Transient dynamics in metapopulations depend on the nature of density-dependence of growth

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Abstract. Single species discrete population growth is modelled using one-dimensional uni-modal maps having different types of density dependent functions specific to the species life history. These models exhibit similar sequence of bifurcation dynamics – from a fixed point to chaotic – with increasing growth rates. A metapopulation of single species subpopulations, coupled through inter-patch migration, can be modelled using the coupled map lattice (CML) formalism. Even though dynamical behavior of such metapopulation models has been done under many conditions, a systematic analysis of the transient behaviors exhibited in these CMLs is lacking. In this study, first a detailed characterization of the spatiotemporal transient states is developed for one-dimensional CMLs. Then the role of three specific single species growth models, having different density dependent functions (viz, logistic, Ricker, and Hassell), is studied to evaluate their influence in developing and maintaining transient states for local and non-local couplings. Our results show that, even when the growth functions (maps) belong to the same universality class and show similar period doubling route to chaos, the three different metapopulations exhibit significant differences in their transient states. The CML with logistic growth function shows opposite trends when compared to the CMLs with Ricker and Hassell growth functions. Our results demonstrate that transient dynamics in metapopulations depends specifically on the nature of density-dependence of the species growth functions. This can have important implications in biodiversity and conservation practices in ecology, where understanding the growth dynamics of different species in the metapopulation scenario are crucial.

Keywords. Transient states; coupled map lattices; chimera states.

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1. Introduction

Several ecological systems exhibit dynamics on short and intermediate time-scales that are functionally relevant and different from their asymptotic stable state behavior [1–3]. These transient phenomena are also observed in other areas such as neuroscience [4–6], development [7] and gene expression [8]. Tools from dynamical systems are increasingly being used in modelling and analyzing transient biological phenomenon, e.g. population dynamics [9, 10], pattern formation in tissues [11] and activity of single neurons or their network [12].

In ecology, species growth is modelled using both difference and differential equations based on the type of reproduction. Many species in nature undergo reproduction where generations do not overlap. Examples are many semelparous organisms (insects, such as butterflies and beetles, fishes, such as the Pacific salmon, and annual plants, such as rice) that lay a set of eggs/seeds in their lifetime and die shortly after oviposition/seed generation. The population dynamics of such species are modelled using discrete equations of the form $u_{t+1} = f(u_t)$. On the other hand, for species, such as humans, perennial plants, and many other animals, where the successive generations overlap, the continuous differential equation models are used to study their growth. Populations of different species that have non-overlapping generations, growing under limited resources, are modelled using one-dimensional uni-modal maps, such as the logistic, Ricker and Hassell maps [13]. These were all shown to belong to the same universality class, exhibiting a period doubling route to chaos with increasing growth rate [13, 14]. Dynamics of metapopulation, consisting of various sub-populations, have been modelled using coupled map lattices (CML).
of these maps, coupled through migration, such as logistic (LCML), Ricker (RCML) and Hassell (HCML) [15–17]. These models often exhibit a vast range of dynamical behavior spanning from regular spatial and/or temporal patterns to irregular/chaotic ones [18]. Here we attempt to understand the transient behavior of these systems.

Transience is often defined as a brief change in the state of a system [19]. Transience in ecological systems has been defined as dynamics that are exhibited over ecologically relevant time scales and differ from stable asymptotic behavior of the system. In a spatiotemporal system, we define ‘transient state’ as the dynamics of the state variable over a finite interval of space and time, which is qualitatively different from that outside of the interval. For a systematic analysis here, we focus on transients consisting of intervals that are not trivially short.

In this study, we first characterize and quantify the transient states occurring in locally (nearest neighbour) coupled CMLs. We analyse the normalized coefficient of variation (CV) of the spatiotemporal distribution of values, by taking each lattice site, across a moving window of time. We then study how the transient dynamics is altered as the coupling strength is varied. Our results show that locally coupled CMLs with different maps exhibit qualitatively different transient behavior as the coupling strength is varied, in spite of all the maps belonging to the same universality class.

Subpopulations in a metapopulation can also have direct migration to other sites beyond its first neighbour. Such scenario was modelled using the non-locally coupled CMLs. Here the notion of transience was expanded beyond temporal transience. We focus on spatial synchronization in dynamics (or lack thereof), as exhibited in chimera patterns [20–22]. These patterns exhibit simultaneous existence of regions of spatial coherence and incoherence, where we interpret coherence as synchronized stable dynamics over a set of neighbouring lattice sites [23]. Our studies show that non-locally coupled RCML exhibit chimera states more frequently than LCML. Possible interpretations of these results are discussed in the light of the importance of the role of biological factors regulating the life history of species.

