fundamentally different from other definitions such as indirect effects or non-additive effects, Billick and Case 1994). For example, focusing on the higher-order terms in Eq. 2, b_{ijk} represents the constant, direct, triple-wise effect. Similarly, $h_{ijk}(N_i, N_j, N_k)$ represents the functional form of the triple-wise direct effect among species i , j and k – representing the constant change in the per capita growth rate of species i under a small change in density of species j and k (O’Dwyer 2018, Letten and Stouffer 2019). Other higher-order direct effects (such as quadruple-wise effect) can be similarly defined (Bailey et al. 2016). Note that the parametric approach, regardless of the specific formalism, can be applied under the assumptions of equilibrium and non-equilibrium dynamics (Case 2000).

In turn, the nonparametric approach typically measures species interactions as the local (state-dependent) aggregated (direct and higher-order) effects between two species. Different from the parametric approach, the nonparametric one does not assume any particular governing population dynamics (Sugihara and May 1990, Ye et al. 2015). Because the local aggregated effect counts all the pathways (including direct and higher-order effects) at a given point in time, it can only be defined pairwise (Deyle et al. 2016, Cenci and Saavedra 2018b, Ushio et al. 2018). That is, the nonparametric pairwise interaction between two species is measured as the change in the growth rate of species i under a small change in density of species j . Formally, this can be written as

$$J_{ij}(t) = \frac{\partial \left(\frac{dN_i(t)}{dt} \right)}{\partial N_j} = N_i \frac{\partial f_i}{\partial N_j} + \delta_{ij} f_i = \begin{cases} N_i \frac{\partial f_i}{\partial N_j} + f_i, & \text{if } i = j \\ N_i \frac{\partial f_i}{\partial N_j}, & \text{if } i \neq j \end{cases} \quad (3)$$

where the Kronecker delta δ_{ij} is 1 if $i=j$, 0 otherwise. The matrix $\mathbf{J}=\{J_{ij}\}$ is called the Jacobian matrix. Similarly, this approach can be applied to both equilibrium (May 1972, Allesina and Tang 2012) and non-equilibrium dynamics (Sugihara 1994, Ushio et al. 2018, Cenci and Saavedra 2019). Note that under equilibrium dynamics, the Jacobian matrix has also been called the community matrix (Levins 1968, May 1972, Case 2000, Novak et al. 2016).

Both measures have their own strengths and weaknesses: within parametric approaches, measures have a mechanistic or phenomenological interpretation of a direct effect between species, but the magnitude and dimension of such parametric measures are model-dependent (Cenci and Saavedra 2018a, AlAdwani and Saavedra 2019, Letten and Stouffer 2019). Instead, within the nonparametric approach, measures can be estimated directly from data (such as time series of species abundance) with statistical methods, but they are often hard to be biologically interpreted (Sugihara and May 1990, Ushio et al. 2018, Cenci et al. 2019). Additionally, regardless of the specific methods, the two approaches hold different conceptualizations about how species interactions can be decomposed: within the parametric approach, measures can be decomposed into intraspecific (the effect of a species on itself), interspecific (the effect of a species on another) and higher-order interactions (the effect of two or more species on another). In contrast, within the nonparametric approach, measures can only be decomposed into intraspecific and interspecific interactions (Deyle et al. 2016, Cenci and Saavedra 2018b, Ushio et al. 2018). Yet, it remains unclear under what conditions parametric and nonparametric views of species interactions tell a similar story, and what can be learned when they do not coincide.

Importantly, even in equilibrium dynamics, the subtle but central differences in the measure of species interactions between these two approaches have sometimes been a cause of confusion in the literature (Lawlor 1980, Abrams 1981). Take the complexity–stability debate as an example, one of the most controversial topics in theoretical and community ecology (May 1972, McCann 2000, Ives and Carpenter 2007, Landi et al. 2018, Xu et al. 2019). As it has been shown (Logofet 2005), much of the debate has been generated by aiming to generalize ecological dynamics and species interactions under a nonparametric approach. However, the merger between parametric and nonparametric approaches to species interactions in such a context is only possible under the (often implicitly) assumption of a LV model and equal equilibrium states for all species (Haydon 1994, Vázquez et al. 2007, Novak et al. 2016). While researchers have been increasingly recognizing these assumptions in equilibrium dynamics (Berlow et al. 2004, Novak et al. 2016), it remains unclear whether the two approaches can be transferable in non-equilibrium dynamics, and more importantly, whether the transferability may reveal hidden ecological dynamics.

