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NONLINEAR DIFFUSION IN THE MULTI-PATCH LOGISTIC MODEL *

BILEL ELBETCH [†]AND ALI MOUSSAOUI* [‡]

Abstract. In this work, we study a multi-patch model, where the patches are coupled by 4 nonlinear asymmetrical migration terms, and each patch follows a logistic law. First, used the 5 6 theory of a cooperative differential system, we prove the global stability of the model. Next, in the case of perfect mixing, i.e when the migration rate tends to infinity, the total population follows a logistic law with a carrying capacity which in general is different from the sum of the n carrying 8 capacities, and depends on the migration terms. Second, we determine, in some particular cases, 9 10 the conditions under which fragmentation and nonlinear asymmetrical migration can lead to a total 11 equilibrium population greater or smaller than the sum of the carrying capacities. Finally, for the 12 two-patch model, we give a complete classification of the model parameter space as to whether nonlinear dispersal is beneficial or detrimental to the sum of two carrying capacities. 13

14 Key words. Population Dynamics, Logistic equation, Nonlinear diffusion, Slow-fast systems; 15 Tikhonov's theorem, Perfect mixing.

16 **AMS subject classifications.** 37N25, 92D25, 34D23, 34D15.

1. Introduction. There are many factors affecting the growth and the general dynamics of population. One such important factor is the dispersal amounts and in random ways. These dispersal can cause disturbances to the various ecosystems as well as to the persistence or extinction of organisms. Bibliographies can be found in the work of Levin [27, 28], Holt [25], Allen [1, 2, 3], and Gurney and Nisbet[24].

In [1], Allen considered the *n*-patch general model given by the following equations: In [1], [

24 (1.1)
$$\frac{dx_i}{dt} = r_i x_i \left(1 - \frac{x_i}{K_i}\right) + \Upsilon_i(x), \quad i = 1, \dots, n,$$

where r_i and K_i are positive constants; $x = (x_1, \ldots, x_n)^T$ where x_i represents the population density in the *i*-th patch. The function Υ_i represent one of the three types of different mechanisms. The mechanism for linear diffusion is given by:

28 (1.2)
$$\Upsilon_i(x) = \sum_{j=1, j \neq i}^n \beta_{ij} \left(x_j - \gamma_{ij} x_i \right), \quad , i = 1, \dots, n,$$

where β_{ij} and γ_{ij} are positive constants. Dispersal by linear diffusion implies that the species is able to move to all locations within its environment with equal probability. The mechanism for biased diffusion is given by:

32 (1.3)
$$\Upsilon_{i}(x) = \sum_{j=1, j \neq i}^{n} \beta_{ij} x_{i} \left(x_{j} - \gamma_{ij} x_{i} \right), \quad , i = 1, \dots, n,$$

where β_{ij} and γ_{ij} are positive constants. Note that, the term 'biased' means that the diffusion rate is a function of population density. The diffusion rate is regulated by

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population density, increasing for large populations and decreasing for small populations. The third type of mechanism, is the directed diffusion which is formulated by Current and Nick et [24], given by:

37 Gurney and Nisbet [24], given by:

38 (1.4)
$$\Upsilon_{i}(x) = \sum_{j=1, j \neq i}^{n} \beta_{ij} \left(x_{j}^{2} - \gamma_{ij} x_{i}^{2} \right), \quad , i = 1, \dots, n,$$

³⁹ where β_{ij} and γ_{ij} are positive constants. Dispersal by directed diffusion implies that ⁴⁰ the individuals move from high population concentration to low ones, i.e., the move-⁴¹ ment is a function of species density. For more information on the biological interpre-⁴² tation and also the continuous version of those types of diffusion, we refer the readers ⁴³ to [1] and [24].

The objective of the work of Allen [1] is to study the effect of different types of the dispersion on the persistence and extinction of the species. The persistence and extinction behavior is completely determined in a two-patch model (1.1)(1.2) for n = 2 (see Theorem 1 in [1]). For model (1.1)(1.3), Allen [1, Theorem 2] showed that a population modelled with biased diffusion is always persistent and in fact represents a strongly persistent population. For more details on the results of persistence and extinction, see Theorem 3 of [1] for *n*-patch model (1.1)(1.3) and Proposition 1 of [1] for 2-patch case; Theorem 4 of [1] for the *n*-patch model (1.1)(1.4).

Lu and Takeuchi [29] have also considered the multi-patch logistic model with nonlinear diffusion terms, i.e the system (1.1)(1.4). They obtained the sufficient and necessary conditions for the system to be globally stable (see Theorem 3 in [29]).

DeAngelis and Zhang [12], DeAngelis et *al.* [13] and Zhang et *al.* [35] have considered the model (1.1) with

57 (1.5)
$$\Upsilon_i(x) = \sum_{j=1, j \neq i}^n (x_{i-1} - 2x_i + x_{i+1}), \qquad i = 1, \cdots, n,$$

where we denote $x_0 = x_n$ and $x_{n+1} = x_1$, allowing the patches to join in a circle so that the same relationships hold between x_i, x_{i-1} and x_{i+1} for all values of *i*. An interesting result of (1.1)(1.5) is that in the case $r_i = K_i$, for $i = 1, \dots, n$, the total population at steady state satisfies

62 (1.6)
$$\sum_{i=1}^{n} x_i^* > \sum_{i=1}^{n} K_i.$$

Our aim in this work is to study the model of n patches coupled by nonlinear migration terms (same type of dispersion (1.4)). In particular, we are interested in studying the effect of nonlinear dispersion on the dynamics of population, and to compare some results for the nonlinear dispersion with those obtained for the linear dispersion in [14, 15] for the model (1.7). In 2021, Elbetch et *al.* [15] have considered the model of multi-patch logistic growth, coupled by asymmetric linear migration terms

70 (1.7)
$$\frac{dx_i}{dt} = r_i x_i \left(1 - \frac{x_i}{K_i}\right) + \beta \sum_{j=1, j \neq i}^n \left(\theta_{ij} x_j - \theta_{ji} x_i\right), \qquad i = 1, \cdots, n,$$

where n is the number of patches in the system. The parameters r_i and K_i are respectively the intrinsic growth rate and the carrying capacity of patch i. The term

on the right hand side of the system (1.7) describes the effect of the linear migration between the patches, where β is the migration rate and $\Theta := (\theta_{ij})$ is the matrix representing the migrations between the patches. Note that, the system (1.7) is studied also by Elbetch et *al.* [14] and Takeuchi [31] in the case when the matrix Θ is symmetric. We recall that, when the matrix of migration Θ is irreducible, System (1.7) admits a unique positive equilibrium which is globally asymptotically stable (GAS), see [7, Theorem 2.2], [6, Theorem 1] or [14, Theorem 6.1], when $\beta \to \infty$, this equilibrium tend to

$$\frac{\sum_i \delta_i r_i}{\sum_i \delta_i^2 \alpha_i} (\delta_1, \dots, \delta_n),$$

where $\alpha_i = \frac{r_i}{K_i}$ and $(\delta_1, \dots, \delta_n)^T$ the vector which generate the vector space ker Θ (see Section 3).

In [14, 15], Elbetch et al. have answered in some particular cases of the model 73 (1.7) to the following important question: Is it possible, depending on the migration 74rate, that the total equilibrium population be larger than the sum of the capacities 75 $\sum_{i} K_{i}$? This question is of ecological importance since the answer gives the conditions under which the linear dispersal is either beneficial or detrimental to total equilibrium 77 population. Note that, this question has been studied by many researches (see 78[4, 5, 8, 10, 11, 12, 13, 14, 15, 17, 18, 19, 22, 34, 35] and [20, 21] and on susceptible-79 infected-susceptible (SIS) patch-model). They proved that, if all the patches do not 80 differ with respect to the intrinsic growth rate (i.e., $r_1 = \ldots = r_n$), then the effect 81 of linear migration is always detrimental. In the case when $(K_1, \ldots, K_n)^T \in \ker \Theta$ 82 (if the matrix Θ is symmetric, the condition $(K_1, \ldots, K_n)^T \in \ker \Gamma$ means that the 83 patches do not differ with respect to the carrying capacity), linear migration has 84 no effect on the total equilibrium population. An example when the effect of linear 85 migration is always beneficial, is in the case when Θ is symmetric and all the patches 86 do not differ with respect to the parameter $\alpha = r/K$ quantifying intraspecific 87 competition (i.e., $\alpha_1 = \ldots, \alpha_n$) (see also [15, Prop. 4.2]). 88

This paper is organized as follows: in Section 2, we introduce the mathematical 89 model and we give some definitions and notations. Next, in Section 3, we study the 90 asymptotic behavior of the stability modulus of the matrix A given by (2.7), and we 91 prove that the stability modulus of A is strictly decreasing as function of the migration 92 rate and it is always negative. This result is used in Section 4 to prove the global 94 stability of the model (2.1). In Section 5, we study the behavior of the system (2.1) in the case when the migration rate goes to infinity by direct method and also by using 95 perturbation arguments. In Section 6, we compare the total equilibrium population 96 with the sum of the n carrying capacities for some parameter space, and by using 97 the same method as Arditi et al. [5], we give a complete analysis of two-patch case 98 in Section 7. In Section 8, two-patch model where one growth rate is much larger 99 than the second one is considered, we compare the total equilibrium population with 100 the sum of two capacities in this case. We perform some numerical simulations to 101 illustrate our results in this paper and give a brief concluding remark. 102

2. The mathematical model. We consider the model of multi-patch logisticgrowth, coupled by nonlinear migration terms given by:

105 (2.1)
$$\frac{dx_i}{dt} = r_i x_i \left(1 - \frac{x_i}{K_i} \right) + \beta \sum_{j=1}^n (\theta_{ij} x_j^2 - \theta_{ji} x_i^2), \qquad i = 1, \cdots, n,$$

where x_i is the population in patch *i*, the parameters r_i and K_i are respectively the intrinsic growth rate and the carrying capacity patch *i*, *n* is the number of the patches

3

in the system. The parameter β represents the dispersal rate of the population; $\theta_{ij} \ge 0$ denotes the flux between patches j and i, for $j \ne i$. Note that if $\theta_{ij} > 0$ there is a flux of migration between patches j and i and if $\theta_{ij} = 0$ there is no migration. The system (2.1) of differential equations can be written:

112 (2.2)
$$\frac{dx_i}{dt} = r_i x_i \left(1 - \frac{x_i}{K_i}\right) + \beta \sum_{j=1}^n \theta_{ij} x_j^2, \qquad i = 1, \cdots, n,$$

113 where

115 denotes the outgoing flux of patch *i*. We denote by Θ the following matrix

116 (2.4)
$$\Theta = \begin{pmatrix} -\sum_{k \neq 1} \theta_{k1} & \theta_{12} & \dots & \theta_{1n} \\ \theta_{21} & -\sum_{k \neq 2} \theta_{k2} & \dots & \theta_{2n} \\ \vdots & \vdots & \vdots \\ \theta_{n1} & \dots & \theta_{n,n-1} & -\sum_{k \neq n} \theta_{kn} \end{pmatrix}.$$

¹¹⁷ We call Θ the movement matrix of the system (2.1). Its columns sum to 0 since the ¹¹⁸ diagonal elements θ_{ii} are defined by (2.3). The matrix

119 (2.5)
$$\Theta_0 := \Theta - \operatorname{diag}(\theta_{11}, \dots, \theta_{nn})$$

which is the same as the matrix Θ , except that the diagonal elements are 0, is called the connectivity matrix. It is the adjacency matrix of the weighted directed graph \mathcal{G} , which has exactly *n* vertices (the patches), and there is an arrow from patch *j* to patch *i* precisely when $\theta_{ij} > 0$, with weight θ_{ij} assigned to the arrow.