2. Models and methods

2.1 Models

We start with a CML of the following form [18]:

\[ u_s^{t+1} = (1 - \epsilon)f(u_s^t) + \frac{\epsilon}{2P} \sum_{p=s+P, p \neq s} f(u_p^t). \]  

Here \( u_s^t \) are real dynamic variables \((s = 1, \ldots, N)\), \( s \) is the spatial variable denoting the lattice site, \( N \) is the lattice size, \( t \) denotes the time-step, \( \epsilon \) is the coupling strength, and \( P \) describes the range of neighbours connected to \( s \). For all our simulations, \( N = 100 \).

We consider periodic boundary conditions, such that \( u_s^t = u(s + N)^t \) for all \( s \) and \( t \). \( f(u) \) is the one-dimensional map at the local lattice site representing the subpopulation. The details of \( f(u) \) used are as follows:

**Logistic map:** \( f(u) = r_Lu(1 - u) \).

**Ricker map:** \( f(u) = ue^{r_R(1-u)} \).

**Hassell map:** \( f(u) = r_Hu(1 + u)^b \).

The growth functions of these maps are shown in figure 1. Even though these three discrete models belong to the same universality class in nonlinear dynamics – of single hump maps exhibiting similar bifurcation scenario with changing growth parameters – yet ecologically they are different in the nature of the density dependences of species growth. The logistic map, popular with theoreticians for its simplicity, has quadratic density dependence, i.e., the reduction in growth function at high population density is quadratic \((-u^2)\). The map has severe practical deficiencies as species growth model, since there are both limits to the growth rate \((r_L = 4)\) and maximum population size of one, after which it goes negative. Still it is used for its analytical simplicity.

The Ricker model was proposed in fisheries [24] and the Hassell model has been tested on many insects [25]. Both the Ricker and Hassel maps have no bounds on growth rates and maximum population size, even though, as is clear from the nature of the growth functions (figure 1), they show a severe reduction in growth at larger population size and higher growth rates. The nature of density dependence of these two maps is different from the logistic map – they have an inflexion point in their long tail in the functional form at high density [26]. Additionally both logistic
and Ricker models are one-parameter maps, where all ecological interactions have been compacted in a single growth rate. The Hassell model has two parameters, the rate of reproduction $r$ and degree of resource distribution among the individuals through competition $b$ [25, 27].

In all simulations, the parameters chosen in the three maps are as follows: $r_L = 3.9$, $r_R = 3.42$, and $r_H = 90$, $b = 10$, so that the chaotic dynamics exhibited in all three maps have similar Lyapunov exponents. When $P = 1$, only the adjacent (i.e., the nearest two neighbours) lattice sites in the one-dimensional CMLs are connected to the site $s$. These locally coupled CMLs can exhibit a vast range of spatiotemporal dynamics [28]. For the analysis of non-local coupling in this study, $P$ has been varied from 2 to 49.

### 2.2 Methods

We study the dynamics of a lattice of these maps (as described earlier) by examining the values of $u$ at each lattice site over time. The set of values of $u$ at all lattice sites at a given time is defined as the ‘state’ of the lattice at that time. A state is considered to be temporally transient if there are patterns of synchronized activity in lattice sites that exist only for a short duration of time. Here, pairs of lattice sites are considered synchronized if they both exhibit stable state dynamics or dynamics with similar periodicity. We do not consider states as transient if the synchronization occurs for less than 50 steps or less than 5 spatial sites. The space–time–amplitude plot in figure 2a is an example of such a transient state. Several transient states may occur in a given time frame.