Here, we revisit and show how to bridge two of the most used measures of species interactions across the parametric and nonparametric approaches. We show that bridging parametric and nonparametric approaches present new ecological insights

that cannot be revealed without this bridging. Specifically, we study species interactions under three categories: intraspecific, interspecific and higher-order interactions. In the reminder, we begin by showing that the measures in parametric and nonparametric approaches can be linked if and only if all species interactions are pairwise (i.e. no higher-order interactions are present) regardless of the dynamics assumed. Next, we demonstrate that interspecific interactions are more transferable across measures than intraspecific interactions. Next, we show two applications by building on the differences between approaches. Finally, we discuss how and when these measures can be combined to gain further insights about non-equilibrium ecological dynamics and higher-order interactions.

The translucent mirror between measures

Intraspecific interactions

Under the parametric approach, a negative, constant, direct, intraspecific effect a_{ii} is often considered as self-regulation or intraspecific density dependence (Case 2000). However, under the nonparametric approach, the interpretation of the local aggregated intraspecific term J_{ii} is more complicated. For example, following the general parametric formalism defined in Eq. 2, the diagonal elements of the Jacobian matrix are defined as

$$J_{ii} = r_i + a_{ii} \left(s_i + N_i \frac{\partial s_i}{\partial N_i} \right) + \sum_{j \neq i} a_{ij} \left(g_{ij} + N_i \frac{\partial g_{ij}}{\partial N_i} \right) + \sum_{j \neq k; k \neq i} b_{ijk} \left(b_{ijk} + N_i \frac{\partial b_{ijk}}{\partial N_i} \right) + \dots \quad (4)$$

and when the system is at equilibrium (i.e. $f_i^* = 0$ in Eq. 3), it reduces to

$$J_{ii}^* = a_{ii} N_i^* \frac{\partial s_i}{\partial N_i} + \sum_{j \neq i} a_{ij} N_i^* \frac{\partial g_{ij}}{\partial N_i} + \sum_{j \neq k; k \neq i} b_{ijk} N_i^* \frac{\partial b_{ijk}}{\partial N_i} + \dots \quad (5)$$

Note that the notation for s_i , g_{ik} and b_{ijk} in Eq. 4 and thereafter has been simplified, but they are still functions of the species abundances N . Therefore, regardless of the presence of higher-order effects (whether b_{ijk} are all zeros) or the system is at the equilibrium (N_i^* , $\frac{dN_i}{dt} = 0$), the term J_{ii} measures the local aggregated effect across all the pathways under which species i can affect itself (not only the direct self-loop from i to i).

Hence, it is natural to ask what is the link between a_{ii} and J_{ii} . In general, a negative sign in J_{ii} does not imply a constant direct self-regulation ($a_{ii} < 0$), and vice versa (Somorjai and Goswami 1972, Haydon 1994). This property can be easily illustrated using the logistic population dynamics of a single species,

$$\frac{dN_i}{dt} = N_i (r_i + a_{ii} N_i) \quad (6)$$

where r_i and a_{ii} correspond to the intrinsic growth rate and the direct self-regulation of the single species i , respectively.

At the equilibrium ($K_i = N_i^* = -a_{ii} / r_i$), the constant, direct, intraspecific effect is given by a_{ii} , which is interpreted as a constant self-regulation. In turn, from Eq. 5 the Jacobian J_{ii} equals $r_i + 2a_{ii}N_i = r_i(1 - \frac{2N_i}{K_i})$, which is always positive

when $N_i < K_i/2$, negative otherwise. This implies that, in general, the interpretation of intraspecific interactions across the parametric and nonparametric are not the same.

Then, when can J_{ii} be directly transferable into a_{ii} ? If we require that the signs of a_{ii} and J_{ii} be the same, we need the system at equilibrium following LV dynamics. The reasoning is that, no higher order effects exist in LV dynamics (i.e. $b_{ijk} = 0$) and the partial derivative of g_{ij} with respect to N_i is 0 (i.e. $\frac{\partial g_{ij}}{\partial N_i} = \frac{\partial N_j}{\partial N_i} = 0$), thus that the second and third terms on the right-side of Eq. 5 vanish. If we additionally require that $a_{ii} = J_{ii}$, then on top of the two previous requirements, we need all equilibrium abundances to be exactly the same (May and Mac Arthur 1972, Song and Saavedra 2018). While it is not explicit, note that previous work (May 1972, Coyte et al. 2015) on the complexity–stability debate operates under these assumptions.

