

CHCRUS

This is the accepted manuscript made available via CHORUS. The article has been published as:

Impact of colonization history on the composition of ecological systems

Nannan Zhao, Serguei Saavedra, and Yang-Yu Liu Phys. Rev. E **103**, 052403 — Published 5 May 2021 DOI: 10.1103/PhysRevE.103.052403 2

3

4

5

6

7

8

9

10

11

12

13

14

15

16

17

18

19

20

21

22

23

24

25

26

27

The impact of colonization history on the composition of ecological systems

Nannan Zhao,^{1,2} Serguei Saavedra,³ and Yang-Yu Liu^{1,4,*}

¹Channing Division of Network Medicine, Brigham and Women's

Hospital and Harvard Medical School, Boston, MA, 02115, USA

²Department of Applied Mathematics, Northwestern Polytechnical University, Xi'an, 710129, China

³Department of Civil and Environmental Engineering, Massachusetts Institute of Technology,

77 Massachusetts Avenue, Cambridge, MA, 02139, USA

⁴Center for Cancer Systems Biology, Dana Farber Cancer Institute, Boston, MA, 02115, USA

(Dated: April 23, 2021)

Observational studies of ecological systems have shown that different species compositions can arise from distinct species arrival orders during community assembly—also known as colonization history. The presence of multiple interior equilibria in the positive orthant of the state space of the population dynamics will naturally lead to history dependency of the final state. However, it is still unclear whether and under which conditions colonization history will dominate community composition in the absence of multiple interior equilibria. Here, by considering that only one species can invade at a time and there are no recurrent invasions, we show clear evidence that the colonization history can have a big impact on the composition of ecological systems even in the absence of multiple interior equilibria. In particular, we first derive two simple rules to determine whether the composition of a community will depend on its colonization history in the absence of multiple interior equilibria and recurrent invasions. Then we apply them to communities governed by generalized Lotka-Volterra (gLV) dynamics and propose a numerical scheme to measure the probability of colonization history dependence. Finally, we show, via numerical simulations, that for gLV dynamics with a single interior equilibrium the probability that community composition is dominated by colonization history increases monotonically with community size, network connectivity, and the variation of intrinsic growth rates across species. These results reveal that in the absence of multiple interior equilibria and recurrent invasions community composition is a probabilistic process mediated by ecological dynamics via the interspecific variation and the size of regional pools.

56

28

I. INTRODUCTION

Ecological communities are formed by co-occurring 29 and interacting species in a given place and time [1-3]. 30 It has been shown that within these communities, the 31 specific composition of species is a function of several 32 ecological, evolutionary, and stochastic processes [3-6]. 33 Importantly, one of the main factors affecting community 34 composition is the order of species arrival—also known 35 as colonization history [7–11]. That is, colonization his-36 tory can introduce priority effects, where the persistence 37 of species depends on the order at which they join a given 38 community. 39

Many mathematical or physical tools have been used 69 40 to investigate the impact of colonization history on com-70 41 munity composition. For example, Ref. [12] introduced a 42 toy model of ecosystem assembly to map out all assembly 71 43 pathways generated by external invasions. The coloniza-72 44 tion process was characterized as a finite Markov chain, 73 45 and proved to exhibit a unique set of recurrent states (the 74 46 end state of the process) that are resistant to invasions. 75 47 This also shows that the end state is independent of the 76 48 assembly history. For replicator systems and the gLV $_{77}$ 49 model, a phase transition was found from a phase where 78 50 a unique globally attractive fixed point exists to a phase 79 51 where multiple dynamical attractors exist [13-20]. The $_{80}$ 52 latter phase naturally leads to history-dependent com- 81 53 munity properties. 82 54

Although many other studies have also shown history dependent or independent communities in different theoretical models [21-27], these studies do not allow us to find general conditions under which colonization history can have the highest (or lowest) chance to affect community composition. In fact, it is still unclear whether and under which conditions colonization history will dominate community composition in the absence of multiple interior equilibria and recurrent invasions. Note that in the presence of a single interior equilibrium, if we allow for recurrent invasion, then sooner or later this interior equilibrium will be reached, and the assembly process (in the long run) will be trivially history independent. Therefore, in this work we are interested in the history dependency by considering that only one species can invade at a time, and there are no recurrent invasions.