124 The system (2.1) can be also rewritten in matrix form as follow:

125 (2.6)
$$\frac{dx}{dt} = \operatorname{diag}(r_1, \dots, r_n)x + Ax^2,$$

126 where $x = (x_1, \ldots, x_n)^T, x^2 := (x_1^2, \ldots, x_n^2)^T$ and A the matrix defined by

127 (2.7)
$$A := \beta \Theta - \operatorname{diag} \left(\alpha_1, \dots, \alpha_n \right).$$

128 where $\alpha_i = \frac{r_i}{K_i}$. First, we start by giving some definitions.

DEFINITION 2.1. A matrix $M = (m_{ij})$ is called cooperative if $m_{ij} \ge 0$ for all $i \ne j$. Parall that the differential autom

Recall that the differential system

$$\frac{dx}{dt} = F(x),$$

129 is said to be cooperative, if its jacobian matrix is cooperative, i.e., for all $i \neq j$; 130 $(\partial F_i/\partial x_j) \geq 0$, for all x positive.

131 DEFINITION 2.2. The stability modulus of a matrix M is given by

132 (2.8)
$$s(M) = \max \{ \operatorname{Re}(\lambda) : \lambda \text{ is an eigenvalue of } M \}.$$

133 Note that, the matrix A is a non linear part of the system (2.1) and it is a cooperative

134 matrix.

3. Asymptotic behavior of the stability modulus of the matrix A. Using 135 some results proven by Gao and Dong [22] on SIS patch-model. we give in this section 136some proprieties of the stability modulus of the matrix A defined by (2.7), which is 137a non linear part of the differential system (2.1). First for all, we recall that, if Θ is 138irreducible, then 0 is a simple eigenvalue of Θ and all non-zero eigenvalues of Θ have 139negative real part. Moreover, the kernel of the matrix Θ is generated by a positive 140 vector (see Lemma 2 in [6]). In all of this paper, we denote by $\delta := (\delta_1, \ldots, \delta_n)^T$ 141 this positive vector. For the existence, uniqueness, and positivity of δ see Lemma 1421 of Cosner et al. [9], Lemma 4.1 and Lemma 1 of Elbetch et al. [14, 15]. Note 143that, if the matrix Θ is symmetric, then ker Θ is generated by $\delta = (1, \dots, 1)^T$. On 144the other hand, it is shown in Guo et al. [23, Lemma 2.1] and Gao and Dong [22, 145Lemma 3.1] that the vector $(\Theta_{11}^*, \ldots, \Theta_{nn}^*)^T$ is a right eigenvector of Θ associated with the zero eigenvalue. Here, Θ_{ii}^* is the cofactor of the *i*-th diagonal entry of Θ , 146 147and $sgn(\Theta_{ii}^*) = (-1)^{n-1}$. As in our work, the matrix Θ is assumed to be irreducible, then $(-1)^{n-1}(\Theta_{11}^*, \ldots, \Theta_{nn}^*)^T$ is strictly positive, i.e $\delta_i = (-1)^{n-1}\Theta_{ii}^* > 0$ for all *i*. 148149Therefore, we have explicit formula for the components of the vector δ , as functions 150of the coefficients of Θ , at our disposal. For two patches we have $\delta = (\theta_{12}, \theta_{21})^T$, and 151for three patches we have $\delta = (\delta_1, \delta_2, \delta_3)^T$, where 152

$$\begin{cases} \delta_1 = \theta_{12}\theta_{13} + \theta_{12}\theta_{23} + \theta_{32}\theta_{13}, \\ \delta_2 = \theta_{21}\theta_{13} + \theta_{21}\theta_{23} + \theta_{31}\theta_{23}, \\ \delta_3 = \theta_{21}\theta_{32} + \theta_{31}\theta_{12} + \theta_{31}\theta_{32}. \end{cases}$$

In Lemma 2.1 of Guo et al. [23] gives explicit formulas of the components of the 154vector δ , with respect of the coefficients of Θ as follow: 155

156 (3.2)
$$\delta_k = \sum_{T \in \mathcal{T}_k} \prod_{(i,j) \in E(T)} \theta_{ij}, \qquad k = 1, \dots, n,$$

where \mathcal{T}_k is the set of all directed trees of n vertices rooted at the k-th vertex, and 157E(T) denotes the set of arcs in a directed tree T. 158

Proposition 3.1. The stability modulus $\lambda^*(\beta) := s(A)$, with 159

160
$$A = \beta \Theta - \text{diag} \{\alpha_1, \dots, \alpha_n\}$$
 satisfie

 $\begin{array}{l} \beta \Theta - \text{diag} \left\{ \alpha_1, \dots, \alpha_n \right\} \text{ satisfies} \\ 1. \ \lambda^* \text{ is strictly decreasing in } \beta \in [0, +\infty[. \end{array}$ 161

162 2.
$$\lambda^* \to -\max\{\alpha_1, \ldots, \alpha_n\} \text{ as } \beta \to 0$$

3. $\lambda^* \to \lambda^*_{\infty} := -\sum_{i=1}^n \alpha_i \delta_i / \sum_{i=1}^n \delta_i \text{ as } \beta \to \infty$. In addition, if the matrix Θ is symmetric, then $\lambda^*_{\infty} = -\frac{1}{n} \sum_{i=1}^n \alpha_i$. 163164

Proof. The proof is derived from Corollary 3.5 in Gao and Dong [22]. Indeed, it was shown by Gao and Dong [22] for a SIS patch model that, the function $\beta \rightarrow$ $s(F - D + \beta \Theta)$ is strictly decreasing in $\beta \in [0, \infty)$ where F and D be a two positive diagonal matrix. Therefore, for $F = \mathbb{I}$ and $D = \text{diag}(\alpha_1, \ldots, \alpha_n)$, we get

$$0 > \frac{d}{d\beta}s(\mathbb{I} - \operatorname{diag}(\alpha_1, \dots, \alpha_n) + \beta\Theta) = \frac{d}{d\beta}\left(1 + s(-\operatorname{diag}(\alpha_1, \dots, \alpha_n) + \beta\Theta)\right) = \frac{d\lambda^*}{d\beta}(\beta).$$

It is clear that limit λ^* tend to $-\max\{\alpha_1,\ldots,\alpha_n\}$ as $\beta \to 0$. 165

When $\beta \to \infty$, by Corollary 3.5 in Gao and Dong [22] for the choice F - D =166 $-\operatorname{diag}(\alpha_1,\ldots,\alpha_n)$ we obtain the limit λ_{∞}^* of λ^* . In particular, if Θ is symmetric, one 167has $\delta_i = 1$ for all *i*. 168

- As corollary of the previous proposition, we have the result: 169
- COROLLARY 3.2. Consider the matrix A defined by (2.7), then s(A) < 0. 170

4. Global dynamics. In this section, our goal is to study the dynamics of the system (2.1). Note that, in the absence of migration, i.e the case where $\beta =$ 0, the system (2.1) admits (K_1, \ldots, K_n) as a non trivial equilibrium point, which furthermore is GAS, and the origin as trivial equilibrium which is unstable. The problem is whether or not, the equilibrium continues to be exist and GAS for any $\beta > 0$. First, we prove the following result:

177 PROPOSITION 4.1. The positive cone \mathbb{R}^n_+ is positively invariant for the system 178 (2.1).

Proof. Suppose that, at a given time t, one of the state variables of the system (2.1) is at a boundary of \mathbb{R}^n_+ , meaning that at least one population is at 0. We suppose that $x_i = 0$, and $x_j \ge 0$ for all $j \ne i$, then the dynamics of x_i is given by

$$\frac{dx_i}{dt} = \beta \sum_{j \neq i} \theta_{ij} x_j^2 \ge 0.$$

So each trajectory initiated at a boundary of \mathbb{R}^n_+ either remains at the boundary or goes to the interior of \mathbb{R}^n_+ . According to [30, Proposition B.7, page 267], no trajectory comes out of \mathbb{R}^n_+ . Therefore, \mathbb{R}^n_+ is positively invariant for (2.1).

182 To establish the boundedness of solutions of (2.1), we have the following result:

183 PROPOSITION 4.2. For any non negative initial condition, the solutions of the 184 system (2.1) remain non negative and positively bounded. Moreover, the set

185 (4.1)
$$\Lambda = \left\{ (x_1, \dots, x_n) \in \mathbb{R}^n : 0 \le \sum_{i=1}^n x_i \le \frac{\xi_2^*}{\xi_1^*} \right\}$$

is positively invariant and is a global attractor for (2.1), where $\xi_1^* = \min_{1 \le i \le n} r_i$ and $\xi_2^* = \sum_{i=1}^n r_i K_i$.

188 *Proof.* To show that all solutions are bounded, we consider the quantity defined 189 by $X_T(t) = \sum_{i=1}^n x_i(t)$. So, we have

190 (4.2)
$$\dot{X}_T(t) = \sum_{i=1}^n r_i x_i(t) \left(1 - \frac{x_i(t)}{K_i}\right).$$

191 For all $r_i, K_i \in \mathbb{R}^*_+$, we have the following inequality:

192 (4.3)
$$r_i x_i \left(1 - \frac{x_i}{K_i}\right) \le r_i (K_i - x_i).$$

193 Substituting Equation (4.3) into (4.2), we get

194 (4.4)
$$\dot{X}_T(t) \le -\xi_1^* X_T(t) + \xi_2^*$$
 for all $t \ge 0$,

195 which gives

196 (4.5)
$$X_T(t) \le \left(X_T(0) - \frac{\xi_2^*}{\xi_1^*}\right) e^{-\xi_1^* t} + \frac{\xi_2^*}{\xi_1^*}, \quad \text{for all } t \ge 0.$$

197 Hence,

198 (4.6)
$$X_T(t) \le \max\left(X_T(0), \frac{\xi_2^*}{\xi_1^*}\right), \quad \text{for all } t \ge 0.$$

199 Therefore, the solutions of system (2.1) are positively bounded and defined for all 200 $t \ge 0$. From (4.5) it can be deduced that the set Λ is positively invariant and it is a 201 global attractor for the system (2.1).

THEOREM 4.3. Assume that the matrix $\Theta = (\theta_{ij})_{n \times n}$ (or equivalently, the connectivity matrix Θ_0) is irreducible. The model (2.1) has a unique positive equilibrium point which is GAS in the positive cone $\mathbb{R}^n_+ \setminus \{0\}$.