Interspecific interactions

Assuming that all direct effects are pairwise as described in Eq. 2, the local, aggregated, interspecific effect can be derived as

$$J_{ij} = a_{ij}N_i \frac{\partial g_{ij}}{\partial N_j} \quad (i \neq j) \quad (7)$$

which only includes the direct effect (functional form) g_{ij} between species i and j . Under this assumption, J_{ij} and a_{ij} ($i \neq j$) always have the same sign because $\frac{\partial g_{ij}}{\partial N_j} > 0$. Biologically, $\frac{\partial g_{ij}}{\partial N_j} > 0$ means that effects are stronger with larger species abundances, which is true for all types of classical Holling functional responses.

Instead, assuming that constant direct interactions include higher-order effects as in Eq. 2, the Jacobian (the local aggregated effects) can be derived as

$$J_{ij} = a_{ij}N_i \frac{\partial g_{ij}}{\partial N_j} + \sum_{k \neq i, j} b_{ijk}N_i \frac{\partial h_{ijk}}{\partial N_j} + \dots \quad (i \neq j) \quad (8)$$

where J_{ij} encodes not only the direct interspecific effects, but also the higher-order effects coming from species other than species i and j . Therefore, J_{ij} can be interpreted as the local (state-dependent) direct effect between species i and j if and only if all (parametric) direct effects are pairwise. That is, under higher-order effects, there is no simple link between (parametric) a_{ij} and (nonparametric) J_{ij} interspecific interactions. This also shows that the interspecific J_{ij} ($i \neq j$) is fundamentally different from the intraspecific J_{ii} .

Learning from the differences between approaches

Debates on self-regulation and stability

Importantly, the differences between approaches (measures) can offer an opportunity to gain further insights about non-equilibrium ecological dynamics and higher-order interactions without modeling them (AlAdwani and Saavedra 2019). For example, focusing on dynamics and building from the classic complexity–stability debate (May 1972), it is assumed that a community can be dynamically stable only if most of the constant, direct, intraspecific terms are negative ($a_{ii} < 0$), i.e. if ‘the population of each species would by itself be stable’ (May 1972). This assumption comes from the observation that dynamical stability requires that most of the local, aggregated, intraspecific terms are also negative ($J_{ii} < 0$) (May 1972, Yodzis 1980, Sterner et al. 1997, McCann 2011, Moore and de Ruiter 2012, Barabás et al. 2017). Yet, there is few empirical evidence to support the addition of direct self-regulation ($a_{ii} < 0$) for primary consumers and top predators (Pimm and Lawton 1977, Tilman 1982, Chesson 2013), which would make most systems unstable.

This apparent contradiction arises from the ill perception that a negative J_{ii} requires a negative a_{ii} . However, recall the link between J_{ii} and a_{ii} (Eq. 4), J_{ii} can be expressed in the absence of self-regulation ($a_{ii} = 0$) as

$$J_{ii} = \begin{cases} r_i + \sum_{j \neq i} a_{ij}(g_{ij} + N_i \frac{\partial g_{ij}}{\partial N_j}) + \sum_{j \neq k; k \neq i} b_{ijk}(h_{ijk} + \frac{\partial h_{ijk}}{\partial N_i}) + \dots, & \text{if non-equilibrium} \\ \sum_{j \neq i} a_{ij}N_i \frac{\partial g_{ij}}{\partial N_j} + \sum_{j \neq k; k \neq i} b_{ijk}N_i \frac{\partial h_{ijk}}{\partial N_i} + \dots, & \text{if equilibrium} \end{cases} \quad (9)$$

This implies that a negative J_{ii} (in equilibrium and non-equilibrium dynamics) in a non-self-regulated species i (i.e. $a_{ii} \geq 0$) can arise in a broad class of nonlinear ecological dynamics simply by satisfying two conditions (Song et al. 2018): 1) a negative intrinsic growth rate (i.e. $r_i < 0$), and 2) at least one negative, constant, direct, interspecific effect (i.e. $a_{ij} < 0$). Note that those conditions do not apply to LV dynamics in equilibrium because of the linearity of the dynamics (i.e. $\frac{\partial g_{ij}}{\partial N_j} = 0$). Figure 1 shows a simple example in a three-species food chain: both the consumer and the top predator have no constant, direct self-regulation; yet they can exhibit negative, local, aggregated, intraspecific effects. In contrast, the primary producer does have constant, direct self-regulation; yet it does not always exhibit a negative, local, aggregated, intraspecific effect. Hence, apart (or instead) of local aggregated self-regulation mechanisms, these (or other conditions) can be taken as stabilization sources of ecological communities.