The complexity of factors affecting community assembly has undercut our ability to anticipate whether a given regional pool of species can be more susceptible to colonization history than another. Yet, knowing this can advance our understanding about the probabilistic nature and predictability of ecological communities. In this paper, we try to address the following key questions: In the absence of multiple interior equilibria and recurrent invasions, are there any conditions under which colonization history will completely dominate community composition? Does the type of interspecific interactions affect the probability that community composition depends on colonization history? How do the intrinsic properties of ⁵⁴
species affect the impact of colonization history on com- ⁵⁵
munity composition? In the face of an accelerating rate of ⁵⁶
species turnover, answering these questions is important ⁵⁷
in order to understand and anticipate key biodiversity ⁵⁸
changes in ecological communities. ⁵⁹

The rest of the paper is organized as follows: Section II 60 7 provides two motivating examples, and then introduces 61 8 two simple rules to determine the relationship between 62 9 community composition and colonization history. Sec- 63 10 tion III defines a community model with gLV dynamics 64 11 and proposes a numerical scheme to measure the proba- 65 12 bility of colonization history dependence. Section IV dis-66 13 cusses the effects of both community and intrinsic prop-67 14 erties on the history dependence. Section V is devoted to 68 15 a discussion on the limitations of our current work and $_{69}$ 16 some potential extensions. 17 70

II. MOTIVATING EXAMPLES

18

To illustrate the scope and assumptions behind our 75 19 study, we start our analysis by considering a small pool 76 20 of 3 species that can coexist at a unique interior equilib- 77 21 rium, as shown in Fig. 1. It is worth mentioning that in 78 22 order to increase the tractability of the problem, here we 79 23 assume that only one species can invade at a time and the ⁸⁰ 24 ecological dynamics is fast enough to reach a boundary ⁸¹ 25 equilibrium (i.e., with some of the S species having zero ⁸² 26 abundance) before the next species invasion. Thus, in 83 27 this example, there are 6 possible colonization histories 84 28 (or assembly paths), one unique interior equilibrium, and 85 29 6 different boundary equilibria from which an ecological ⁸⁶ 30 community of 3 species can be assembled by introducing 87 31 one species at a time, i.e., via successive invasions to an ** 32 empty community \emptyset (see Fig. 1b and Fig. 1e). 89 33

As shown in Fig. 1b, species 2 and 3 cannot coexist on 90 34 their own (i.e., the boundary equilibrium $\{2, 3\}$ is infea- 91 35 sible), the assembly paths (of length 3): $\emptyset \to 3 \to 2 \to 1$ 92 36 and $\varnothing \rightarrow 2 \rightarrow 3 \rightarrow 1$ cannot achieve the final community $_{93}$ 37 $\{1, 2, 3\}$, while other assembly paths (of length 3) can. 94 38 Note that if we allow for recurrent invasion, then the as- 95 39 sembly path (of length 4): $\emptyset \rightarrow 2 \rightarrow 3 \rightarrow 1 \rightarrow 2$ can 96 40 eventually achieve $\{1, 2, 3\}$. Hence, the history depen- 97 41 dence we are interested in is equivalent to the existence 98 42 of non-optimal assembly paths (of length > S) to assem- ⁹⁹ 43 ble a community formed by S species, that is, there is₁₀₀ 44 at least one infeasible boundary equilibrium. And his-101 45 tory independence means that starting from the empty₁₀₂ 46 community all the S! assembly paths (of optimal length $_{103}$ 47 S) can lead to the final state with S species stably co-10448 exist, that is, all boundary equilibria are feasible. For₁₀₅ 49 example, for the system shown in Fig. 1e, any subset of 106 50 the 3 species can coexist at their equilibria. In this case, 107 51 the final community composition is independent of the108 52 colonization history, and any optimal assembly paths (of₁₀₉ 53

length S) can assemble a community formed by S species.

Based on the above observations, in the absence of multiple interior equilibria and recurrent invasions, we have two simple rules to determine the relationship of community composition and colonization history:

First, if there exists a set of species $\{S\}$ that can coexist at a unique equilibrium, but a smaller subset of species $\{\mathcal{T}\} (\subset \{\mathcal{S}\})$ cannot, then the final community composition formed by the $S (= |\{S\}|)$ species depends on the colonization history. This rule can be understood as follows. For a given regional pool $\{S\} = \{1, ..., S\},\$ without loss of generality, let us assume there is only one subcommunity $\{\mathcal{T}\} = \{1, ..., T\}$ (with T < S) that does not have a feasible boundary equilibrium, then the following two assembly paths (of the same length S): (1) $\emptyset \to 1 \to \cdots \to T - 1 \to T \to T + 1 \to \cdots \to S;$ (2) $\varnothing \rightarrow 1 \rightarrow \cdots \rightarrow T - 1 \rightarrow T + 1 \rightarrow T \rightarrow$ $\cdots \rightarrow S$ will yield different states. The former leads to $\{1, \dots, T-1, T+1, \dots, S\}$ with S-1 species present, while the latter leads to $\{1, \dots, S\}$ with all the S species present. Similar arguments can be applied to the case of more infeasible subcommunities. Basically, the assembly paths (of length S) that avoid those roadblocks (infeasible subcommunities) will naturally lead to $\{1, \dots, S\}$ with all the S species present, while those assembly paths (of length S) that encounter those roadblocks (infeasible subcommunities) will lead to different final states, in the absence of recurrent invasions.