Because of differences in periodicity, spatial extent and duration in dynamics, it may be difficult to visualize short-lived transient states on the space–time–amplitude plots with chaos in the background. Thus a visualization technique is developed to separate the transient states from the background of chaotic dynamics. This allows easy characterization of the spatial extent and number of transient states. First, we consider the set of values in a time window (of width $T$) at each lattice site, $U^*_s = \{u'_s|\tau \in [t, t + T]\}$. We then calculate the frequency distribution of $U^*_s$. This frequency distribution allows us to parametrize the nature of dynamics of a given lattice. In other words, whether a lattice site has periodic dynamics or chaos in a given window of time $T$, can be surmised from this distribution. We compute the coefficient of variation (CV = standard deviation/mean) of this frequency distribution for each site to indicate its nature of dynamics in the window $T$. Compared to a periodic time series, a chaotic time-series has a broadband frequency distribution and hence has a lower CV value across all frequency bins. The purpose of dividing the standard deviation by the mean is to come up with a quantity that is largely independent of the time window $T$. The CV values can also be normalized because for a given $T$ and bin size, the CV is maximum when all the values in $U^*_s$ fall into a single bin, which takes place when the given lattice site stabilizes to a fixed point. For all work reported here, $T = 50$ and number of bins = 100. The CV plot therefore shows large values (hot colours) in the regions of periodic dynamics and low values (cooler colours) in the regions that exhibit chaos. These CV plots are convolved with a Gaussian filter with standard deviation of one time-bin. CV plot for the transient state corresponding to figure 2a is shown in figure 2b. We have kept $T = 50$.

Using the CV plots, the number and spatial extent of the transient states occurring between $t = 2000–5000$ steps are quantified for $\varepsilon = 0.4, 0.6, 0.8$. For each $\varepsilon$ we performed 100 replicates with random initial values of $u$. We then calculate the median values of spatial extent and number of transient states for each $\varepsilon$ to compare how these quantities vary with $\varepsilon$ in different CMLs (LCML, RCML, and HCML). In order to compare the significance of difference in medians of the transient states estimated from different initial conditions across different coupling strengths, the Wilcoxon rank sum/Mann–Whitney $U$ test [29] is used. We failed to observe any systematic differences in transient behavior based on the choice of time interval. In cases where multiple transient states are present within the time period of simulation, we consider the one that has the largest spatial spread, i.e., occupies the maximum number of lattice sites. The spatial spread of a transient state is defined as the number of lattice sites covered by the smallest rectangle that can circumscribe a patch of region with normalized CV > 0.34. Choice of this threshold is arbitrary in the sense that CV = 0.34 corresponds to a lattice site that

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**Figure 2.** (a) Space–time–amplitude plot of a transient state between the lattice-sites 55–98, around the time steps 2000 in an LCML. (b) The corresponding CV plot of the transient state helpful in visualization.
takes up at least nine different values of $u$ in the time window of $T = 50$ time-steps.

Our main results, describing the effect of change in spatial extent and number of transient states with respect to coupling strength across different maps, do not depend upon the precise value of this threshold. This is because, for a wide range of CV values, either the estimated quantities are invariant with respect to the threshold (e.g. the number of transient states), or the variation with respect to the threshold is similar for all maps and coupling strengths (e.g. in case of spatial extent). Qualitatively, no systematic effects were observed in the change of spatial extent with respect to the CV threshold across coupling strengths in all three locally coupled maps. Two regions separated by a spatial distance smaller than five sites or duration less than 50 time steps are considered as a single region. When the lattice exhibits global synchronization, the width of these states is taken as the size of the lattice and the number of transient states is not calculated. It may be noted that for some simulations, nearby regions of transient synchronization could not be disambiguated because of large overlap. In such cases, the spatial extent of transience was taken as the spatial extent of the largest transient state.

For non-local coupling ($P > 1$), we investigate the time series for a long duration (>50,000 time steps) and count the number of initial conditions (out of the 20 sets of initial conditions of $u$ in the lattice of $N = 100$), that exhibit spatial incoherence at a particular coupling strength $\varepsilon$ and range of neighbours $P$. These chimera-like transient states also can be visualized easily in the CV plots. We compare the probability of observing a chimera state in the LCML and RCML as follows. First, we test 20 initial conditions for the simultaneous existence of lattice sites with $CV > 0.7$ (fixed point or low periodicity) and $CV < 0.2$ (chaos). For each of these 20 initial conditions we check $\varepsilon$ from 0.01 to 0.96 in steps of 0.05, and $P$ from 1 to 49 in steps of 3. We then count the number of initial conditions for each pair of $\varepsilon$ and $P$ that show such chimera patterns for both LCML and RCML, and construct probability maps of observing chimera states in them.

### 3. Results

The study results are organized for local coupling (i.e., $P = 1$) representing migration to the nearest two neighbours on both sides of each subpopulation, and then for non-local coupling (i.e., $P > 1$) in one-dimensional lattice metapopulations, having all three growth functions (LCML, RCML, and HCML).