Detection of higher-order interactions

Ecology has seen the re-emergence of interest in higher-order interactions (Grilli et al. 2017, Levine et al. 2017, Mayfield and Stouffer 2017). However, it remains challenging to

convincingly detect the presence of higher-order interactions in empirical data (Kleinhesselink et al. 2019, Letten and Stouffer 2019, Xiao et al. 2020). The different interpretations of J_{ij} in the presence of higher-order effects provide a new method to detect their existence. For example, it has been found that J_{ij} can change its sign across time in a community (Ushio et al. 2018). If we assume that the governing population dynamics only consists of pairwise direct effects (Eq. 2), then this result should be interpreted as the change of the type of the constant, direct, interspecific effect (i.e. the sign of the parameters in the governing population dynamics have to change). However, if we assume that the governing population dynamics is fixed, then this result should be interpreted as the presence of higher-order direct effects. Figure 2 shows a simple three-species competing system with and without higher-order direct effects that illustrates these points. Of course, the assumption relies on our belief of how nature operates. For example, previous work (Ushio et al. 2018) has assumed that the governing population dynamics is fixed, implying the presence of higher-order direct effects.

Discussion

Traditionally, the parametric and nonparametric approaches have considered different measures and interpretations of species interactions. That is, species interactions are measured as constant-direct and local-aggregated effects within the parametric and nonparametric approaches, respectively.

However, their interpretations have been occasionally used interchangeably (e.g. when describing the stability conditions of an ecological community, May 1972, Coyte et al. 2015), limiting our opportunity to use their differences to gain new insights about ecological systems. In this line, here we have provided a bridge between these two approaches (measures) and illustrated its utility. In particular, we have shown three fundamental properties of species interactions. First, the local, aggregated, intraspecific effect summarizes all potential pathways through which one species impacts itself, which can be negative without any direct self-regulation mechanism (Fig. 1). Second, the local, aggregated, interspecific effect only measures the direct effect between two species if and only if the population dynamics does not have any higher-order direct effects (Fig. 2A–B). Third, higher-order direct effects can be detected by studying the changes of interaction signs within a nonparametric approach (Fig. 2C–D).

Species interactions are a multidimensional concept (Callaway et al. 2002, Nakazawa 2020), which naturally resulted in multiple definitions, ranging from mechanistically motivated characterizations to highly phenomenological representations (White and Marshall 2019). However, despite the fact that these definitions are distinct mathematical entities, their construction implies that they must be inherently linked given that they all describe properties of species interactions. Importantly, most of the definitions can be classified as either parametric or nonparametric. The parametric approach decomposes species interactions in biologically interpretable intraspecific, interspecific and high-order direct