71

72

73

74

Second, if any subcommunities of $\{S\}$ can coexist at a unique boundary equilibrium, then the final community composition formed by the *S* species does not depend on the colonization history. This result can be explained via the following example: when a new species is added to a species pool to build a new community $\{\mathcal{I}\} = \{1, 2, ..., I\}$, the community with $I \ (< S)$ species can stably coexist in a unique boundary equilibrium, which is stable and feasible. Following these steps to add more and more species one at a time, we will always reach the unique interior equilibrium with all the *S* species present, regardless of the detailed assembly path. Thus, the final state is independent of the colonization history.

We emphasize that the above two simple rules hold for a wide class of population dynamics models where all the S species can coexist at a unique interior equilibrium and recurrent invasions are not allowed. However, we still lack a numerical scheme to quantitatively study the impact of colonization history on community assembly. Directly constructing the assembly graph for large systems is computationally intractable. Indeed, for a species pool of size S, suppose the S species can coexist at a stable interior equilibrium, then starting from the empty community, with one species can invade at a time, there are S! potential assembly paths to reach the final state where all the S species present, and there are $(2^S - 2)$ possible subcommunities (with at least one and at most S - 1 species). If there are some subcommunities



FIG. 1. Ecological communities can display different dependencies on colonization history. For illustration purposes, we show the assembly of a 3-species community $\{1, 2, 3\}$ by the invasion or colonization of one species at a time, following the gLV dynamics. There are in total 3! = 6 different colonization trajectories. (a) The ecological network depicts the pairwise interactions among the three species (which are also encoded in the interaction matrix **A**). The feasible intrinsic growth rate vector **r** is set to be $(\frac{1}{3}, \frac{1}{3}, \frac{1}{3})^{\mathsf{T}}$. (b) Starting from an empty ecological community \emptyset (top node), the three species are added successively into the community via different orders. Since species-2 and 3 cannot coexist (gray node), the community composition will be dependent on colonization history. That is, the final state of the three species together cannot be assembled if we follow the trajectory $\emptyset \to 3 \to 2 \to 1$ or $\emptyset \to 2 \to 3 \to 1$, while the other four trajectories will lead to the desired final state. (c) As an example, we show two different trajectories and their final community compositions. Panels (d-f) show a similar case as the previous example, but with different interaction matrix **A**. In this case, the community composition is independent on colonization history.

35

36

37

38

that do not have feasible boundary equilibria, they will 22 1 serve as roadblocks in some assembly paths (or isolated 23 2 nodes in the assembly graph, e.g., $\{2,3\}$ in Fig. 1b). For 24 3 large S, we know that both S! and $(2^{S} - 2)$ are notori- 25 4 ously large, rendering the construction of the assembly ²⁶ 5 graph computationally intractable. Without the assem- 27 6 bly graph at hand, it is very hard, if not impossible, 28 7 to identify which assembly paths (of optimal length S) will lead to the final state with all S species present. 9 Moreover, once we encounter a roadblock in a particular 10 assembly path, it is very challenging to predict exactly 11 how many recurrent invasions will be needed to eventu-12 ally reach the final state with all S species present, if we 13 do not have the assembly graph. Therefore, for ecosys-14 tems with only one attracting interior equilibrium, even ³⁰ 15 though the community assembly with recurrent invasions³¹ 16 allowed is trivially history independent in the long run, $^{\scriptscriptstyle 32}$ 17 it becomes highly nontrivial without recurrent invasions.³³ 18 34

19

III. MODEL DEFINITION

In this work we choose the classical gLV model to 39 quantitatively study the impact of colonization history 40 on community composition. This model includes parameters that govern the intrinsic growth rates of different species and pairwise interactions among different species, and it is tractable enough to allow us to investigate the conditions under which community composition depends on colonization history.

The gLV model can be written as follows

$$\frac{\mathrm{d}N_i(t)}{\mathrm{d}t} = N_i(t) \left(r_i + \sum_{j=1}^{S} A_{ij} N_j(t) \right), i = 1, \cdots, S, \ (1)$$

where N_i is the abundance (or biomass) of species-*i*, *S* corresponds to the number of species in the community, $\mathbf{A} = [A_{ij}]_{S \times S}$ is the interaction matrix whose elements denote the per capita effect of one species on the per capita growth rate of another species, and r_i is the intrinsic growth rate of species-*i*.