205 Proof. Consider the system (2.1). According to a result of Lu and Takeuchi [29, 206 Theorem 3] for the nonlinear diffusion system with logistic growth rate functions, the 207 system (2.1) possesses a globally stable positive equilibrium if the matrix A given by 208 (2.7) is stable, (i.e., there exists a positive diagonal matrix C such that $CA + A^T C$ 209 is negative definite), which equivalent s(A) < 0 by Lemma 3 of [29]. According to 210 Corollary 3.2, the model (2.1) has a unique positive equilibrium point which is GAS 211 in the positive cone $\mathbb{R}^n_+ \setminus \{0\}$.

212 REMARK 1. The matrix Θ being irreducible means that the set of patches cannot 213 be partitioned into two nonempty disjoint subsets, I and J, such that there is no 214 migrations between a patch in subset I and a patch in subset J. The matrix Θ is 215 assumed to be irreducible throughout the rest of the paper. Therefore species can reach 216 any patch from any patch either directly or through other patches.

In all of this work, the GAS equilibrium of the system (2.1), whose existence is shown in Theorem 4.3, is denoted by $E_n^*(\beta) = (x_1^*(\beta), \dots, x_n^*(\beta))$, and by $T_n^*(\beta)$ the total equilibrium population

220 (4.7)
$$T_n^*(\beta) = \sum_{i=1}^n x_i^*(\beta).$$

5. Large diffusion rate. In this section our aim is to study the behavior of $E_n^*(\beta)$ and $T_n^*(\beta)$, defined by (4.7), for large migration rate, i.e when $\beta \to \infty$.

5.1. The fast dispersal limit. We have the following result:

THEOREM 5.1. We have:

225 (5.1)
$$\lim_{\beta \to +\infty} E_n^*(\beta) = \frac{\sum_{i=1}^n \sqrt{\delta_i} r_i}{\sum_{i=1}^n \delta_i \alpha_i} (\sqrt{\delta_1}, \dots, \sqrt{\delta_n})$$

where $\alpha_i = r_i/K_i$. Moreover, if the matrix Θ is symmetric, then the equilibrium $E_n^*(\beta)$ converges to an element of ker Θ

228 (5.2)
$$\lim_{\beta \to +\infty} E_n^*(\beta) = \frac{\sum_{i=1}^n r_i}{\sum_{i=1}^n \alpha_i} (1, \dots, 1).$$

229 *Proof.* The equilibrium E_n^* is a solution of the algebraic system:

230 (5.3)
$$0 = r_i x_i \left(1 - \frac{x_i}{K_i} \right) + \beta \sum_{j=1, j \neq i}^n (\theta_{ij} x_j^2 - \theta_{ji} x_i^2), \quad i = 1, \dots, n.$$

231 The sum of these equations shows that $E_n^*(\beta)$ satisfies the following equation

232 (5.4)
$$\sum_{i=1}^{n} r_i x_i \left(1 - \frac{x_i}{K_i} \right) = 0.$$

233 Therefore $E_n^*(\beta)$ belongs to the ellipsoid:

234 (5.5)
$$\mathbb{E}^{n-1} := \left\{ x \in \mathbb{R}^n : \Upsilon(x) := \sum_{i=1}^n r_i x_i \left(1 - \frac{x_i}{K_i} \right) = 0 \right\}.$$

Note that, this ellipsoid is independent of the migration terms β and θ_{ij} . The ellipsoid \mathbb{E}^{n-1} passes through the points O, and $\mathcal{A} = (K_1, \ldots, K_n)$.

So, the equilibrium E_n^* is the solution in the positive cone, of the equation $F_\beta = 0$, where

239 (5.6)
$$F_{\beta}(x) := \left(F_1^{\beta}(x), \dots, F_{n-1}^{\beta}(x), \sum_{i=1}^n r_i x_i \left(1 - \frac{x_i}{K_i}\right)\right),$$

240 with

241 (5.7)
$$F_i^{\beta}(x) = \frac{1}{\beta} r_i x_i \left(1 - \frac{x_i}{K_i} \right) + \sum_{j=1, j \neq i}^n (\theta_{ij} x_j^2 - \theta_{ji} x_i^2), \qquad i = 1, \dots, n-1.$$

242 On the other hand, the limit equations (obtained when $\beta \to \infty$) are given by:

243 (5.8)
$$F_{\infty}(x) := \left(F_1^{\infty}(x), \dots, F_{n-1}^{\infty}(x), \sum_{i=1}^n r_i x_i \left(1 - \frac{x_i}{K_i}\right)\right),$$

244 with

245 (5.9)
$$F_i^{\infty}(x) = \sum_{j=1, j \neq i}^n (\theta_{ij} x_j^2 - \theta_{ji} x_i^2), \qquad i = 1, \dots, n-1$$

According to Lemma B.1 of [15], the system (5.9) admits unique solution given by: $x_i = \sqrt{\frac{\delta_i}{\delta_n}} x_n$ for all $i = 1, \dots, n-1$. So, the solutions of the equation $F_{\infty}(x) = 0$ is given by the solutions of the following system:

249 (5.10)
$$\begin{cases} x_i = \sqrt{\frac{\delta_i}{\delta_n}} x_n, \quad i = 1, \cdots, n-1 \\ \sum_{i=1}^n r_i x_i \left(1 - \frac{x_i}{K_i}\right) = 0, \end{cases}$$

which admits $x_n = 0$ and $x_n = \frac{\sum_{i=1}^n \sqrt{\delta_i} r_i}{\sum_{i=1}^n \delta_i \alpha_i} \sqrt{\delta_n}$ as solutions. So, the equation $F_{\infty} = 0$ admits two solutions, 0 and

$$E_n^*(\infty) := \frac{\sum_{i=1}^n \sqrt{\delta_i} r_i}{\sum_{i=1}^n \delta_i \alpha_i} (\sqrt{\delta_1}, \dots, \sqrt{\delta_n}).$$

The ellipsoid \mathbb{E}^{n-1} is compact, so the equilibrium $E_n^*(\beta)$ has at least one limit point in the ellipsoid, when β goes to infinity. By the same reason as in [15, Proof of Theorem 3.3], we prove the convergence of $E_n^*(\beta)$ to $E_n^*(\infty)$.

If the matrix Θ is symmetric, one has $\delta_i = 1$, for all *i*.

As a corollary of the previous theorem we obtain the following result which describes the total equilibrium population for large growth rate: 256 COROLLARY 5.2. We have

257 (5.11)
$$T_n^*(+\infty) = \left(\sum_{i=1}^n \sqrt{\delta_i}\right) \frac{\sum_{i=1}^n \sqrt{\delta_i} r_i}{\sum_{i=1}^n \delta_i \alpha_i}$$

258 Moreover, if the matrix Θ is symmetric, then:

259 (5.12)
$$T_n^*(+\infty) = n \frac{\sum_{i=1}^n r_i}{\sum_{i=1}^n \alpha_i}.$$

260 Proof. The sum of the *n* components of the point $E_n^*(\infty)$ immediately gives the 261 equation (5.11).

We remark that, the total equilibrium population for large migration rate (5.12) is equal the total equilibrium population for large migration rate of the multi-patch logistic model with linear diffusion obtained in [14, Equation 24]. This result show that, if the movement between the *n* patches is symmetric, the nonlinear diffusion has no influence on the total equilibrium population for large migration rate.

5.2. Two time scale dynamics. We can use the theory of singular perturbations to obtain a better understanding of the behavior of the system in the case of perfect mixing. We have the following result:

THEOREM 5.3. Let $(x_1(t,\beta),\ldots,x_n(t,\beta))$ be the solution of the system (2.1) with initial condition (x_1^0,\cdots,x_n^0) satisfying $x_i^0 \ge 0$ for $i = 1,\ldots,n$. Let Y(t) be the solution of the equation

273 (5.13)
$$\frac{dX}{dt} = rX\left(1 - \frac{X}{\left(\sum_{i=1}^{n} \sqrt{\delta_i}\right) K}\right),$$

274 where

275 (5.14)
$$r = \frac{\sum_{i=1}^{n} \sqrt{\delta_i} r_i}{\sum_{i=1}^{n} \sqrt{\delta_i}}, \quad K = \frac{\sum_{i=1}^{n} \sqrt{\delta_i} r_i}{\sum_{i=1}^{n} \delta_i \alpha_i} \quad and \quad \alpha_i = r_i/K_i.$$

276 Then, when $\beta \to \infty$, we have

277 (5.15)
$$\sum_{i=1}^{n} x_i(t,\beta) = Y(t) + o_{\beta}(1) \quad uniformly \text{ for } t \in [0,+\infty)$$

278 and, for any $t_0 > 0$, we have (5.16)

279
$$x_i(t,\beta) = \frac{\sqrt{\delta_i}}{\sum_{i=1}^n \sqrt{\delta_i}} Y(t) + o_\beta(1) \qquad i = 1, \dots, n, \text{ uniformly for } t \in [t_0, +\infty).$$

280 Proof. Let $X(t,\beta) = \sum_{i=1}^{n} x_i(t,\beta)$. We rewrite the system (2.1) using the vari-281 ables (X, x_1, \dots, x_{n-1}) , and get:

282 (5.17)
$$\begin{cases} \frac{dX}{dt} = \sum_{i=1}^{n} r_i x_i \left(1 - \frac{x_i}{K_i}\right), \\ \frac{dx_i}{dt} = r_i x_i \left(1 - \frac{x_i}{K_i}\right) + \beta \sum_{j=1, j \neq i}^{n} (\theta_{ij} x_j^2 - \theta_{ji} x_i^2), \quad i = 1, \dots, n-1. \end{cases}$$

This system is actually a system in the variables (X, x_1, \dots, x_{n-1}) , since, whenever 283 284 x_n appears in the right hand side of (5.17), it should be replaced by

285 (5.18)
$$x_n = X - \sum_{i=1}^{n-1} x_i.$$

286When $\beta \to \infty$, (5.17) is a *slow-fast* system, with one *slow variable*, X, and n-1 fast variables, x_i for $i = 1 \dots n - 1$. As suggested by Tikhonov's theorem [26, 32, 33], we 287 consider the dynamics of the fast variables in the time scale $\tau = \beta t$. We get 288

289 (5.19)
$$\frac{dx_i}{d\tau} = \frac{1}{\beta} r_i x_i \left(1 - \frac{x_i}{K_i} \right) + \sum_{j=1, j \neq i}^n (\theta_{ij} x_j^2 - \theta_{ji} x_i^2), \qquad i = 1, \dots, n-1.$$

where x_n is given by (5.18). In the limit $\beta \to \infty$, we find the *fast dynamics*

$$\frac{dx_i}{d\tau} = \sum_{j=1, j \neq i}^n (\gamma_{ij} x_j^2 - \gamma_{ji} x_i^2), \qquad i = 1, \cdots, n-1.$$

This is an (n-1)-dimensional non linear differential system. According to [15, Lemma B.1, we can deduced that, this system admits unique equilibrium GAS given by

$$\left(\frac{\sqrt{\delta_1}}{\sum_{i=1}^n \sqrt{\delta_i}} X, \dots, \frac{\sqrt{\delta_{n-1}}}{\sum_{i=1}^n \sqrt{\delta_i}} X\right)^T.$$