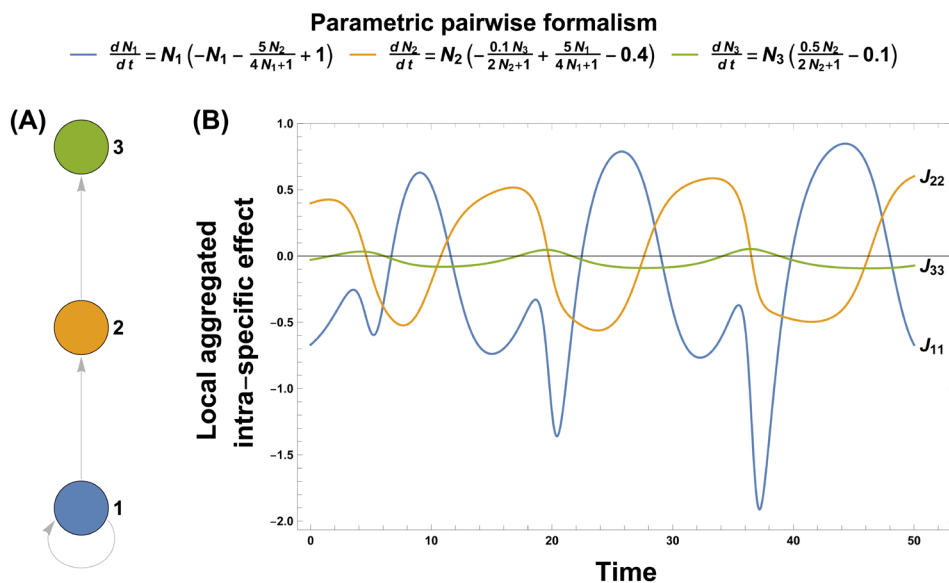


Figure 1. Local, aggregated, intraspecific effects can be negative without a constant, direct, self-regulation mechanism. (A) shows a simple three-level trophic chain with a primary producer (bottom circle), a consumer (middle circle) and a top predator (top circle). These species are linked by arrows showing the standard energy/biomass flow. Note that only the primary producer has a constant direct self-regulation (typically used in parametric approaches), i.e. $a_{11} < 0$, whereas $a_{22} = a_{33} = 0$. The governing equations describing the population dynamics of the three-species trophic chain are shown on the top. (B) shows the local (state-dependent), aggregated, intraspecific effects J_{ii} (typically used in nonparametric approaches) when the trophic chain is governed by a type II functional response (parameters are taken from Hastings and Powell 1991). Top predator (J_{33}) shows mostly negative, local, aggregated effects to itself; whereas both the consumer (J_{22}) and the primary producer (J_{11}) show anti-correlated oscillatory sign patterns of local, aggregated effects to themselves.