To ensure that the *S* species can coexist at a unique interior equilibrium, following previous studies [28, 29], we focus on diagonally stable interaction matrices **A** (i.e., there is a positive definite diagonal matrix **D** such that $\mathbf{DA} + \mathbf{A}^{\top}\mathbf{D}$ is a negative definite symmetric matrix [30]). A diagonally stable interaction matrix **A** guarantees that

the gLV model has a single, globally, attractive equilib- $_{51}$ rium [31]. We emphasize that the assumption of a diagonally stable interaction matrix **A** is deeply driven by the complexity of this problem and allows us to focus on the feasibility of the system—the necessary condition for species coexistence [32, 33]. To construct the **A** matrix, we first capture its binary $_{56}$

7 structure by constructing an Erdős-Rényi (ER) random 57 8 graph. We begin with S isolated nodes (species). For 58 9 each of the S(S-1)/2 node pairs, we construct an undi- 59 10 rected edge between the two nodes with probability $C_{.60}$ 11 It is worth noting that C represents the connectance of $_{61}$ 12 the community (i.e., the ratio between actual and po-62 13 tential interactions in the ecological network). Once the 63 14 ER graph is constructed, we assign the interspecific in- 64 15 teraction strengths to the edges (here we treat edges 65 16 as bidirectional). The interaction strengths $A_{ij}(i \neq j)$ 66 17 are drawn from a normal distribution $\mathcal{N}(0,\sigma^2)$, where σ 18 $\sigma = 1/\sqrt{S(2+\epsilon)}$ denotes the characteristic interspecific ⁶⁸ 19 interaction strength, and ϵ is a constant [34]. The diago- 69 20 nal elements are set to be $A_{ii} = -d$ with d representing 70 21 the intrinsic damping time scale of each species. 71 22

We consider three interaction types: (1) random (no 72 23 sign structure). A_{ij} and A_{ji} are independently sampled ⁷³ 24 from $\mathcal{N}(0, \sigma^2)$. (2) predator-prey (+, -): We generate ⁷⁴ 25 a random number p from a uniform distribution $\mathcal{U}[0,1]$.⁷⁵ 26 If $p \leq 0.5$, we draw A_{ij} from a half-normal distribution ⁷⁶ $|\mathcal{N}(0,\sigma^2)|$, and A_{ji} from $-|\mathcal{N}(0,\sigma^2)|$. If p > 0.5, we ⁷⁷ 27 28 do the opposite. (3) mixture of competition (-, -) and ⁷⁸ 29 mutualism (+, +): we generate a random number p from ⁷⁹ 30 $\mathcal{U}[0,1]$. If $p \leq 0.5$, we draw A_{ij} and A_{ji} independently ⁸⁰ 31 from $|\mathcal{N}(0,\sigma^2)|$. If p > 0.5, we draw A_{ij} and A_{ji} inde-⁸¹ 32 82 pendently from $-|\mathcal{N}(0,\sigma^2)|$. 33

To ensure the randomly-generated interaction matrix **A** is diagonally stable, we set $\epsilon = 0.01$ and d = 1 [34]. Furthermore, to ensure the coexistence of the whole community with S species, we use the feasibility domain to construct feasible vector of intrinsic growth rates [35]. When the interaction matrix **A** is given, the feasibility domain can be determined as an algebraic cone:

$$D_F(\mathbf{A}) = \{ \mathbf{r} = N_1^* \mathbf{v}_1 + \dots + N_S^* \mathbf{v}_S \}, \qquad (2)$$

88

89

where $N_i^* > 0$ is the equilibrium abundance of species 9041 i, and \mathbf{v}_i is the spanning vector of the algebraic cone, 42 whose *j*-th component is given by $v_{ij} = \frac{-A_{ji}}{\sqrt{\sum_{k=1}^{S} A_{ki}^2}}$. If 43 the vector of intrinsic growth rates \mathbf{r} is chosen inside the $_{92}$ 44 feasibility domain $D_F(\mathbf{A})$, the community with S species ₉₃ 45 will always be feasible. This feasible vector can be de- $_{94}$ fined as follows: $\mathbf{r} = \sum_{i=1}^{S} n_i^* \mathbf{v}_i$, where $n_i^* \in (0, 1)$ and $_{95}$ 46 47 $\sum_{i=1}^{S} n_i^* = 1$. This procedure guarantees that there is at 96 48 least one assembly path that can given rise to the whole 97 49 community formed by S-coexisting species. 98 50

IV. ANALYSIS AND RESULTS

As noted in the simple rules mentioned in Sec. II, whether all subsets of species can coexist at their boundary equilibria will determine if the community composition depends on colonization history. Under the gLV dynamics, this coexistence is guaranteed if the equilibria of system (1) are feasible (i.e., all present species have positive abundance) and globally stable for all subcommunities. It has been proved that if the interaction matrix **A** is diagonally stable, then all sub-matrices $(\hat{\mathbf{A}})$ are diagonally stable as well [30], and the non-trivial positive equilibrium will be globally asymptotically stable (that is, species can stably coexist) [31]. These matrix properties imply that we only need to guarantee the feasibility of the boundary equilibria for all subcommunities. The unique boundary equilibrium of every subcommunity with k species (k < S) under gLV dynamics can be calculated as $\hat{\mathbf{N}}^* = (\hat{N}_1^*, \cdots, \hat{N}_k^*) = -\hat{\mathbf{A}}^{-1}\hat{\mathbf{r}}$, where $\hat{\mathbf{A}}$ and $\hat{\mathbf{r}}$ are the reduced interaction matrix $(k \times k)$ and intrinsic growth rate vector $(k \times 1)$ of the corresponding subcommunity, and when $\hat{N}_i^* > 0 (i = 1, \dots, k),$ this subcommunity is feasible, otherwise, it is infeasible. Thus, we can obtain a numerical scheme to determine for the gLV model whether the community composition depends on colonization history: For a community $\{S\}$ that follows the gLV dynamics characterized by a diagonally stable interaction matrix **A** and a feasible intrinsic growth rate vector \mathbf{r} , in the absence of recurrent invasions, if there exists an infeasible subcommunity $\{\mathcal{T}\}$, then the final community composition of the community $\{\mathcal{S}\}\$ depends on colonization history. Otherwise, it will be colonization-history independent.

