# Appendix A from D. L. DeAngelis et al., "The Effect of Travel Loss on Evolutionarily Stable Distributions of Populations in Space" 

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## Calculation of the Optimal Movement Coefficients of an Evolutionarily Stable Strategy

To understand the stability of any such equilibrium $E^{*},\left(\overline{0}, P^{*}, R^{*}, M^{*}\right)$, a standard approach is to determine the real parts of the eigenvalues of the matrix $J$, the Jacobian matrix for the system (9) evaluated at this equilibrium solution. If we let $J_{(8)}$ denote the Jacobian matrix for system (8) evaluated at $E_{(8)}^{*}, J$ has the form

$$
J=\left[\begin{array}{cc}
D & \hat{0} \\
* & J_{(8)}
\end{array}\right]
$$

where $\hat{0}$ denotes the $N \times 3 N$ matrix with all components equal to 0 , the components of the $N \times N$ matrix $D$ are given by

$$
D_{i j}=\left\{\begin{array}{lr}
\left(1-\varepsilon_{j i}\right) \hat{m}_{j i} \\
b_{i} a_{i} R_{i}^{*}-d_{i}-f_{i} M_{i}^{*}-\sum_{j=1}^{N} \hat{m}_{i j} \quad \begin{array}{l}
i \neq j \\
i
\end{array}, ~ \text {, }
\end{array}\right.
$$

for $i, j \in\{1, \ldots, N\}$, where the asterisk indicates a $3 N \times N$ matrix with components that are not involved in our discussion below.

Because of the special structure of the matrix, it follows that any eigenvalue $\lambda$ must satisfy

$$
\operatorname{det}\left(J-\lambda I_{4 N}\right)=\operatorname{det}\left(J_{(8)}-\lambda I_{3 N}\right) \operatorname{det}\left(D-\lambda I_{N}\right)=0
$$

where $I_{m}$ denotes the $m \times m$ identity matrix for any positive integer $m$.
In this appendix, we focus our discussion on the matrix $D$, usually referred to as the invasion matrix. Since we are assuming $\left(\mathrm{H}_{2}\right)$ (see text), it follows that the nonnegative matrix with components $\left(\hat{m}_{i j}\right)$ is irreducible. If $c$ is a large enough positive constant so that the diagonal entries of $\bar{D}=D+c I_{N}$ are positive, and if $\lambda$ is any eigenvalue of $\bar{D}$ with associated eigenvector $v$, then $\lambda-c$ is an eigenvalue of $D$ with the same eigenvector. So the following is a consequence of the Perron-Frobenius theorem (Horn and Johnson 1999):

- The matrix $D$ has a dominant eigenvalue, denoted by $\lambda_{1}$, such that $\lambda_{1}$ is real, and the real parts of all other eigenvalues are strictly less than $\lambda_{1}$.
- Both the right and the left eigenspace associated with $\lambda_{1}$ is one-dimensional. In particular, all of the components of the left and right eigenvectors corresponding to $\lambda_{1}$ can be chosen to be positive, and for all eigenvectors of other eigenvalues there exists a component that is not positive.
- $\lambda_{1}$ is a simple root of the characteristic polynomial of $D$. Using the implicit function theorem, it follows that $\lambda_{1}$ is a smooth function of $\hat{m}_{i j}$ and $m_{i j}, i, j \geq 1$.
In order to justify the rates given in equations (17), we establish two preliminary results. For every $2 \leq i \leq N$, set $V_{i}=\left(D_{i 2}, \ldots, D_{i N}\right)^{\mathrm{T}}$, where T denotes the transpose.

Lemma 1. Suppose that $\hat{m}_{i j}=m_{i j}$ for every $i, j$. If $m_{1 i}>0$ for every $2 \leq i \leq N, V_{2}, \ldots, V_{N}$ are linearly independent and thus form a basis of $\mathbb{R}^{N-1}$.

Proof. Let $\left(D_{i j}\right)_{i, j \geq 2}$ denote the $(N-1) \times(N-1)$ matrix obtained by removing the first row and first column of matrix $D$. We claim that if $m_{1 i}>0$ for every $2 \leq i \leq N$, then $\left(D_{i j}\right)_{i, j \geq 2}$ is invertible. To see this, since the offdiagonal entries of $\left(D_{i j}\right)_{i, j \geq 2}$ are all nonnegative, by the Perron-Frobenius Theorem there exists some eigenvalue of $\left(D_{i j}\right)_{i, j \geq 2}$, denoted by $\eta_{1}$, that is real, and the real parts of all other eigenvalues are less than or equal to $\eta_{1}$.