Thus, the slow manifold of System (5.17) is given by 290

291 (5.20)
$$x_i = \frac{\sqrt{\delta_i}}{\sum_{i=1}^n \sqrt{\delta_i}} X, \qquad i = 1, \dots, n-1.$$

As this manifold is GAS, Tikhonov's theorem ensures that after a fast transition toward the slow manifold, the solutions of (5.17) are approximated by the solutions of the reduced model, which is obtained by replacing (5.20) into the dynamics of the slow variable, that is:

$$\frac{dX}{dt} = \sum_{i=1}^{n} r_i \frac{X}{\sum_{i=1}^{n} \sqrt{\delta_i}} \sqrt{\delta_i} \left(1 - \frac{X}{\left(\sum_{i=1}^{n} \sqrt{\delta_i}\right) K_i} \sqrt{\delta_i} \right) = rX \left(1 - \frac{X}{\left(\sum_{i=1}^{n} \sqrt{\delta_i}\right) K} \right),$$

where r and K are defined in (5.14). Therefore, the reduced model is (5.13). The system (5.13) admits

$$X^* = \left(\sum_{i=1}^n \sqrt{\delta_i}\right) K = \left(\sum_{i=1}^n \sqrt{\delta_i}\right) \frac{\sum_{i=1}^n \sqrt{\delta_i} r_i}{\sum_{i=1}^n \delta_i \alpha_i}$$

292 as a positive equilibrium point, which is GAS in the positive axis, the approximation

given by Tikhonov's theorem holds for all $t \ge 0$ for the slow variable and for all $t \ge 0$ 293 $t_0 > 0$ for the fast variables, where t_0 is as small as we want. Therefore, letting Y(t)294be the solution of the reduced model (5.13) with initial condition $Y(0) = X(0,\beta) =$ 295

 $\sum_{i=1}^{n} x_i^0$, then, when $\beta \to \infty$, we have the approximations (5.15) and (5.16). 296

Note that, in the case of perfect mixing, the approximation (5.15) shows that, the total population behaves like the unique logistic equation (5.13) and then, when t and β tend to ∞ , the total population $\sum x_i(t, \beta)$ tends toward

$$\left(\sum_{i=1}^{n} \sqrt{\delta_i}\right) K = \left(\sum_{i=1}^{n} \sqrt{\delta_i}\right) \frac{\sum_{i=1}^{n} \sqrt{\delta_i} r_i}{\sum \delta_i \alpha_i}$$

as stated in Theorem 5.1. The approximation (5.16) shows that, with the exception of a thin initial boundary layer, where the density population $x_i(t,\beta)$ quickly jumps from its initial condition x_i^0 to the average $\sqrt{\delta_i}X_0/\sum_{i=1}^n \sqrt{\delta_i}$, each patch of the model behaves like the single logistic equation

$$\frac{du}{dt} = ru\left(1 - \frac{u}{\sqrt{\delta_i}K}\right), \qquad i = 1, \dots, n$$

where r and K are given in (5.14). Hence, when t and β tend to ∞ , the density population $x_i(t,\beta)$ tends toward $K = \sqrt{\delta_i} \frac{\sum_{i=1}^n \sqrt{\delta_i} r_i}{\sum_{i=1}^{\delta_i} \alpha_i}$ as stated in Theorem 5.1. As a corollary of the previous theorem we obtain the following result which de-

As a corollary of the previous theorem we obtain the following result which describes the behavior of the system (2.1) for perfect mixing and nonlinear symmetrical dispersal:

302 COROLLARY 5.4. Assume that the matrix Θ is symmetric. Let $(x_1(t,\beta),\ldots,x_n(t,\beta))$ 303 be the solution of the system (2.1) with initial condition (x_1^0,\cdots,x_n^0) satisfying $x_i^0 \ge 0$ 304 for $i = 1 \cdots n$. Let Y(t) be the solution of the equation

305 (5.21)
$$\frac{dX}{dt} = rX\left(1 - \frac{X}{nK}\right),$$

306 where

307 (5.22)
$$r = \frac{\sum_{i=1}^{n} r_i}{n}, \quad K = \frac{\sum_{i=1}^{n} r_i}{\sum_{i=1}^{n} \alpha_i} \quad and \quad \alpha_i = r_i/K_i.$$

308 Then, when $\beta \to \infty$, we have

309 (5.23)
$$\sum_{i=1}^{n} x_i(t,\beta) = Y(t) + o_{\beta}(1) \quad uniformly \text{ for } t \in [0,+\infty)$$

310 and, for any $t_0 > 0$, we have

311 (5.24)
$$x_i(t,\beta) = \frac{Y(t)}{n} + o_\beta(1)$$
 $i = 1, ..., n, \text{ uniformly for } t \in [t_0, +\infty).$

³¹² *Proof.* If Θ is symmetric, one has $\delta_i = 1$ for all *i*. Therefore, the formulas (5.13), ³¹³ (5.14), and the approximations (5.15), (5.16) for $\delta_i = 1$, give the proof of the corol-³¹⁴ lary.

5.3. Comparison of $T_n^*(+\infty)$ with $\sum_i K_i$. According to Formula (5.11), it is clear that the total equilibrium population at $\beta = 0$ and at $\beta = +\infty$ are different in general.

In the remainder of this section, we give some conditions, in the space of parameters r_i, K_i, α_i and δ_i , for limit of the total equilibrium population when $\beta \to \infty$ to be greater or smaller than the sum of the carrying capacities. We show that all three cases are possible, i.e $T_n^*(+\infty)$ can be greater than, smaller than, or equal to $T_n^*(0)$. First, we start by giving some particular values of the parameters for which equality holds. PROPOSITION 5.5. Consider the system (2.1). Let we denote $\sqrt{\ker \Theta}$ the vector space generated by the vector $(\sqrt{\delta_1}, \ldots, \sqrt{\delta_n})^T$. If the vector $\left(\frac{1}{\alpha_1}, \ldots, \frac{1}{\alpha_n}\right)^T$ lies in $\sqrt{\ker \Theta}$, then $T_n^*(+\infty) = \sum_i K_i$.

327 Proof. Direct consequence of the equation (5.11).

Note that, if the matrix Θ is symmetric, then, Prop. 5.5 says that if all α_i are equal, then $T_n^*(\infty) = \sum_i K_i$, which is [14, Prop 4.4] obtained for the multi-patch logistic model with linear diffusion.

In the next proposition, we give two cases which ensure that $T_n^*(0)$ can be greater or smaller than $T_n^*(+\infty)$. This result can be stated as the following proposition:

PROPOSITION 5.6. Consider the system (2.1).
1. If
$$\frac{K_1}{\sqrt{\delta_1}} \leq \ldots \leq \frac{K_n}{\sqrt{\delta_n}}$$
 and $\sqrt{\delta_1}\alpha_1 \leq \ldots \leq \sqrt{\delta_n}\alpha_n$, or if $\frac{K_1}{\sqrt{\delta_1}} \geq \ldots \geq \frac{K_n}{\sqrt{\delta_n}}$ and

335
$$\sqrt{\delta_1}\alpha_1 \ge \ldots \ge \sqrt{\delta_n}\alpha_n, \text{ then } T_n^*(+\infty) \ge T_n^*(0).$$

336 2. If
$$\frac{K_1}{\sqrt{\delta_1}} \ge \ldots \ge \frac{K_n}{\sqrt{\delta_n}}$$
 and $\sqrt{\delta_1}\alpha_1 \le \ldots \le \sqrt{\delta_n}\alpha_n$, or if $\frac{K_1}{\sqrt{\delta_1}} \le \ldots \le \frac{K_n}{\sqrt{\delta_n}}$ and

- 337 $\sqrt{\delta_1}\alpha_1 \ge \ldots \ge \sqrt{\delta_n}\alpha_n$, then $T_n^*(+\infty) \le T_n^*(0)$. 338 In both items, if at least one of the inequalities in $\frac{K_1}{\sqrt{\delta_1}} \le \ldots \le \frac{K_n}{\sqrt{\delta_n}}$ or
- 339 $\frac{K_1}{\sqrt{\delta_1}} \ge \ldots \ge \frac{K_n}{\sqrt{\delta_n}}$ is strict, then the inequality is strict in the conclusion.

340 Proof. Apply Lemma B.2 in [15] with the following choice: $w_i = \sqrt{\delta_i}, u_i = \frac{K_i}{\sqrt{\delta_i}}$, 341 and $v_i = \sqrt{\delta_i} \alpha_i$, for all i = 1, ..., n.

- 342 If the matrix Θ is symmetric, one has $\delta_i = 1$, for all *i*, and Prop. 5.6 becomes
- 343 COROLLARY 5.7. Consider the system (2.1). Assume that Θ is symmetric.

344 1. If
$$K_1 \leq \ldots \leq K_n$$
 and $\alpha_1 \leq \ldots \leq \alpha_n$, or if $K_1 \geq \ldots \geq K_n$ and $\alpha_1 \geq \ldots \geq a_n$, then $T_n^*(+\infty) \geq T_n^*(0)$.

346 347 2. If $K_1 \ge \ldots \ge K_n$ and $\alpha_1 \le \ldots \le \alpha_n$, or if $K_1 \le \ldots \le K_n$ and $\alpha_1 \ge \ldots \ge \alpha_n$, then $T_n^*(+\infty) \le T_n^*(0)$.

6. Effect of nonlinear dispersal on total population size. In this section, we will investigate how non linear dispersal affects the total population in all patches. In particular, when is it detrimental or beneficial to the sum of carrying capacities? Mathematically speaking, we will compare, in some particular cases of the system (2.1), the total equilibrium population $T_n^*(\beta)$, with the sum of carrying capacities $T_n^*(0) = \sum_i K_i$, when the rate of migration β varies from zero to infinity. We show that the total equilibrium population, $T_n^*(\beta)$, can either be greater than, smaller than, or equal to the sum of the carrying capacities $T_n^*(0)$ (non dispersal).

6.1. Nonlinear dispersal my be unfavorable to T_n^* . In the next proposition, we show that if the growth rates are equal in all patches, then the total equilibrium population is always smaller than the sum of the carrying capacities:

PROPOSITION 6.1. If $r_1 = \cdots = r_n$, then the total equilibrium population, defined by (4.7) satisfies $T_n^*(\beta) \leq \sum_{i=1}^n K_i$, for all $\beta \in [0, \infty[$.