A. Examples of small communities

To illustrate the application of the above numerical scheme, we consider the two 3-species communities shown in Fig. 1. The community shown in Fig. 1a is characterized by a feasible intrinsic growth rate vector $\mathbf{r} = (\frac{1}{3}, \frac{1}{3}, \frac{1}{3})^{\top}$, and a diagonally stable interaction matrix.

$$\mathbf{A} = \begin{bmatrix} -1.00 & -0.01 & 0.46 \\ -0.10 & -1.00 & -1.02 \\ -0.58 & 0.89 & -1.00 \end{bmatrix}.$$

In this case, we can verify that there exists a feasible interior equilibrium $\mathbf{N}^* = (0.417, 0.104, 0.184)^{\top}$ for the three species, but there is no feasible boundary equilibrium for the species-pair $\{2,3\}$. Thus, based on the above result, the final community composition will depend on the colonization history. Indeed, Figure 1c shows two different final states obtained by two assembly paths. Figure 1d shows a community characterized by the same feasible intrinsic growth rate vector **r**, but with a different diag-51
 onally stable interaction matrix 52

$$\mathbf{A} = \begin{bmatrix} -1.00 & -0.37 & -0.19 \\ -0.40 & -1.00 & 0.06 \\ -0.25 & -0.19 & -1.00 \end{bmatrix}.$$

In this case, all subsets of species have the unique and ⁵⁷ feasible boundary equilibria. Thus, the final community ⁵⁸ composition does not depend on the colonization history: ⁵⁹ any assembly path will eventually yield the same final ⁶⁰ community composition of the three species (see Fig. 1f ⁶¹ for examples of assembly paths).

B. Effects of community properties

10

A big advantage of our numerical scheme is that it ⁶⁷ 11 allows us to perform extensive numerical simulations to 68 12 investigate which properties of the community and indi-69 13 vidual species can affect the probability that community ⁷⁰ 14 composition depend on colonization history. In particu-⁷¹ 15 lar, for a given community $\{S\}$ with gLV dynamics, we ⁷² 16 can numerically check all subsets (subcommunities) to 73 17 search whether there exists any infeasible subset $\{\mathcal{T}\}$, ⁷⁴ 18 and if so, we conclude that the community is history de-75 19 pendent. Furthermore, to study the impact of commu-⁷⁶ 20 nity properties on the history dependence, we systemat-21 ically generate diagonally stable interaction matrices A 22 with different community size (S), network connectance ⁷⁷ 23 (C), and interaction types. In particular, for each inter-24 action type and given (C, S) values, we first randomly ⁷⁸ 25 construct an interaction matrix A, and then generate 79 26 2.000 feasible intrinsic growth rate vectors $\mathbf{r} \in D_F(\mathbf{A})$. 27 From the 2,000 communities (\mathbf{A}, \mathbf{r}) , we count how many ⁸¹ 28 communities having infeasible subcommunities to calcu- ⁸² 29 late the probability that community composition depends 83 30 on colonization history, denoted as P, for a given inter-⁸⁴ 31 action type and (C, S) values. We repeat this process for ⁸⁵ 32 an ensemble of 50 different realizations of A, and then ⁸⁶ 33 calculate the standard error of the mean (SEM) of P for $_{87}$ 34 a given interaction type and (C, S) values. 88 35

We find that the probability P always increases with ⁸⁹ the community size S (Fig. 2-top) or network con- ⁹⁰ nectance C (Fig. 2-bottom), regardless of the interac- ⁹¹ tion type. This indicates that the community composi- ⁹² tion will almost surely dependent on colonization history ⁹³ when an ecological system is composed of a large number ⁹⁴ of species or when species are highly connected. ⁹⁵

To check how this result holds beyond expectations, 96 43 we consider a simple null model as follows. We assume 97 44 that a random subset of species has a fixed probability 98 45 p to have a feasible boundary equilibrium. Then, the $_{99}$ 46 probability to have at least one subset of species that₁₀₀ 47 does not have a feasible boundary equilibrium is given by 101 48 $1-p^n$, where $n=2^S-2$ is the number of possible subsets¹⁰² 49 with at least one and at most (S-1) species. According₁₀₃ 50

to the above result, we conclude that the probability that community composition depends on colonization history is $P_{\text{null}} = 1 - p^n$, where the subscript 'null' stands for the null model.