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Moreover, $\eta_{1}$ has a left eigenvector with all nonnegative components, denoted $\left(v_{2}, \ldots, v_{N}\right)$; that is,

$$
\begin{equation*}
\left(v_{2}, \ldots, v_{N}\right)\left(D_{i j}\right)_{i, j \geq 2}=\eta_{1}\left(v_{2}, \ldots, v_{N}\right) . \tag{A1}
\end{equation*}
$$

Recall that when $\left(\hat{m}_{12}, \ldots, \hat{m}_{1 N}\right)=\left(m_{12}, \ldots, m_{1 N}\right)$, zero is an eigenvalue of $D$ with $P^{*}$ as a right eigenvector. Hence,

$$
\begin{equation*}
\left(D_{i j}\right)_{i, j \geq 2}\left(P_{2}^{*}, \ldots, P_{N}^{*}\right)^{\mathrm{T}}=-P_{1}^{*}\left(\left(1-\varepsilon_{12}\right) m_{12}, \ldots,\left(1-\varepsilon_{1 N}\right) m_{1 N}\right)^{\mathrm{T}}, \tag{A2}
\end{equation*}
$$

where $\left(P_{2}^{*}, \ldots, P_{N}^{*}\right)^{\mathrm{T}}$ denotes the transpose of $\left(P_{2}^{*}, \ldots, P_{N}^{*}\right)$.
Taking the inner product of both sides of equation (A1) with the vector $\left(P_{2}^{*}, \ldots, P_{N}^{*}\right)$, and applying the identity equation (A2), we have

$$
\eta_{1} \sum_{i=2}^{N} v_{i} P_{i}^{*}=-P_{1}^{*} \sum_{i=2}^{N} v_{i}\left(1-\varepsilon_{1 i}\right) m_{1 i} .
$$

Since $m_{1 i}>0, v_{i} \geq 0$ for every $i \geq 2$ and $\left(v_{2}, \ldots, v_{N}\right)$ is a nonzero vector, we see that $\eta_{1}<0$. This implies that the real parts of all eigenvalues of $\left(D_{i j}\right)_{i, \geq 22}$ are negative. Hence, $\left(D_{i j}\right)_{i, j \geq 2}$ is invertible. As $V_{i}=\left(D_{i 2}, \ldots, D_{i n}\right)$, $\left(D_{i j}\right)_{i, \geq 2}=\left(V_{2}, \ldots, V_{N}\right)^{\mathrm{T}}$. Since $\left(D_{i j}\right)_{i, j \geq 2}$ is invertible, $V_{2}, \ldots, V_{N}$ are linearly independent.

We will also use the following result that is a corollary of Cramer's rule.
Lemma 2. Suppose that vectors $V_{1}, \ldots, V_{d}$ form a basis of $\mathbb{R}^{d}$. If some vector $V_{0} \in \mathbb{R}^{d}$ satisfies the property that $V_{1}, \ldots, V_{i-1}, V_{0}, V_{i+1}, \ldots, V_{d}$ are linearly dependent for every $1 \leq i \leq d$, then $V_{0}$ must be the zero vector.

We begin by justifying the rates for scenario 2 first, since the justification for scenario 1 is more difficult.

## Scenario 2: Calculation of $\boldsymbol{m}_{1 i, \mathrm{opt}}, 2 \leq i \leq N$

Theorem 1. Suppose that $R_{i}^{*}>0$ and $M_{i}^{*} \geq 0$ for all $i=1, \ldots, N$ and that assumptions $\left(\mathrm{H}_{0}\right),\left(\mathrm{H}_{1}\right)$, and $\left(\mathrm{H}_{2}\right.$, scenario 2) hold.
a) If there exist $\left\{m_{1, \text { opp }}\right\}_{i=2}^{N}$ with $m_{1 i, \text { opt }}>0$ for $2 \leq i \leq N$ such that $\lambda_{1} \leq 0$ for $\left(m_{12}, \ldots, m_{1 N}\right)=$ ( $m_{12, \text { opp }}, \ldots, m_{1 N, \text { opt }}$ ) and all $\left(\hat{m}_{12}, \ldots, \hat{m}_{1 N}\right)$ in a neighborhood of ( $m_{12, \text { opt }}, \ldots, m_{1 N, \text { opt }}$ ), then for every $2 \leq i \leq N$,