361 Proof. The equation of the tangent space to the ellipsoid \mathbb{E}^{n-1} , defined by (5.5),

at point $\mathcal{A} = (K_1, \ldots, K_n)$ is given by 362

363 (6.1)
$$\sum_{i=1}^{n} (x_i - K_i) \frac{\partial \Upsilon}{\partial x_i}(\mathcal{A}) = 0,$$

where Υ is given by (5.5). Since $\frac{\partial \Upsilon}{\partial x_i}(\mathcal{A}) = -r_i$, (6.1) can be written as follows: 364

365 (6.2)
$$\sum_{i=1}^{n} r_i (x_i - K_i) = 0.$$

If we take $r_1 = \cdots = r_n$ in (6.2), we get that the equation of the tangent plane to \mathbb{E}^{n-1} at the point \mathcal{A} is

$$\sum_{i=1}^n x_i = \sum_{i=1}^n K_i.$$

By the convexity of \mathbb{E}^{n-1} , any point of \mathbb{E}^{n-1} lies in the half-space defined by the inequation $\sum_{i=1}^{n} x_i \leq \sum_{i=1}^{n} K_i$. Therefore $E^*(\beta)$ satisfies

$$\sum_{i=1}^{n} x_i^*(\beta) \le \sum_{i=1}^{n} K_i \quad \text{for all } \beta \ge 0.$$

Which completes the proof of the proposition. 366

The result of the previous proposition is the same as Prop. 3.1 and Prop. 6.2 in [14] 367 for the linear diffusion. 368

6.2. Independence of T_n^* with respect to nonlinear dispersal. In the 369 next proposition we give sufficient and necessary conditions for the total equilibrium population not to depend on the migration rate.

PROPOSITION 6.2. The equilibrium $E_n^*(\beta)$ does not depend on β if and only if 372 $(K_1^2,\ldots,K_n^2)^T \in \ker \Theta$. In this case we have $E_n^*(\beta) = (K_1,\ldots,K_n)$ for all $\beta > 0$. 373

Proof. The equilibrium $E_n^*(\beta)$ is the unique positive solution of the equation 374

375 (6.3)
$$f(x) + \beta \Theta x^2 = 0,$$

where $f(x) = (f_1(x_1), \dots, f_n(x_n))^T$, and $f_i(x_i) = r_i x_i (1 - x_i/K_i), \quad i = 1, \dots, n$. 376 Suppose that the equilibrium $E_n^*(\beta)$ does not depend on β , then we replace in Equation 377 (6.3): 378

379 (6.4)
$$f(E^*(\beta)) + \beta \Theta(E_n^*(\beta))^2 = 0.$$

The derivative of (6.4) with respect to β gives 380

381 (6.5)
$$\Theta(E_n^*(\beta))^2 = 0.$$

382 383

Replacing the equation (6.5) in the equation (6.4), we get $f(E_n^*(\beta)) = 0$, so $E^*(\beta) = (K_1, \ldots, K_n)$. From the equation (6.5), we conclude that $(K_1^2, \ldots, K_n^2)^T \in \ker \Theta$. Now, suppose that $(K_1^2, \ldots, K_n^2)^T \in \ker \Theta$, then (K_1, \ldots, K_n) satisfies the equation (6.3), for all $\beta \ge 0$. So, $E_n^*(\beta) = (K_1, \ldots, K_n)$, for all $\beta \ge 0$, which proves that 384 385 the total equilibrium population is independent of the migration rate β . 386

If the matrix Θ is symmetric, the previous proposition asserts that, the K_i , for 387 $i = 1, \ldots, n$, are equal if and only if $E_n^* = (K, \ldots, K)$, where K is the common value 388 of the K_i . This is [14, Proposition 3.2]. 389

6.3. Nonlinear dispersal my be favorable to T_n^* . In this section, we give a situation where the non linear dispersal is favorable to the total equilibrium population. Mathematically speaking:

PROPOSITION 6.3. Assume that for all j < i, $\alpha_i \sqrt{\theta_{ij}} = \alpha_j \sqrt{\theta_{ji}}$. Then

$$T_n^*(\beta) \ge \sum_{i=1}^n K_i \quad \text{for all } \beta \ge 0.$$

Moreover, if there exist i_0 and $j_0 \neq i_0$ such that $r_{i_0} \neq r_{j_0}$, then $T_n^*(\beta) > \sum_{i=1}^n K_i$, for all $\beta > 0$.

395 Proof. The equilibrium point $E_n^*(\beta)$ satisfies the system

396 (6.6)
$$0 = \alpha_i x_i^*(\beta) \left(K_i - x_i^*(\beta) \right) + \beta \sum_{j=1, j \neq i}^n \left(\theta_{ij}(x_j^*)^2(\beta) - \theta_{ji}(x_i^*)^2(\beta) \right), \quad i = 1 \cdots n$$

Dividing (6.6) by $\alpha_i x_i^*$, one obtains

$$x_i^*(\beta) = K_i + \beta \sum_{j=1, j \neq i}^n \frac{\theta_{ij}(x_j^*(\beta))^2 - \theta_{ji}(x_i^*(\beta))^2}{\alpha_i x_i^*(\beta)}$$

Taking the sum of these expressions shows that the total equilibrium population T_n^* satisfies the following relation:

(6.7)

$$T_{n}^{*}(\beta) = \sum_{i=1}^{n} K_{i} + \beta \sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} \frac{\theta_{ij}(x_{j}^{*}(\beta))^{2} - \theta_{ji}(x_{i}^{*}(\beta))^{2}}{\alpha_{i}x_{i}^{*}(\beta)}$$

$$400 = \sum_{i=1}^{n} K_{i} + \beta \sum_{j < i} \left(\frac{\theta_{ij}(x_{j}^{*}(\beta))^{2} - \theta_{ji}(x_{i}^{*}(\beta))^{2}}{\alpha_{i}x_{i}^{*}(\beta)} + \frac{\theta_{ji}(x_{i}^{*}(\beta))^{2} - \theta_{ij}(x_{j}^{*}(\beta))^{2}}{\alpha_{j}x_{j}^{*}(\beta)} \right)$$

$$401 = \sum_{i=1}^{n} K_{i} + \beta \sum_{j < i} \left(\sqrt{\theta_{ij}}x_{j}^{*}(\beta) + \sqrt{\theta_{ji}}x_{i}^{*}(\beta) \right) \left(\frac{\sqrt{\theta_{ij}}x_{j}^{*}(\beta) - \sqrt{\theta_{ji}}x_{i}^{*}(\beta)}{\alpha_{i}x_{i}^{*}(\beta)} \right)$$

$$402 + \frac{\sqrt{\theta_{ji}}x_{i}^{*}(\beta) - \sqrt{\theta_{ij}}x_{j}^{*}(\beta)}{\alpha_{j}x_{j}^{*}(\beta)} \right) = \sum_{i=1}^{n} K_{i}$$

$$403 + \beta \sum_{j < i} \left(\sqrt{\theta_{ij}}x_{j}^{*}(\beta) + \sqrt{\theta_{ji}}x_{i}^{*}(\beta) \right) \frac{\left(\sqrt{\theta_{ij}}x_{j}^{*}(\beta) - \sqrt{\theta_{ji}}x_{i}^{*}(\beta)\right) \left(\alpha_{j}x_{j}^{*}(\beta) - \alpha_{i}x_{i}^{*}(\beta)\right)}{\alpha_{j}\alpha_{i}x_{j}^{*}(\beta)x_{i}^{*}(\beta)}$$

The conditions $\alpha_i \sqrt{\theta_{ij}} = \alpha_j \sqrt{\theta_{ji}}$ can be written $\omega_{ij} := \alpha_i / \sqrt{\theta_{ji}} = \alpha_j / \sqrt{\theta_{ij}}$ for all j < i, such that $\theta_{ij} \neq 0$ and $\theta_{ji} \neq 0$. Therefore, there exists $\omega_{ij} > 0$ such that

$$\alpha_j = \omega_{ij}\sqrt{\theta_{ij}}$$
 and $\alpha_i = \omega_{ij}\sqrt{\theta_{ji}}$ for all i, j with $\theta_{ij} \neq 0$ and $\theta_{ji} \neq 0$

405 Replacing α_i and α_j in (6.7), one obtains (6.8)

406
$$T_n^*(\beta) = \sum_{i=1}^n K_i + \beta \sum_{j < i} \frac{\omega_{ij} \left(\sqrt{\theta_{ij}} x_j^*(\beta) + \sqrt{\theta_{ji}} x_i^*(\beta)\right) \left(\sqrt{\theta_{ij}} x_j^*(\beta) - \sqrt{\theta_{ji}} x_i^*(\beta)\right)^2}{\alpha_j \alpha_i x_j^*(\beta) x_i^*(\beta)}$$
14

407 Therefore, $T_n^*(\beta) \geq \sum_{i=1}^n K_i$ for all $\beta \geq 0$. As the matrix Θ is assumed irreducible, 408 then the equality holds if and only if $\beta = 0$ or $\sqrt{\theta_{ij}}x_j^*(\beta) - \sqrt{\theta_{ji}}x_i^*(\beta) = 0$, for all 409 *i* and *j*. Let us prove that if at least two patches have different growth rates, then 410 equality cannot hold for $\beta > 0$. Suppose that there exists $\beta^* > 0$ such that the 411 positive equilibrium satisfies

412 (6.9)
$$\forall i, j, \quad \sqrt{\theta_{ij}} x_j^*(\beta^*) = \sqrt{\theta_{ji}} x_i^*(\beta^*) \Longleftrightarrow \forall i, j, \quad \theta_{ij}(x_j^*)^2(\beta^*) = \theta_{ji}(x_i^*)^2(\beta^*).$$

413 Replacing the equation (6.9) in the system (6.6), we get that $x_i^*(\beta^*) = K_i$, for all 414 *i*. Therefore, from (6.9), it is seen that, for all *i* and *j*, $K_j^2 \theta_{ij} = K_i^2 \theta_{ji}$. From these 415 equations and the conditions $\alpha_i \sqrt{\theta_{ij}} = \alpha_j \sqrt{\theta_{ji}}$, we get $r_i = r_j$, for all *i* and *j*. This is 416 a contradiction with the hypothesis that there exist two patches with different growth 417 rates. Hence the equality in (6.8) holds if and only if $\beta = 0$.

- 418 As corollary of the previous proposition, we obtain the following result:
- 419 COROLLARY 6.4. Assume that Θ is symmetric. If $\alpha_1 = \ldots = \alpha_n$, then

420
$$T_n^*(\beta) \ge \sum_i K_i \text{ for all } \beta \ge 0.$$

421 Proof. When the matrix Θ is irreducible and symmetric, the hypothesis of Prop. 422 6.3 implies that $\alpha_i = \alpha_j$ for all i and j. Indeed if two patches i and j are connected 423 (i.e $\theta_{ij} = \theta_{ji} \neq 0$), then we have $\alpha_i = \alpha_j$. As the matrix Θ is irreducible, for two 424 arbitrary patches, there exists a finite sequence (i, \ldots, j) which begins in i and ends 425 in j, such that $\theta_{ab} \neq 0$ for all successive patches a and b in (i, \ldots, j) . Hence $\alpha_a = \alpha_b$ 426 for all a and b in (i, \ldots, j) . Hence, $\alpha_i = \alpha_j$.

427 The result of the corollary 6.4 says that if all α_i are equal, non linear dispersal enhances

428 population growth, which is [14, Prop. 3.3], which has been proven for the multi-patch 429 logistic model with linear diffusion.