53

54

55

56

63

64

65

66

In the top panel of Fig. 2, for a given community size S, we plot P_{null} based on different values of p (horizontal lines). Clearly, lower p yields higher P_{null} , regardless of the connectance C. For example, for S = 10, we have $P_{\text{null}} \sim 0.1$ for p = 0.9999 (green line), and $P_{\text{null}} \sim 1$ for p = 0.99 (yellow line). However, our calculation based on the gLV model indicates that P increases monotonically with increasing C, and for S = 10 we have $P \to 1$ only if C is above 0.6, regardless of the interaction types. In the bottom panel of Fig. 2, for a given value of p, we plot P_{null} as a function of the community size S, finding that P_{null} increases monotonically with S. Note that the S-dependency of P_{null} is heavily driven by the value of p. For example, for p = 0.999 (or 0.9), P_{null} will always underestimate (or overestimate, respectively) P for S <12, regardless of the interaction types. The difference between P_{null} and P shown here suggests that ecological dynamics (as simple as they can be) can fundamentally alter the dependency of the community composition on colonization history. That is, this probability cannot be precisely predicted from the probability of feasibility of each individual subset (as assumed in the null model).

C. Effects of intrinsic properties

To investigate the extent to which the variation of intrinsic properties across species affect the history dependence, we systematically generate feasible vectors of intrinsic growth rates \mathbf{r} with different levels of variability across the elements. In particular, for different interaction types, we sample 2,000 feasible vectors $\mathbf{r} \in D_F(\mathbf{A})$ for each randomly-generated interaction matrix \mathbf{A} with community size S = 8 and network connectance C = 0.4, and then in each case we can calculate different interspecific variations of intrinsic growth rates $\xi = \frac{\langle r^2 \rangle}{\langle r \rangle^2}$. We categorize them (with bin width = 0.05) according to the variation (ξ) across their elements, and use the curves to replace the histogram to show the expected value. Similarly, here we sample 50 different realizations of the matrix \mathbf{A} to calculate the SEM of P for each ξ bin.

From Fig. 3, we can observe that P increases monotonically with increasing ξ , regardless of the interaction type. In other words, the higher the interspecific variation within a community, the higher the probability that community composition depends on colonization history. An intuitive explanation of this phenomenon is as follows. As we increase ξ , different species tend to have quite different intrinsic growth rates, and hence play different "roles" in the community assembly, rendering higher probability that community composition depends on colonization history.



FIG. 2. The probability P that community composition depends on colonization history as a function of community properties. P is calculated as a function of community properties: community size S, connectance C, and interaction types, using the gLV model (line plots with error bars) or the null model (lines). (Top) P as a function of connectance C, with fixed community size S = 10. (Bottom) P as a function of community size S, with fixed connectance C = 0.5. Each column corresponds to a particular interaction type: random interactions, predator-prey, and mixture of competition and mutualism.



FIG. 3. The probability *P* that community composition depends on colonization history as a function of intrinsic properties of species. The probability is calculated for different levels of interspecific variation ξ (intrinsic growth rate) and interaction types, using the gLV model (line plots with error bars) or the null model (lines). We fix community size S = 8 and network connectance C = 0.4. Each column corresponds to a particular interaction type: random interactions, predator-prey, and mixture of competition and mutualism.

Here, for the given community size S, we also plot $P_{\text{null } 10}$ 1 based on different values of p. As shown in Fig. 3 (hor- 11 2 izontal lines), lower p yields higher P_{null} , regardless of 12 3 the interspecific variation ξ and interaction types. For ¹³ example, for S = 8, we have $P_{\text{null}} \sim 0.01$ for p = 0.9999 ¹⁴ 5 (green line), and $P_{\text{null}} \sim 0.9$ for p = 0.99 (yellow line). ¹⁵ 6 However, our calculation based on the gLV model indi- 16 7 cates that P increases monotonically with increasing ξ , 17 and for S = 8 we have $P \to 1$ if ξ is above 2, regardless 18 9

of the interaction types. The difference between P_{null} and P underscores the impact of interspecific variation on the probability that community composition depends on colonization history, which cannot be predicted from the null model. This is acceptable because the simple null model only contains two parameters p and S, while the gLV model of N species contains $N + N^2$ parameters (stored in \mathbf{r} and \mathbf{A}). Although the null model cannot accurately fit the simulation results of the gLV model, $_{\rm 1}~$ it can still offer a theoretical guide to predict the qual- $_{\rm 51}$

 $_{\rm 2}$ $\,$ itative trend so that we can better appreciate why the $_{52}$

 $_3$ $\,$ colonization history matters for large and complex eco- $_{53}$

⁴ logical communities.