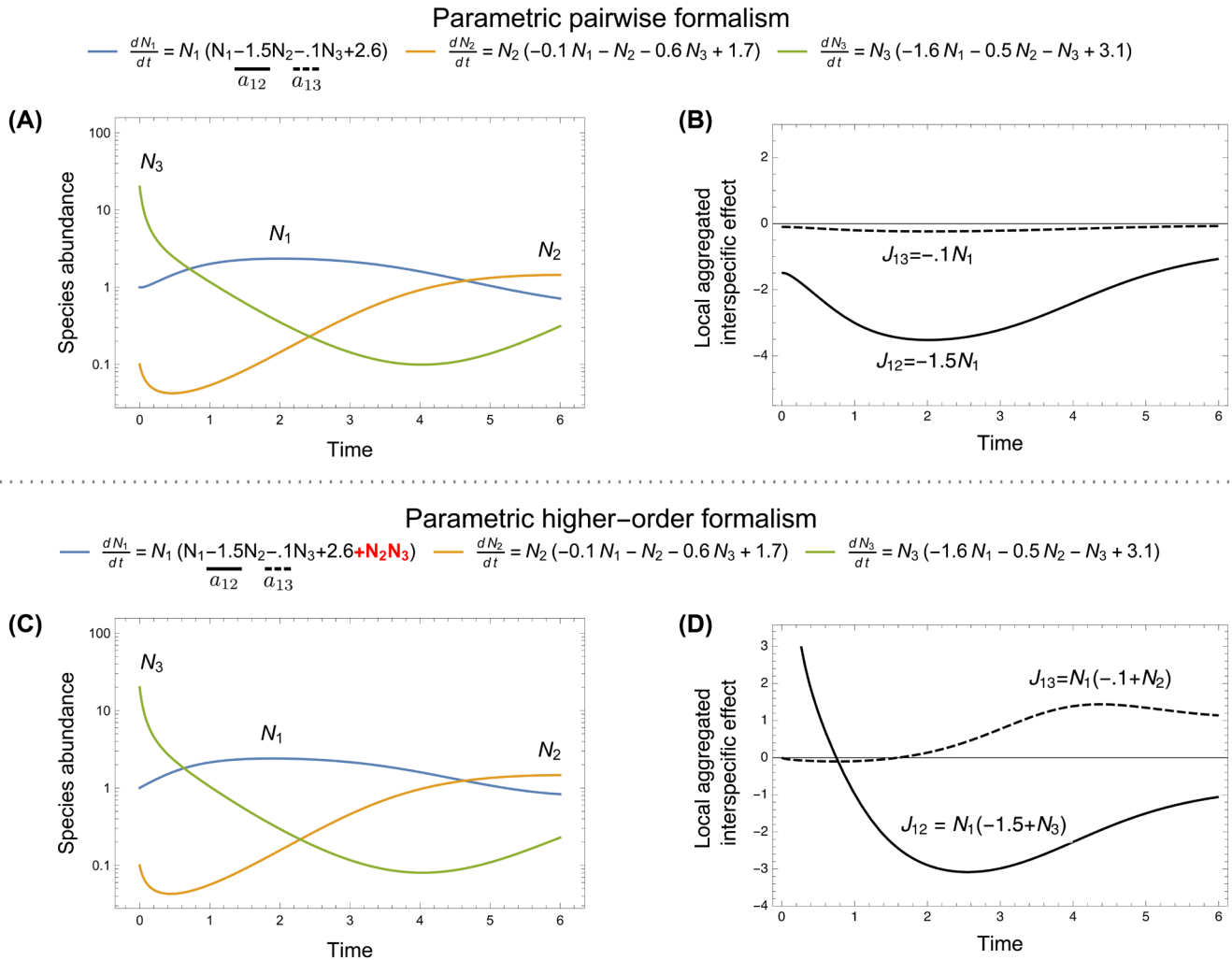


Figure 2. Local, aggregated, interspecific effects and constant, direct effects have the same sign if and only if all direct effects are pairwise based (i.e. absent of higher-order direct effects). (A–B) Three competing species are governed by Lotka–Volterra dynamics without any higher-order direct effects (shown above panels; parameters adopted from *saavedra et al. 2017*). (A) shows the time series of species abundances. (B) shows the corresponding local, aggregated, interspecific effects (typically used in nonparametric approaches) that species 2 and 3 have on species 1, where both J_{13} and J_{12} are always negative. (C–D) Three competing species are governed by Lotka–Volterra dynamics with an added higher-order direct effect from species 2 and 3 on species 1 (highlighted in red; shown above panels). This formulation of higher-order effects is conceptually inspired by *Levine et al. (2017)* and mathematically adopted from *Letten and Stouffer (2019)*. (C) shows the time series of species abundances, which exhibit similar patterns as the model without higher-order interactions shown in (A). However, (D) shows that both J_{12} and J_{13} change their sign, which are fundamentally different from the patterns shown in (B).

effects. In turn, the nonparametric approach decomposes species interactions in computationally feasible intraspecific and interspecific aggregated effects. Therefore, instead of linking specific definitions case-by-case, we have bridged these two approaches by focusing on their high-level conceptual links.

We hope this paper can open a dialogue between the parametric and the nonparametric approaches. The parametric approach has dominated community ecology (*Kingsland 2015*), while the nonparametric approach has recently received increasing attention in the past decade (*Deyle et al. 2016*, *Ushio et al. 2018*, *Cenci and Saavedra 2019*, *Bray and Wang 2020*, *Karakoç et al. 2020*, *Ushio 2020*, *Yu et al. 2020*). While both approaches have shaped our understanding of ecological dynamics, little is known about when and how we

can transfer the knowledge from one approach to the other. Importantly, we have shown that the transferability is necessary and provides a new perspective that each approach itself cannot offer. For example, the Achilles' heel of the parametric approach is to evaluate whether the model has included enough details of the system under investigation. Indeed, if we assume a pairwise formalism, while the system is actually governed by a high-order formalism (Box 1), then we are likely to make false predictions of the system (*Letten and Stouffer 2019*). However, the computational methods emerging from the parametric approach are difficult to distinguish (e.g. functional responses and higher-order interactions) (*AlAdwani and Saavedra 2019*). Yet, relying upon the computational feasibility of the nonparametric approach (*Deyle et al. 2016*,

Martin et al. 2018, Cenci and Saavedra 2019), we may be able to distinguish the nature of species interactions acting on a system. Therefore, we believe that a better understanding of both the measures and assumptions used across parametric and nonparametric approaches can improve our knowledge of species interactions and ecological dynamics in general.

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Author contributions

Chuliang Song: Conceptualization (equal); Data curation (lead); Formal analysis (lead); Investigation (lead); Methodology (lead); Project administration (lead); Software (lead); Validation (lead); Visualization (lead); Writing – original draft (equal); Writing – review and editing (lead). **Serguei Saavedra:** Conceptualization (equal); Formal analysis (supporting); Funding acquisition (lead); Methodology (supporting); Project administration (lead); Supervision (lead); Writing – original draft (equal); Writing – review and editing (supporting).

Data availability

No empirical data is used. The Mathematica code is archived at <https://github.com/clsong/Oikos-Song_Saavedra-2021>.

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