REMARK 2. For three patches or more, if the matrix Θ does not verify the condition $(\forall i, j, \ \theta_{ij} = 0 \iff \theta_{ji} = 0)$, then the hypothesis of Prop. 6.3, that for all j < i, $\alpha_i \sqrt{\theta_{ij}} = \alpha_j \sqrt{\theta_{ji}}$ cannot be satisfied. Note that the hypothesis $\alpha_i \sqrt{\theta_{ij}} = \alpha_j \sqrt{\theta_{ji}}$ implies that $\alpha_i^2 \theta_{ij} = \alpha_j^2 \theta_{ji}$, which implies, for all $i = 1, \ldots, n$, one has

$$\sum_{j=1}^{n} \frac{\theta_{ij}}{\alpha_j^2} = \sum_{j=1, j \neq i}^{n} \frac{\theta_{ij}}{\alpha_j^2} - \sum_{j=1, j \neq i}^{n} \frac{\theta_{ji}}{\alpha_i^2} = \sum_{j=1, j \neq i}^{n} \frac{\alpha_i^2 \theta_{ij} - \alpha_j^2 \theta_{ji}}{\alpha_i^2 \alpha_j^2} = 0.$$

430 Therefore, the hypothesis of Prop. 6.3 implies that $(\frac{1}{\alpha_1^2}, \ldots, \frac{1}{\alpha_n^2})^T \in \ker \Theta$.

431 6.4. Derivative of T_n^* at $\beta = 0$.

432 PROPOSITION 6.5. The derivative of the total equilibrium population $T_n^*(\beta)$ at 433 $\beta = 0$ is given by:

434 (6.10)
$$\frac{dT_n^*}{d\beta}(0) = \sum_{i=1}^n \left(\frac{1}{r_i} \sum_{j=1}^n \theta_{ij} K_j^2\right).$$

Proof. By differentiating the equation (6.7) at $\beta = 0$, we get:

$$\frac{dT_n^*}{d\beta}(0) = \sum_{i=1}^n \sum_{j=1, j \neq i}^n \frac{\theta_{ij}(x_j^*(0))^2 - \theta_{ji}(x_i^*(0))^2}{\alpha_i x_i^*(0)}$$

15

435 which gives (6.10), since $x_i^*(0) = K_i$ for all i = 1, ..., n.

The derivative (6.10) can be written in matrix form as follows:

$$\frac{dT_n^*}{d\beta}(0) = \mathcal{R}^T \Theta K^2,$$

436 with $\mathcal{R} = \left(\frac{1}{r_1}, \dots, \frac{1}{r_n}\right)^T$ and $K^2 = (K_1^2, \dots, K_n^2)^T$. Note that, if the growth rates are 437 equal in all patches, or, (K_1^2, \dots, K_n^2) lies in the vector space ker Θ , then the derivative 438 of the total equilibrium population T_n^* at $\beta = 0$ equal to zero.

439 **7. Two-patch case.** In this section, we concentrate on the two-patch model:

440 (7.1)
$$\begin{cases} \frac{dx_1}{dt} = r_1 x_1 \left(1 - \frac{x_1}{K_1} \right) + \beta \left(\theta_{12} x_2^2 - \theta_{21} x_1^2 \right), \\ \frac{dx_2}{dt} = r_2 x_2 \left(1 - \frac{x_2}{K_2} \right) + \beta \left(\theta_{21} x_1^2 - \theta_{12} x_2^2 \right). \end{cases}$$

The total equilibrium population of the model (7.1) in the perfect mixing case (i.e $\beta \to \infty$) is given by the following formula:

443 (7.2)
$$T_2^*(+\infty) = \left(\sqrt{\theta_{12}} + \sqrt{\theta_{21}}\right) \frac{\sqrt{\theta_{12}}r_1 + \sqrt{\theta_{21}}r_2}{\theta_{12}r_1/K_1 + \theta_{21}r_2/K_2},$$

444 and the derivative of the total equilibrium population $T_2^*(\beta)$ at $\beta = 0$ becomes

445 (7.3)
$$\frac{dT_2^*}{d\beta}(0) = \left(\theta_{12}K_2^2 - \theta_{21}K_1^2\right)\left(\frac{1}{r_1} - \frac{1}{r_2}\right).$$

446 The equilibrium of the system (2.1) is the solutions of the following algebraic system:

447 (7.4)
$$\begin{cases} 0 = r_1 x_1 \left(1 - \frac{x_1}{K_1} \right) + \beta \left(\theta_{12} x_2^2 - \theta_{21} x_1^2 \right), \\ 0 = r_2 x_2 \left(1 - \frac{x_2}{K_2} \right) + \beta \left(\theta_{21} x_1^2 - \theta_{12} x_2^2 \right). \end{cases}$$

The sum of two equations of (7.4) shows that the equilibrium points are in ellipse noted \mathbb{E} , where its equation is given by:

450 (7.5)
$$\mathbb{E}: r_1 x_1 \left(1 - \frac{x_1}{K_1} \right) + r_2 x_2 \left(1 - \frac{x_2}{K_2} \right) = 0$$

- The ellipse \mathbb{E} passes through the points $(0,0), (K_1,0), (0,K_2)$ and $\mathcal{A} := (K_1, K_2)$. Note that, it is independent of migration rate β and θ_{ij} (shown in red in Fig. 1).
- Solving the first equation of system (7.4) for x_2 yields a hyperbola noted \mathcal{H}_{β} defined by

$$\mathcal{H}_{\beta}: h_{\beta}(x_1) := \sqrt{\frac{1}{\theta_{12}}} \left(\theta_{21}x_1^2 - \frac{r_1}{\beta}x_1\left(1 - \frac{x_1}{K_1}\right)\right).$$

As our study is limited in the positive cone, then we are interested only in the positive branch of \mathcal{H}_{β} . The hyperbola \mathcal{H}_{β} (shown in blue in Fig. 1) depend on the migration rate β . It always passes through the origin and the point $\mathcal{B} := \left(K_1, \frac{\theta_{21}}{\theta_{12}}K_1\right)$. Notice that, the hyperbola \mathcal{H}_{β} intersect the axis (Ox_1) at 0 and a second positive point $x_1 = \frac{r_1/\beta}{\theta_{21}+\alpha_1/\beta}$ which always smaller than K_1 . So, the equilibrium points are the 16

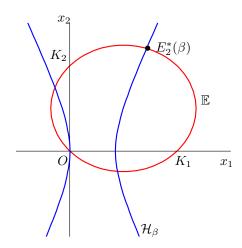


FIG. 1. The ellipse \mathbb{E} and the hyperbola \mathcal{H}_{β} . The equilibrium points are the intersection in the positive cone between \mathbb{E} and \mathcal{H}_{β} , this intersections contains the origin and a second positive point $E^*(\beta).$

non negative intersection between the ellipse \mathbb{E} and \mathcal{H}_{β} . There are two equilibrium 458points. The first is the trivial point (0,0) and the second is a non trivial point 459 $E_2^*(\beta) = (x_1^*(\beta), x_2^*(\beta))$ whose position depend on migration rate β (see Fig. 1). 460

When $\beta \to 0$, the left branch of hyperbola \mathcal{H}_{β} tend to the vertical line $x_1 = 0$ and the right branch into the vertical line \mathcal{H}_0 : $x_1 = K_1$. Moreover, $\mathbb{E} \cap \mathcal{H}_0 =$ $\{(K_1, 0), (K_1, K_2)\}$. In the case when $\beta \to \infty$, the hyperbola \mathcal{H}_β tend to the oblique line \mathcal{H}_{∞} : $x_2 = \sqrt{\frac{\theta_{21}}{\theta_{12}}} x_1$. Moreover,

$$\mathbb{E} \cap \mathcal{H}_{\infty} = \left\{ (0,0), \left(\sqrt{\theta_{12}} \frac{\sqrt{\theta_{12}}r_1 + \sqrt{\theta_{21}}r_2}{\theta_{12}r_1/K_1 + \theta_{21}r_2/K_2}, \sqrt{\theta_{21}} \frac{\sqrt{\theta_{12}}r_1 + \sqrt{\theta_{21}}r_2}{\theta_{12}r_1/K_1 + \theta_{21}r_2/K_2} \right) \right\}$$

It was shown by Arditi et al. [4, Proposition 2, page 54] that only three situations 461 462can occur: the case where the total equilibrium population is always greater than the sum of carrying capacities, the case where it is always smaller, and a third case, where 463the effect of migration is beneficial for lower values of the migration coefficient β and 464 detrimental for the higher values. More precisely, it was shown in [4] that, if n = 2 in 465(1.7), the following trichotomy holds 466

467

• If $T_2^*(+\infty) > K_1 + K_2$ then $T_2^*(\beta) > K_1 + K_2$ for all $\beta > 0$. • If $\frac{dT_2^*}{d\beta}(0) > 0$ and $T_2^*(+\infty) < K_1 + K_2$, then there exists $\beta_0 > 0$ such that $T_2^*(\beta) > K_1 + K_2$ for $0 < \beta < \beta_0$, $T_2^*(\beta) < K_1 + K_2$ for $\beta > \beta_0$ and 468 469 470

471

 $T_{2}^{*}(\beta_{0}) = K_{1} + K_{2}.$ • If $\frac{dT_{2}^{*}}{d\beta}(0) < 0$, then $T_{2}^{*}(\beta) < K_{1} + K_{2}$ for all $\beta > 0$. Therefore, the condition $T_{2}^{*}(\beta) = K_{1} + K_{2}$ holds only for $\beta = 0$ and at most for one positive value β_{0} . The value β_{0} exists if and only if $\frac{dT_{2}^{*}}{d\beta}(0) > 0$ and $T_{2}^{*}(+\infty) < 0$. 472473 $K_1 + K_2.$ 474

In the remainder of this section, we analyze the effect of nonlinear dispersal on 475the total equilibrium population for the two-patch system (7.1). Using the method of 476Arditi et al. [5], we describe the position affects the equilibrium $E^*(\beta)$ of (7.1) when 477

the migration rate varies from zero to infinity, we will give the condition whether T_2^* is greater or smaller than sum of carrying capacity $T_2^*(0) = K_1 + K_2$. We prove there are only three cases as in the 2-patch logistic model with linear diffusion can occur. We consider the regions in the set of the parameters θ_{21} and θ_{12} , denoted $\mathcal{J}_0, \mathcal{J}_1$

482 and \mathcal{J}_2 , depicted in Fig. 2 and defined by:

$$483 \quad (7.6) \qquad \begin{cases} \text{If } r_2 > r_1 \text{ then } \begin{cases} \mathcal{J}_1 = \left\{ (\theta_{21}, \theta_{12}) : \frac{\theta_{12}}{\theta_{21}} > \frac{\alpha_2^2}{\alpha_1^2} \right\} \\ \mathcal{J}_0 = \left\{ (\theta_{21}, \theta_{12}) : \frac{\alpha_2^2}{\alpha_1^2} \ge \frac{\theta_{12}}{\theta_{21}} > \frac{K_1^2}{K_2^2} \right\} \\ \mathcal{J}_2 = \left\{ (\theta_{21}, \theta_{12}) : \frac{K_1^2}{K_2^2} > \frac{\theta_{12}}{\theta_{21}} \right\} \end{cases} \\ \mathcal{J}_1 = \left\{ (\theta_{21}, \theta_{12}) : \frac{\theta_{12}}{\theta_{21}} < \frac{\alpha_2^2}{\alpha_1^2} \right\} \\ \mathcal{J}_0 = \left\{ (\theta_{21}, \theta_{12}) : \frac{\alpha_2^2}{\alpha_1^2} \le \frac{\theta_{12}}{\theta_{21}} < \frac{K_1^2}{K_2^2} \right\} \\ \mathcal{J}_2 = \left\{ (\theta_{21}, \theta_{12}) : \frac{\alpha_2^2}{\alpha_1^2} \le \frac{\theta_{12}}{\theta_{21}} < \frac{K_1^2}{K_2^2} \right\} \end{cases}$$

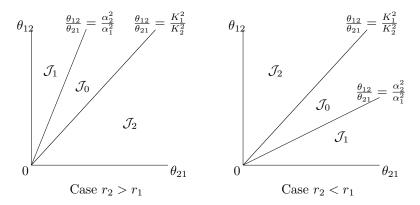


FIG. 2. The domains $\mathcal{J}_0, \mathcal{J}_1$ and \mathcal{J}_2 . In the figure $\alpha_1 = r_1/K_1$ and $\alpha_2 = r_2/K_2$.