5

V. DISCUSSION

In summary, here we offered simple rules linking colo- $^{\rm 55}$ 6 nization history and community composition in the absence of multiple interior equilibria and recurrent inva-8 sions. Moreover, we applied those rules to communi- 59 9 ties that are governed by gLV dynamics and proposed 60 10 a numerical scheme to measure the probability that ⁶¹ 11 community composition depends on colonization history.⁶² 12 Through extensive simulations, we demonstrated that $^{\rm 63}$ 13 this probability increases monotonically with commu-14 nity size, network connectance, and variation of intrin-66 15 sic growth rates across species. Moreover, we proposed 67 16 a simple null model to fit the above numerical results. 68 17 However, due to the complexity of the gLV model, espe-⁶⁹ 18 cially the various parameter settings of species number, ⁷⁰ 19 network connectance, or growth rate heterogeneity, the ⁷¹ 20 effects cannot be precisely predicted from the null model $\frac{1}{73}$ 21 that only considers the probability of feasibility of each 74 22 each sub-community of species. 23 75

It is worth noting that our current framework has sev- 76 24 eral limitations. First, it focuses on the coexistence of ⁷⁷ 25 species at a globally stable interior equilibrium[36] based ⁷⁸ 26 on the assumption of a diagonally stable interaction ma- $\frac{79}{2}$ 27 trix. But the coexistence of species could be driven by $\frac{1}{81}$ 28 not only an equilibrium state, but also different dynam-29 ical behavior, such as limit cycles or chaos, those more 83 30 complicated scenarios deserve a more dedicated research ⁸⁴ 31 effort [37]. Second, the simulation framework is appli-⁸⁵ 32 cable to gLV dynamics with linear functional responses.⁸⁶ 33 Extending the calculations to population dynamics mod-⁸⁷ 34 els with more complicated functional response will also 35 be an interesting future direction [33, 38]. Third, our ex-36 planation of the probability P increasing with the vari- $_{91}$ 37 ation ξ of species intrinsic growth rates (Fig. 3) is very ⁹² 38 conceptual. We call for more quantitative explanations 93 39 of this very interesting phenomenon. Despite those limi-⁹⁴ 40 tations, the simplicity of our work allows us to provide a 41 first-order classification of the conditions modulating the $\frac{1}{27}$ 42 impact of colonization history. This work can serve as a $_{98}$ 43 basis for future work aiming to study the extent to which 99 44 it is possible to reconstruct (or to partially reconstruct)¹⁰⁰ 45 the species arrival order in a community. 101 46

⁴⁶ the species arrival order in a communit

47

ACKNOWLEDGMENT

102

103

104

105

106

- 48 N.Z. was supported by grant No.201806290054 from 107
- ⁴⁹ China Scholarship Council (CSC). Y.-Y.L. was supported¹⁰⁸
- ⁵⁰ by grants R01AI141529, R01HD093761, R01AG067744,¹⁰⁹

UH3OD023268, U19AI095219, and U01HL089856 from National Institutes of Health (NIH). S.S. was supported by grant No. DEB-2024349 from National Science Foundation (NSF).

- * Corresponding author: yyl@channing.harvard.edu
- Jared M Diamond. Assembly of species communities. In Ecology and Evolution of Communities, pages 342–444. Harvard University Press, Cambridge, MA, 1975.
- [2] Eugene P Odum. The strategy of ecosystem development. In *The Ecological Design and Planning Reader*, pages 203–216. Springer, 2014.
- [3] Mark Vellend. The theory of ecological communities (MPB-57). Princeton University Press, 2016.
- [4] Robert M May. How many species are there on earth? Science, 241(4872):1441–1449, 1988.
- [5] Tadashi Fukami. Community assembly dynamics in space. In *Community Ecology: Processes, Models, and Applications*, pages 45–54. Oxford University Press, Oxford, 2010.
- [6] Tadashi Fukami. Historical contingency in community assembly: integrating niches, species pools, and priority effects. Annu. Rev. Ecol. Evol. Syst., 46:1–23, 2015.
- [7] David Tilman. Resource competition and community structure. Princeton university press, 1982.
- [8] Peter Jay Morin. Odonate guild composition: experiments with colonization history and fish predation. *Ecology*, 65(6):1866–1873, 1984.
- Maarit Jaarola, Hakan Tegelström, and Karl Fredga. Colonization history in fennoscandian rodents. *Biol. J. Linnean Soc.*, 68(1-2):113–127, 1999.
- [10] Dina M Fonseca and David D Hart. Colonization history masks habitat preferences in local distributions of stream insects. *Ecology*, 82(10):2897–2910, 2001.
- [11] Inés Martínez, Maria X Maldonado-Gomez, João Carlos Gomes-Neto, Hatem Kittana, Hua Ding, Robert Schmaltz, Payal Joglekar, Roberto Jiménez Cardona, Nathan L Marsteller, and Steven W Kembel. Experimental evaluation of the importance of colonization history in early-life gut microbiota assembly. *Elife*, 7:e36521, 2018.
- [12] José A Capitán, José A Cuesta, and Jordi Bascompte. Statistical mechanics of ecosystem assembly. *Phys. Rev. Lett.*, 103(16):168101, 2009.
- [13] Sigurd Diederich and Manfred Opper. Replicators with random interactions: A solvable model. *Phys. Rev. A*, 39(8):4333, 1989.
- [14] Manfred Opper and Sigurd Diederich. Phase transition and 1/f noise in a game dynamical model. *Phys. Rev. Lett.*, 69(10):1616, 1992.
- [15] Manfred Opper and Sigurd Diederich. Replicator dynamics. Comput. Phys. Commun., 121:141–144, 1999.
- [16] Johannes Berg and Martin Weigt. Entropy and typical properties of nash equilibria in two-player games. *EPL*, 48(2):129, 1999.
- [17] Tobias Galla and J Doyne Farmer. Complex dynamics in learning complicated games. PNAS, 110(4):1232–1236, 2013.
- [18] Tobias Galla. Two-population replicator dynamics and number of nash equilibria in matrix games. EPL, 78(2):20005, 2007.