#### 3.1 Local coupling

For nearest-neighbour migration ($P = 1$) the transient behavior of the LCML, namely the number and spatial extent of the transient states of partial synchrony, is highly variable and sensitive to initial conditions. Despite this variability with initial conditions, there is a clear increase – both in the spatial extent of the largest transient state and the number of transient states – with increasing coupling strength, when averaged over 100 initial conditions (figure 3). To examine this, we compare the distributions of spatial extent and number of transient states obtained for a set of 100 initial conditions in the CMLs and compare their box plots for different coupling strengths. As shown in figure 3a, the median spatial extent for $\varepsilon = 0.4$ is significantly less than that for $\varepsilon = 0.6$ (rank sum test, $p < 0.05$), and similarly the median spatial extent for $\varepsilon = 0.6$ is also significantly less than that for $\varepsilon = 0.8$ (rank sum test, $p < 0.01$). Figure 3b shows that there is a similar statistically significant increase in the median number of transient states for increasing $\varepsilon$ from 0.4 to 0.6 and 0.8 (rank sum test, $p < 0.01$). Thus, with logistic growth in subpopulations, the size and number of transient states increase with increasing migration between the two neighbouring subpopulations.

Interestingly, when the subpopulation growth functions are either exponential (Ricker model) or, in general of polynomial form (Hassell model), the metapopulations (RCML and HCML) exhibit the exact opposite trend in transient states with increasing migration rates (figure 4). At lower coupling strengths, there are larger regions of locally synchronized spatiotemporally transient regions, which decrease significantly as $\varepsilon$ is increased. For long-term dynamics in both RCML and HCML, global synchronization is observed for $\varepsilon = 0.4$ for some initial conditions, which is absent at higher coupling strengths ($\varepsilon = 0.6$ and 0.8 for 500,000 time-steps) in all 100 initial conditions. When the spatial extent of transient states, for a given coupling strength, is averaged across all 100 initial conditions, the spatial extent

![Figure 3](image_url)
extents show a large significant decrease with increasing coupling strengths in these lattices (figure 4). For HCML (figure 4a), median spatial extent for $\varepsilon = 0.4$ is halved for $\varepsilon = 0.6$; and further reduced by one-fourth for $\varepsilon = 0.8$ (Wilcoxon rank sum test, $p < 0.01$). For RCML (figure 4b), the significant (Wilcoxon rank sum test, $p < 0.01$) decrease in median spatial extent for $\varepsilon = 0.6$ from that of $\varepsilon = 0.4$ is more (one-fourth), but further reduction in the size of the transient states is smaller for $\varepsilon = 0.8$ (Wilcoxon rank sum test, $p < 0.05$). The number of transient states could not be quantified in the RCML and HCML because of the difficulty in distinguishing them due to their proximity and overlap at lower coupling strengths. Unlike the spatial extent of transient states, we did not observe a systematic change in the duration of transient states across different coupling strengths for any of the coupled maps (LCML, RCML or HCML).

It is clear from the box plots in figure 3, that the spreads of the spatial extents over 100 initial conditions, for each $\varepsilon$, is not normally distributed. To examine the distribution of spatial extents of transient states in LCML, for a given coupling strength, we plot their frequency distributions for coupling strengths $\varepsilon = 0.4$, 0.6 and 0.8 for 100 initial conditions in figures 5a–c. The distributions show heavy-tails, and follow a power law distribution with an exponent independent of the coupling strength as shown in the log–log plots in figures 5d–f. For this analysis we focus on the tail of the distribution after the first bin with non-zero bin entries on the log–log plot. These plots reveal that the exponent of power law for $\varepsilon = 0.4$ is $-2.69 \pm 0.36$, for $\varepsilon = 0.6$ it is $-2.78 \pm 0.34$ and for $\varepsilon = 0.8$ it is $-2.71 \pm 0.24$. Slopes of all the regressions are significantly different from zero ($F$-test, $p < 0.005$). Interestingly, unlike the LCML, the histograms of the spatial extent of the transient states do not follow a power-law distribution. Histograms of the spatial extent for $\varepsilon = 0.6$ for HCML and RCML are shown in figures 5g and h. Regression coefficients for HCML ($F$-test, $p = 0.16$) and RCML ($F$-test, $p = 0.9$) for $\varepsilon = 0.6$ are not significant.