$$
\begin{equation*}
m_{1 i, \text { opt }}=\left(1-\varepsilon_{i 1}\right) \frac{P_{i}^{*}}{P_{1}^{*}} m_{i 1}+\frac{1}{P_{1}^{*}} \sum_{j=2}^{N}\left[\frac{\left(1-\varepsilon_{i j}\right)}{\left(1-\varepsilon_{1 j}\right)} m_{i j} P_{i}^{*}-\frac{\left(1-\varepsilon_{j i}\right)}{\left(1-\varepsilon_{1 i}\right)} m_{j i} P_{j}^{*}\right] . \tag{A3}
\end{equation*}
$$

b) Suppose that $m_{1, \text { opt }}$ is positive for every $i \geq 2$. If $\left(m_{12}, \ldots, m_{1 N}\right)=\left(m_{12, \text { opp }}, \ldots, m_{1 N, \text { opp }}\right)$, then $\lambda_{1} \equiv 0$ for any $\hat{m}_{1 j}>0, j \geq 2$.

Under assumption ( $H_{2}$, scenario 2), the invasion matrix $D$ has components

$$
D_{i j}=\left\{\begin{array}{ll}
b_{1} a_{1} R_{1}^{*}-d_{1}-f_{1} M_{1}^{*}-\sum_{h=1}^{N} \hat{m}_{1 h} & i=j=1 \\
b_{i} a_{i} R_{i}^{*}-d_{i}-f_{i} M_{i}^{*}-\sum_{h=1}^{N} m_{i h} & i=j \geq 2 \\
\left(1-\varepsilon_{1 i}\right) \hat{m}_{1 i} & i \geq 2, j=1 \\
\left(1-\varepsilon_{j i}\right) m_{j i} & i \geq 1, j \geq 2, i \neq j
\end{array} .\right.
$$

We first note that

$$
\left.\lambda_{1}\right|_{\left(\hat{m}_{12}, \ldots, \hat{m}_{1 N}\right)=\left(m_{1}, \ldots, m_{1 N}\right)}=0 .
$$

Biologically, this is because the invader $\hat{P}$ is a cloned copy of the resident $P$. The mathematical reasoning is as follows: when $\left(\hat{m}_{12}, \ldots, \hat{m}_{1 N}\right)=\left(m_{12}, \ldots, m_{1 N}\right), 0$ is an eigenvalue of $D$, with $P^{*}$ as a right eigenvector. Since all components of $P^{*}$ are all positive, 0 is the dominant eigenvalue of $D$; that is, equation (A4) holds.

Proof of Theorem 1(a). If there exist some ( $m_{12}, \ldots, m_{1 N}$ ) with $m_{1 i}>0$ for every $2 \leq i \leq N$ such that $\lambda_{1} \leq 0$

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for all $\left(\hat{m}_{12}, \ldots, \hat{m}_{1 N}\right)$ in a neighborhood of $\left(m_{12}, \ldots, m_{1 N}\right)$, then

$$
\begin{equation*}
\left.\frac{\partial \lambda_{1}}{\partial \hat{m}_{1 i}}\right|_{\left(\hat{m}_{12}, \ldots, \hat{m}_{1 N}\right)=\left(m_{12}, \ldots, m_{1 N}\right)}=0 \tag{A5}
\end{equation*}
$$

for every $i \geq 2$.
Under assumption ( $H_{2}$, scenario 2), the matrix $D-\lambda_{1} I_{N}$, has components

$$
\left(D-\lambda_{1} I_{N}\right)_{i j}= \begin{cases}b_{1} a_{1} R_{1}^{*}-d_{1}-f_{1} M_{1}^{*}-\sum_{h=1}^{N} \hat{m}_{1 h}-\lambda_{1} & i=j=1, \\ b_{i} a_{i} R_{i}^{*}-d_{i}-f_{i} M_{i}^{*}-\sum_{h=1}^{N} m_{i h}-\lambda_{1} & i=j \geq 2 \\ \left(1-\varepsilon_{1 i}\right) \hat{m}_{1 i} & i \geq 2, j=1 \\ \left(1-\varepsilon_{j i}\right) m_{j i} & i \geq 1, j \geq 2, i \neq j\end{cases}
$$