- [19] Laura Sidhom and Tobias Galla. Ecological communities 33
 from random generalized lotka-volterra dynamics with 34
 nonlinear feedback. *Phys. Rev. E*, 101(3):032101, 2020. 35
- [20] Guy Bunin. Ecological communities with lotka-volterra 36
 dynamics. Phys. Rev. E, 95(4):042414, 2017. 37
- [21] Wilfred M Post and Stuart L Pimm. Community assem- 38
 bly and food web stability. *Math. Biosci.*, 64(2):169–192, 39
 1983. 40
- [22] James A Drake. The mechanics of community assembly 41 and succession. J. Theor. Biol, 147(2):213–233, 1990. 42
- [23] Richard Law and R Daniel Morton. Alternative per-43
 manent states of ecological communities. *Ecology*, 44
 74(5):1347-1361, 1993.
- [24] Julie L Lockwood, Robert D Powell, M Philip Nott, and 46
 Stuart L Pimm. Assembling ecological communities in 47
 time and space. *Oikos*, 80(3):549–553, 1997.
- [25] Yohsuke Murase, Takashi Shimada, Nobuyasu Ito, and 49
 Per Arne Rikvold. Effects of demographic stochasticity 50
 on biological community assembly on evolutionary time 51
 scales. *Phys. Rev. E*, 81(4):041908, 2010. 52
- [26] Shay Be'er, Michael Assaf, and Baruch Meerson. Colo- 53
 nization of a territory by a stochastic population under a 54
- strong allee effect and a low immigration pressure. *Phys.* 55
 Rev. E, 91(6):062126, 2015. 56
- [27] Ignacio A Rodriguez-Brenes, Dominik Wodarz, and Na- 57
 talia L Komarova. Beyond the pair approximation: Mod- 58
 eling colonization population dynamics. *Phys. Rev. E*, 59
 101(3):032404, 2020.
- [28] Serguei Saavedra, Rudolf P Rohr, Jordi Bascompte, Os- 61
 car Godoy, Nathan JB Kraft, and Jonathan M Levine. A 62
- 31 structural approach for understanding multispecies coex- 63
- istence. Ecol. Monogr., 87:470–486, 2017.

- [29] Carlos A Serván, José A Capitán, Jacopo Grilli, Kent E Morrison, and Stefano Allesina. Coexistence of many species in random ecosystems. *Nat. Ecol. Evol.*, 2:1237, 2018.
- [30] Eugenius Kaszkurewicz and Amit Bhaya. Matrix diagonal stability in systems and computation. Springer Science and Business Media, 2012.
- [31] Bo S Goh. Global stability in many-species systems. Am. Nat., 111(977):135–143, 1977.
- [32] Josef Hofbauer and Karl Sigmund. Evolutionary games and population dynamics. Cambridge University Press, 1998.
- [33] S. Cenci and S. Saavedra. Structural stability of nonlinear population dynamics. *Phys. Rev. E*, 97:012401, 2018.
- [34] Travis E Gibson, Amir Bashan, Hong-Tai Cao, Scott T Weiss, and Yang-Yu Liu. On the origins and control of community types in the human microbiome. *PLoS Comput. Biol.*, 12(2):e1004688, 2016.
- [35] Chuliang Song and Serguei Saavedra. Will a small randomly assembled community be feasible and stable? *Ecology*, 99(3):743–751, 2018.
- [36] R. C. Lewontin. The meaning of stability. Brookhaven Symp. Biol., 22:13–24, 1969.
- [37] Sebastian J Schreiber, Masato Yamamichi, and Sharon Y Strauss. When rarity has costs: coexistence under positive frequency-dependence and environmental stochasticity. *Ecology*, 100:e02664, 2019.
- [38] Mohammad AlAdwani and Serguei Saavedra. Is the addition of higher-order interactions in ecological models increasing the understanding of ecological dynamics? *Math. Biosci.*, 315:108222, 2019.