We have the following result which gives the conditions for which patchiness is beneficial or detrimental in model (7.1).

THEOREM 7.1. The total equilibrium population of (7.1) satisfies the following properties

488 1. If $r_1 = r_2$ then $T_2^*(\beta) \le K_1 + K_2$ for all $\beta \ge 0$.

489 490

2. If
$$r_2 \neq r_1$$
, let \mathcal{J}_0 , \mathcal{J}_1 and \mathcal{J}_2 , be defined by (7.6). Then we have:

• if
$$(\theta_{21}, \theta_{12}) \in \mathcal{J}_0$$
 then $T_2^*(\beta) > K_1 + K_2$ for any $\beta > 0$

• if
$$(\theta_{21}, \theta_{12}) \in \mathcal{J}_1$$
 then $\overline{T_2^*}(\beta) > K_1 + K_2$ for $0 < \beta < \beta_0$ and $\overline{T_2^*}(\beta) < K_1 + K_2$ for $\beta > \beta_0$, where

$$\beta_0 = \frac{r_2 - r_1}{\frac{\sqrt{\theta_{12}}}{\alpha_2} - \frac{\sqrt{\theta_{21}}}{\alpha_1}} \frac{1}{\alpha_1 + \alpha_2}.$$

491 • if $(\theta_{21}, \theta_{12}) \in \mathcal{J}_2$ then $T_2^*(\beta) < K_1 + K_2$ for any $\beta > 0$

492 • If
$$\frac{\theta_{12}}{\theta_{21}} = \frac{K_1^2}{K_2^2}$$
, then $x_1^*(\beta) = K_1$ and $x_2^*(\beta) = K_2$ for all $\beta \ge 0$. Therefore
493 $T_2^*(\beta) = K_1 + K_2$ for all $\beta \ge 0$.

Proof. To facilitate comparison of the total equilibrium population $T_2^*(\beta)$ and 494 $T_2^*(0) = K_1 + K_2$, we define a straight line $\Delta : x_1 + x_2 = K_1 + K_2$. If the intersection 495of the ellipse \mathbb{E} and the hyperbola \mathcal{H}_{β} , i.e., the equilibrium $(x_1^*(\beta), x_2^*(\beta))$, is on or 496 below the line Δ , then $T_2^*(\beta) \leq T_2^*(0)$, whereas if the intersection is above the line, 497then $T_2^*(\beta) \geq T_2^*(0)$. The equilibrium point $E_2^*(\beta)$ is always in ellipse, then, for 498 $\beta = 0$, the equilibrium point states at \mathcal{A} , and when β increases, $E_2^*(\beta)$ describes an 499arc of the ellipse and ends at point $E_2^*(\infty)$. 500

If we take $r_1 = r_2$, we get that the equation of tangent space to the ellipse \mathbb{E} at 501point \mathcal{A} is the equation of Δ . By Prop. 6.1, we deduce $T_2^*(\beta) \leq T_2^*(0)$ for all $\beta \geq 0$. 502

In the case when $r_1 \neq r_2$, direct calculation finds that the ellipse \mathbb{E} and the line Δ have two intersections:

$$\mathcal{A} = (K_1, K_2), \text{ and } C = \left(\alpha_2 \frac{K_1 + K_2}{\alpha_1 + \alpha_2}, \alpha_1 \frac{K_1 + K_2}{\alpha_1 + \alpha_2}\right)$$

We denote by Σ the straight line joint the origin and C. The slope of Σ is equal to $\frac{\alpha_2^2}{\alpha_1^2}$. We distinguish three cases relative position of the three points $\mathcal{A}, E_2^*(\infty)$, and C, or equivalently, the three lines $[O\mathcal{A})$, \mathcal{H}_{∞} and Σ whose slopes are

$$\frac{K_2}{K_1}$$
, $\sqrt{\frac{\theta_{21}}{\theta_{12}}}$ and $\frac{\alpha_2}{\alpha_1}$.

By the method graphic of Arditi et al. [5], we conclude the complete proof. 503

The result of the previous theorem show that the nonlinear dispersal can lead to an 504increased, a decreased the total population size in two patches. This prove that, the 505effect of nonlinear dispersal is the same as the effect of linear dispersal in two-patch 506logistic model [4, 5]. Moreover, if the movement between two patches is symmetric, 507508 then we have the same results. In particular, Theorem 7.1, formula of equilibrium for large migration rate. 509

For the two-patch model (7.1), we plot in the figure 4.2, the curves of the total 510equilibrium population T_2^* and the line $K_1 + K_2$ in term of the migration rate β , for 511the sets of parameters choosing in Table 1. 512

TABLE 1

Parameters values of the three case used in Fig. 3-a,3-b and Fig 3-c. The perfect mixing abundance $T_2^*(+\infty)$ is computed with Eq. (7.2) and the derivative of the total equilibrium population at $\beta = 0$ is computed with Eq. (7.3).

								$T_2^*(+\infty)$
3-a 3-b	1	2	3.5	1	1	1	-5.62	2.62
3-b	6	2	5.5	1	1	1	3.75	4.30
3-c	5	1	3.5	1	1	1	-5.62 3.75 9.00	4.94

513

8. Two-patch model where one growth rate is much larger than the 514515second one. Recently, in [16], Elbetch is interested in some biological situations that can be found in the nature, that is, the case where several sub-populations grow 516with different speed. Mathematically speaking, he studied the system (1.7) under the hypothesis that some growth rates tend to infinity (i.e $r_i \to \infty$ for some i). In this 518section, we consider the two-patch model (2.1) and we assume that the growth rate

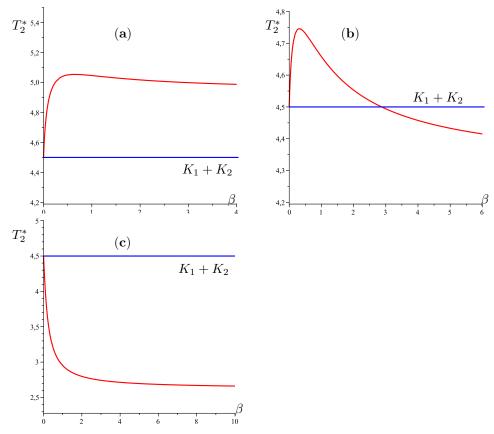


FIG. 3. Total equilibrium population T_2^* of the system (7.1) as a function of the migration rate β for the sets of the parameter values given in Table 1. The horizontal line is $K_1 + K_2$.

520 r_2 is much larger than r_1 . For simplicity we denote $\theta_2 := \theta_{12} > 0$ the migration rate 521 from patch 2 to patch 1 and $\theta_1 := \theta_{21} > 0$ from patch 1 to patch 2. The model is 522 written:

523 (8.1)
$$\begin{cases} \frac{dx_1}{dt} = r_1 x_1 \left(1 - \frac{x_1}{K_1} \right) + \beta \left(\theta_2 x_2^2 - \theta_1 x_1^2 \right), \\ \frac{dx_2}{dt} = \frac{r_2}{\epsilon} x_2 \left(1 - \frac{x_2}{K_2} \right) + \beta \left(\theta_1 x_1^2 - \theta_2 x_2^2 \right), \end{cases}$$

where ϵ is assumed to be a small positive number. Denote $E_2^*(\beta, \epsilon) = (x_1^*(\beta, \epsilon), x_2^*(\beta, \epsilon))$ the positive equilibrium of (8.1), and $T_2^*(\beta, \epsilon)$, the total equilibrium population. We recall that the derivative of $T_2^*(\beta, \epsilon)$ with respect to β at $\beta = 0$ is written as follow:

527 (8.2)
$$\frac{dT_2^*}{d\beta}(0,\epsilon) = (\theta_2 K_2^2 - \theta_1 K_1^2) \left(\frac{1}{r_1} - \frac{\epsilon}{r_2}\right).$$

528 The total equilibrium population of the model (8.1) for perfect mixing (i.e $\beta \to \infty$) 529 is given by the following formula:

530 (8.3)
$$T_2^*(+\infty,\epsilon) = (\sqrt{\theta_1} + \sqrt{\theta_2}) \frac{\epsilon\sqrt{\theta_2}r_1 + \sqrt{\theta_1}r_2}{\epsilon\theta_2\alpha_1 + \theta_1\alpha_2},$$

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531 where $\alpha_i = r_i/K_i$. First, we have the result:

THEOREM 8.1. Let $(x_1(t,\epsilon), x_2(t,\epsilon))$ be the solution of the system (8.1) with initial condition (x_1^0, x_2^0) satisfying $x_i^0 \ge 0$ for i = 1, 2. Let u(t) be the solution of the differential equation

535 (8.4)
$$\frac{dx_1}{dt} = r_1 x_1 \left(1 - \frac{x_1}{K_1} \right) + \beta(\theta_2 K_2^2 - \theta_1 x_1^2) =: \varphi(x_1),$$

536 with initial condition $u(0) = x_1^0$. Then, when $\epsilon \to 0$, we have

537 (8.5) $x_1(t,\epsilon) = u(t) + o_{\epsilon}(1), \qquad \text{uniformly for } t \in [0,+\infty)$

538 and, for any $t_0 > 0$, we have

539 (8.6)
$$x_2(t,\epsilon) = K_2 + o_{\epsilon}(1), \quad uniformly \text{ for } t \in [t_0, +\infty).$$

540 Proof. When $\epsilon \to 0$, the system (8.1) is a slow-fast system, with one slow variable, 541 x_1 , and one fast variable, x_2 . Tikhonov's theorem [26, 32, 33] prompts us to consider 542 the dynamics of the fast variables in the time scale $\tau = \frac{1}{\epsilon}t$. One obtains

543 (8.7)
$$\frac{dx_2}{d\tau} = r_2 x_2 \left(1 - \frac{x_2}{K_2}\right) + \epsilon \beta (\theta_1 x_1^2 - \theta_2 x_2^2).$$

544 In the limit $\epsilon \to 0$, we find the *fast dynamics*

545 (8.8)
$$\frac{dx_2}{d\tau} = r_2 x_2 \left(1 - \frac{x_2}{K_2}\right).$$

The slow manifold is given by the positive equilibrium of the system (8.8), i.e $x_2 = K_2$, which is GAS in the positive axis. When ϵ goes to zero, Tikhonov's theorem ensures that after a fast transition toward the slow manifold, the solutions of (8.1) converge to the solutions of the *reduced model* (8.4), obtained by replacing $x_2 = K_2$ into the dynamics of the slow variable.