### 3.2 Non-local coupling

The differences observed between LCML and CMLs with other maps (Ricker and Hassell) continue to exist even for non-local coupling ($P > 1$), where along with the nearest-neighbours, consecutive non-adjacent lattice sites are also connected. For non-locally coupled maps, however, transience is manifested spatially in the form of chimera states that show coexistence of regions of synchronization, in an otherwise asynchronous lattice, for long periods of time. Examples of chimera patterns (stable up to 500,000 time steps) for RCML ($\varepsilon = 0.32$, $P = 15$) and LCML ($\varepsilon = 0.29$, $P = 15$) are shown in figures 6a and b respectively.

Along with the initial conditions, the two other key parameters, that play important roles in chimera formation in the CMLs, are the coupling strength ($\varepsilon$) and the number of neighbours ($P$). To assess the efficacy of these two parameters in developing chimera states in LCML and RCML, a two parameter sweep is done.
Figure 6. Chimera states marked by regions of incoherence, in – top panel (time 500,000 to 501,000): (a) RCML (lattice sites 35–60); and (b) LCML. Bottom panel: space–time amplitude maps (time 500,000 to 500,030) for (a) RCML and (b) LCML.

Figure 7. Probability of obtaining a chimera state for different $\varepsilon$ and $P$ obtained from 20 initial conditions in (a) RCML and (b) LCML.

for all 20 sets of initial conditions, and the frequency of success plotted as a probability map of observing chimera states for a range of $\varepsilon$ and $P$ – shown in figures 7a and b for the RCML and LCML, respectively. We observe that the probability of observing a chimera state in the RCML is higher (i.e., spans larger range of parameter values) than that in the LCML (Wilcoxon rank sum test, $p < 0.05$). In fact, more than 95 percent of pairs of $\varepsilon$ and $P$ have a higher probability of exhibiting such chimera states in RCML compared to LCML. This suggests that metapopulations of species having the Ricker growth function (RCML) will exhibit a higher prevalence of chimera states for nonlocal migration compared to that having the logistic growth function (LCML).

4. Conclusion

Studies on transient phenomena are gaining importance in different areas of science. Mathematical solutions aim to find asymptotic behavior of any system, but the time taken to reach such asymptotic states may be quite long in many cases. The system may move through different types of non-asymptotic dynamics during this period depending on the time scales involved and the structure of the phase space and basin boundaries [30–32]. Many of these non-asymptotic dynamics (labelled as ‘transients’) may persist for functionally relevant time scales, and, therefore, can have important implications in real system behavior [19].

In this study, we examine the temporal and spatial transient phenomena observed in the spatiotemporal dynamics of metapopulations, modelled using CMLs, with different ecologically relevant discrete population growth functions: the logistic, Ricker and Hassell maps. The three growth functions differ in the details of the functional forms of their density dependence – the logistic being symmetric and quadratic, whereas the Ricker and Hassell maps have long tails. However all the three uni-modal maps are known to belong to the single universality class that shows period doubling route to chaos. Our results, surprisingly, show a wide range of differences in the transient dynamics of logistic-CML compared to the Ricker-CML and Hassell-CML.

The three lattice metapopulations are studied for both nearest-neighbour migration (local coupling) and migration to non-adjacent sites (non-local coupling). The three growth functions are studied for growth rates in the chaotic region, such that the chaotic dynamics for all had the same Lyapunov exponent. To quantify the transient states in these spatiotemporal systems, we develop a simple and easy-to-implement visualization method using the CV. Even though CV efficiently identifies the regions of transient or incoherent synchronization, they suffer from the drawback of not being able to distinguish between a chaotic time series and a time series with extremely high periodicity. Nevertheless, it is a novel way to visualize transient states across several thousands of time-steps and may be extremely useful in studies that focus on analysing transient states in the presence of non-local coupling, or in more biologically realistic two/three-dimensional lattices.

The spatial extent and the number of transients are studied in the locally coupled CMLs using the method developed. The logistic-CML shows an increase in both spatial extent and number of transient states with increasing coupling strengths, whereas for CMLs with Ricker and Hassell maps show the opposite trend. The size distributions of the transient states for LCML show power law dependence for all coupling strengths, but there is no such pattern in the other two CMLs. The patterns of transient states for non-local coupling are studied through computing the chimera states observed in the long-term dynamics of logistic-CML and Ricker-CML. A detailed analysis of the two
parameters, $P$ (number of neighbours) and $\varepsilon$ (coupling strengths), show that Ricker-CML has higher propensity to develop chimera states than the logistic-CML. Thus, our results clearly show that the CML with symmetric, quadratic map function behaves differently from the CML with the maps with exponentially decreasing tails.

Indeed, instances of manifestation of such difference in the dynamics of these maps under constant migration have been reported earlier [26, 33, 34]. Furthermore, for CMLs, it has been shown that opposing signs of constant external perturbation (pinning) are required to suppress spatiotemporal chaos in logistic-CML and Ricker-CML – locally and globally [17, 35]. There is a suppression of spatiotemporal chaos in the logistic-CML when this perturbation is negative, but for Ricker-CML suppression of chaos happens with small positive external perturbation [36]. In the present study, transient states with localised altered dynamics arise during the initial period for local coupling. In line with previous studies, the opposite response of the logistic-CML and Ricker/Hassell-CML to the spatial extent and number of transient states at higher coupling strengths can be understood in terms of control of chaos under external perturbation.

Similar reasoning may be considered for the non-locally coupled case. In the non-locally coupled case, chimera states occur for low values of $\varepsilon$ for both maps. However, based on the previous studies, we know that the probability of observing a chimera state is higher for Ricker-CML because it is more likely to exhibit suppression of chaos in the presence of small external perturbation [17, 35, 36]. That such patterns are observed in non-local maps is not surprising, since previous studies have shown that chimera patterns become more prominent with the increase in range of coupling [21]. This then raises the question that if two maps with similar properties exhibit opposing transient behavior (with respect to coupling strength), what then ultimately drives the transient behavior in a CML? Although more computational/mathematical analyses are needed to further understand what precise factors determine the transient behavior, our results suggest that in spite of similar bifurcation behavior of these maps, the transient states in the CMLs is determined by the details of their functional forms (the nature of the density dependence), which determine their dynamic response under perturbation due to migration.

It is also instructive to discuss some of the ecological implications of our theoretical results. The current thinking in ecology is in assessing the importance of transients in the possible evolution of population behavior and dynamics [19]. Even though theoreticians have attempted to relate the computational object of chimera states to the spatiotemporal patterns generated by model [37–39], it is not clear if similar patterns, if seen in reality, are indeed chimeras. Unless control field experiments are done to show that the pattern disappears in the presence of local-only connections, characterizing the chimera states is difficult. Field experiments take years to perform and replicate, and teasing out the many regulating factors in field population regulation is difficult. Yet, if and when experimentally proven, these dynamical structures can have important implications in population distribution and abundance in single and multi-species ecosystems, such as the presence of groups of inter-connected cities/towns exhibiting different disease dynamics due to parasite/vector population variations, compared to other less connected subpopulations.

While discussing transient states in an ecological context, the excellent review [19] elaborates the implications of transients for ecology from the point of view of transitions in dynamics (e.g. regime shift, tipping points, insect population extinction, etc.), the behavior of systems far from their final dynamics, and the underlying multiple time scales for these transitions [40, 41]. In this study we highlight the spatially wider and numerically larger number of transient states occurring in metapopulations with different growth functions. Our results, in addition, show that not only the maps exhibit two opposing types of response to increasing local migration rate, their distributional properties are also different (figures 5 and 6). Since these growth models differ in their application to species with different life histories (see Models section), it implies that the spatial range of populations with transient dynamics will be species-dependent, and may increase or decrease with migration rates. It leads to the implication that their response to perturbations (such as anthropogenic removal of individuals – harvest, poaching, sudden migration, etc.) are likely to be different. For transient dynamics, involving oscillations between high and low population sizes, the risk of local extinction is possible due to flood, draught, and disease, at the trough of oscillations with low population sizes.

The above factors clearly indicate that our results on the dependence of species transient population growth dynamics (in the metapopulation scenario) have important implications in biodiversity and conservation studies. Understanding transient dynamics of populations, without only focusing on long-term dynamics, is important for designing effective population management strategies. The different species-specific local responses of subpopulations in a metapopulation context – to environmental disturbances, species life-history, and migration patterns – regulate their local or regional
(spatial extent of transients) patterns in biological diversity, thereby influencing conservation measures, thus negating the one-measure-fits-all policy [42, 43].

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