551 The differential equation (8.4) admits as a positive equilibrium

552 (8.9)
$$x_1^*(\beta, 0^+) := 1/2 \frac{r_1 K_1 + \sqrt{r_1^2 K_1^2 + 4\beta K_1 \theta_2 K_2^2 r_1 + 4\beta^2 K_1^2 \theta_2 K_2^2 \theta_1}}{r_1 + \beta K_1 \theta_1}$$

As $\varphi(x_1) > 0$ for all $0 \le x_1 < x_1^*(\beta, 0^+)$ and $\varphi(x_1) < 0$ for all $x_1 > x_1^*(\beta, 0^+)$ then, the equilibrium $x_1^*(\beta, 0^+)$ is GAS in the positive axis, so, the approximation given by Tikhonov's theorem holds for all $t \ge 0$ for the slow variable and for all $t \ge t_0 > 0$ for the fast variable, where t_0 is as small as we want. Therefore, let u(t) be the solution of the reduced model (8.4) of initial condition $u(0) = x_1^0$, then, when $\epsilon \to 0$, we have the approximations (8.5) and (8.6).

As a corollary of the previous theorem, we have the following result which give the limit of the total equilibrium population $T_2^*(\beta, \epsilon)$ of the model (8.1) when ϵ goes to zero:

563 COROLLARY 8.2. We have:

(8.10)

564
$$T_{2}^{*}(\beta, 0^{+}) := \lim_{\epsilon \to 0} T_{2}^{*}(\beta, \epsilon) = \lim_{\epsilon \to 0} (x_{1}^{*}(\beta, \epsilon) + x_{2}^{*}(\beta, \epsilon))$$
565
$$= 1/2 \frac{r_{1}K_{1} + \sqrt{r_{1}^{2}K_{1}^{2} + 4\beta K_{1}\theta_{2}K_{2}^{2}r_{1} + 4\beta^{2}K_{1}^{2}\theta_{2}K_{2}^{2}\theta_{1}}}{r_{1} + \beta K_{1}\theta_{1}} + K_{2}.$$

Proof. According to the equations (8.5), (8.6) and (8.9), when ϵ goes to zero, the 567 equilibrium $E_2^*(\beta, \epsilon)$ of the model (8.1) is converge to $E_2^*(\beta, 0^+) := (x_1^*(\beta, 0^+), K_2),$ 568where $x_1^*(\beta, 0^+)$ is given in (8.9). The sum of the coordinates of $E_2^*(\beta, 0^+)$ gives the 569formula (8.10).

In the following proposition, we calculate the derivative and the formula of perfect 571 mixing (i.e when $\beta \to \infty$) of the total equilibrium population defined by (8.10). 572

PROPOSITION 8.3. Consider the total equilibrium population (8.10). Then,

574 (8.11)
$$\frac{dT_2^*}{d\beta}(0,0^+) := \frac{-\theta_1 K_1^2 + \theta_2 K_2^2}{r_1}$$

575and

576 (8.12)
$$T_2^*(+\infty, 0^+) := \frac{\sqrt{\theta_1} + \sqrt{\theta_2}}{\sqrt{\theta_1}} K_2.$$

Proof. The derivative of the total equilibrium population $X_T^*(\beta, 0^+)$ defined by 577 (8.10) with respect to β is: 578

(8.13)

579
$$\frac{dT_2^*}{d\beta}(\beta, 0^+) = -1/2 \frac{\left(r_1 K_1 + \sqrt{r_1^2 K_1^2 + 4\beta K_1 \theta_2 K_2^2 r_1 + 4\beta^2 K_1^2 \theta_2 K_2^2 \theta_1}\right) K_1 \theta_1}{(r_1 + \beta K_1 \theta_1)^2}$$

 $+ \frac{4 K_1 \theta_2 K_2^2 r_1 + 8 \beta K_1^2 \theta_2 K_2^2 \theta_1}{(r_1 + \beta K_1 \theta_1) \sqrt{r_1^2 K_1^2 + 4 \beta K_1 \theta_2 K_2^2 r_1 + 4 \beta^2 K_1^2 \theta_2 K_2^2 \theta_1}}$ 581

In particular, the derivative of the total equilibrium population at $\beta = 0$ is given by 582the formula (8.11). 583

By taking the limit of (8.10) when $\beta \to \infty$, we get that the total equilibrium 584population $X_T^*(\beta, 0^+)$ tend to (8.12). 585

REMARK 3. We can deduce $\frac{dT_2^*}{d\beta}(0,0^+)$ by using the equation (8.2). Indeed, the limit of (8.2) when ϵ goes to zero gives: 586 587

588
$$\lim_{\epsilon \to 0} \frac{dT_2^*}{d\beta}(0,\epsilon) = \lim_{\epsilon \to 0} \left[\left(\theta_2 K_2^2 - \theta_1 K_1^2\right) \left(\frac{1}{r_1} - \frac{\epsilon}{r_2}\right) \right] = \frac{-\theta_1 K_1^2 + \theta_2 K_2^2}{r_1} = \frac{dT_2^*}{d\beta}(0,0^+).$$

We can also deduce $T_2^*(+\infty, 0^+)$ by compute the limit of (8.3) when ϵ goes to zero: 589

590
$$\lim_{\epsilon \to 0} T_2^*(\infty, \epsilon) = \lim_{\epsilon \to 0} \left[(\sqrt{\theta_1} + \sqrt{\theta_2}) \frac{\epsilon \sqrt{\theta_2} r_1 + \sqrt{\theta_1} r_2}{\epsilon \theta_2 \alpha_1 + \theta_1 \alpha_2} \right] = \frac{\sqrt{\theta_1} + \sqrt{\theta_2}}{\sqrt{\theta_1}} K_2 = T_2^*(\infty, 0^+).$$

We consider the regions in the set of the parameters θ_1 and θ_2 , denoted \mathcal{J}_0 and \mathcal{J}_1 defined by:

593 (8.14)
$$\mathcal{J}_0 = \left\{ (\theta_1, \theta_2) : \frac{\theta_2}{\theta_1} > \frac{K_1^2}{K_2^2} \right\}, \quad \mathcal{J}_1 = \left\{ (\theta_1, \theta_2) : \frac{\theta_2}{\theta_1} < \frac{K_1^2}{K_2^2} \right\}.$$

We have the following result which gives the conditions for which patchiness is bene-594ficial or detrimental in model (8.1) when ϵ goes to zero.

THEOREM 8.4. Let \mathcal{J}_0 and \mathcal{J}_1 be the domains defined in (8.14). Consider the 596total equilibrium population $T_2^*(\beta, 0^+)$ given by (8.10). Then, we have:

- If $(\theta_1, \theta_2) \in \mathcal{J}_0$ then $T_2^*(\beta, 0^+) > K_1 + K_2$, for all $\beta > 0$. If $(\theta_1, \theta_2) \in \mathcal{J}_1$ then $T_2^*(\beta, 0^+) < K_1 + K_2$, for all $\beta > 0$. 598
- 599

600 • If
$$\frac{\theta_2}{\theta_1} = \frac{K_1^-}{K_2^2}$$
, then $x_1^*(\beta, 0^+) = K_1$ and $x_2^*(\beta, 0^+) = K_2$ for all $\beta \ge 0$. Therefore
601 $T_2^*(\beta, 0^+) = K_1 + K_2$ for all $\beta \ge 0$.

Proof. First, we try to solve the equation $T_2^*(\beta, 0^+) = K_1 + K_2$ with respect to β , 602 the solutions of this last equation give the points of intersection between the curve of 603 the total equilibrium population $\beta \mapsto T_2^*(\beta, 0^+)$ and the straight line $\beta \mapsto K_1 + K_2$. 604 605 For any $\beta > 0$, we have

 $T_2^*(\beta, 0^+) = K_1 + K_2$ 606

$$\Longrightarrow \frac{1}{2} \frac{r_1 K_1 + \sqrt{r_1^2 K_1^2 + 4\beta K_1 \theta_2 K_2^2 r_1 + 4\beta^2 K_1^2 \theta_2 K_2^2 \theta_1}}{m + \beta K \theta} = K_1$$

$$\approx \frac{2}{4\beta K_1 \theta_2 K_2^2 r_1 + 4\beta^2 K_1^2 \theta_2 K_2^2 \theta_1 - 4r_1 K_1^3 \beta \theta_1 - 4\beta^2 K_1^4 \theta_1^2}$$

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$$\iff = (\theta_2 K_2^2 - \theta_1 K_1^2) (4\theta_1 K_1^2 \beta^2 + 4r_1 K_1 \beta) = 0$$

$$610 \qquad \Longleftrightarrow \theta_2 K_2^2 = \theta_1 K_1^2$$

$$\underset{612}{\overset{611}{\longleftrightarrow}} \longleftrightarrow \frac{dT_2^*}{d\beta}(0,0^+) = 0.$$

So, if $\frac{dT_2^*}{d\beta}(0,0^+) \neq 0$ then $\beta = 0$ and the curve of the total equilibrium population 613 intersects the straight line $\beta \mapsto K_1 + K_2$ in a unique point which is $(0, K_1 + K_2)$. 614 Therefore, we conclude that the first and second items of the theorem are hold. Π 615

9. Concluding remarks. In summary, this work was aimed to find out whether 616 the total equilibrium population of the n patches connected by nonlinear migration 617 asymmetrical migrations can be greater than the sum of the carrying capacities of the 618 n isolated patches, i.e. at equilibrium. Is there a way to make connections between 619 patches that increases the total population? we have assumed that the population 620 obey a logistic type growth at each patches. 621

We have shown that if the growth rates are equal in all patches, then the total 622 equilibrium population on the n connected patches is always less than or equal to the 623 sum of carrying capacity of the isolated patches. This result can be seen as negative 624 but constitutes in our eyes an interesting result. We then addressed this issue in the 625 general case when the growth rates are different, we have determined criteria for which 626 the total population size of the n connected patches at equilibrium may be greater 627 than the sum of carrying capacities of n isolated patches. we have shown that for high 628 movement rates between the patches, the total equilibrium population cloud exceed 629 630 total carrying capacity of the n patches for certain combinations of the parameters r_i, K_i and δ_i . For two-patch model, the parameter space is fully classified as to 631 whether nonlinear dispersal is beneficial or detrimental to the sum of two carrying 632 capacities. 633

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