Instead of differentiating the determinant of the matrix $D-\lambda_{1} I$ with respect to $\hat{m}_{1 i}$ directly, we first do the following manipulation. Dividing the $i$ th row of $D-\lambda_{1} I$ by $\left(1-\varepsilon_{1 i}\right)$ and adding it to the first row, and repeating this process for each $2 \leq i \leq n$, we see that matrix $D-\lambda_{1} I$ is transformed into a new matrix, denoted by $\tilde{D}$, which can be expressed by

$$
\begin{aligned}
\begin{cases}b_{1} a_{1} R_{1}^{*}-d_{1}-f_{1} M_{1}^{*}-\lambda_{1} & i=j=1 \\
b_{i} a_{i} R_{i}^{*}-d_{i}-f_{i} M_{i}^{*}-\sum_{h=1}^{N} m_{i h}-\lambda_{1} & i=j \geq 2 \\
\left(1-\varepsilon_{1 i}\right) \hat{m}_{1 i} & i \geq 2, j=1 \\
\left(1-\varepsilon_{j i}\right) m_{j i} & i \geq 2, j \geq 2, i \neq j \\
\frac{1}{\left(1-\varepsilon_{1 j}\right)}\left(b_{j} a_{j} R_{j}^{*}-d_{j}-f_{j} M_{j}^{*}-\sum_{h=1}^{N} m_{j h}-\lambda_{1}\right)+\left(1-\varepsilon_{j 1}\right) m_{j 1}-\sum_{h=2}^{N} \frac{\left(1-\varepsilon_{j h}\right)}{\left(1-\varepsilon_{1 h}\right)} m_{j h} & i=1, j \geq 2 .\end{cases}
\end{aligned}
$$

Clearly, $\left|D-\lambda_{1} I\right|=0$ is equivalent to $|\tilde{D}|=0$. For every $2 \leq i \leq N$, differentiate the determinant of the matrix $\tilde{D}$ with respect to $\hat{m}_{1 i}$ and evaluate the result at $\left(\hat{m}_{12}, \ldots, \hat{m}_{1 N}\right)=\left(m_{12}, \ldots, m_{1 N}\right)$. By applying both equations (A4) and (A5), we find that

$$
\left.\frac{\partial|\tilde{D}|}{\partial \hat{m}_{1 i}}\right|_{\left(\hat{m}_{12}, \ldots, \hat{m}_{1 N}\right)=\left(m_{12}, \ldots, m_{1 N}\right)}=0
$$

if and only if the vectors $V_{2}, \ldots, V_{i-1}, V_{0}, V_{i+1}, \ldots, V_{N}$ are linearly dependent, where the vector $V_{0}$ is given by

$$
V_{0}=\left(\tilde{D}_{12}, \ldots, \tilde{D}_{1 N}\right)
$$

By lemma $1, V_{2}, \ldots, V_{N}$ are linearly independent and form a basis for $\mathbb{R}^{N-1}$. Therefore, by lemma $2, V_{0}$ must be the zero vector in $\mathbb{R}^{N-1}$. Hence, $\tilde{D}_{1 j}=0$ for every $j \geq 2$; that is, noting that $\lambda_{1}=0$ by equation (A4),

$$
\begin{equation*}
\frac{1}{\left(1-\varepsilon_{1 j}\right)}\left(b_{j} a_{j} R_{j}^{*}-d_{j}-f_{j} M_{j}^{*}-\sum_{h=1}^{N} m_{j h}\right)+\left(1-\varepsilon_{j 1}\right) m_{j 1}-\sum_{h=2}^{N} \frac{\left(1-\varepsilon_{j h}\right)}{\left(1-\varepsilon_{1 h}\right)} m_{j h}=0 . \tag{A6}
\end{equation*}
$$

Recall that at equilibrium we have, for every $j \geq 2$,

$$
\begin{equation*}
b_{j} a_{j} R_{j}^{*}-d_{j}-f_{j} M_{j}^{*}-\sum_{h=1}^{N} m_{j h}+\left[\sum_{h=1}^{N}\left(1-\varepsilon_{h j}\right) m_{h j} \frac{P_{h}^{*}}{P_{j}^{*}}\right]=0 . \tag{A7}
\end{equation*}
$$

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Substituting equation (A7) into equation (A6), we have

$$
\begin{equation*}
m_{1 j} \frac{P_{1}^{*}}{P_{j}^{*}}=\left(1-\varepsilon_{j 1}\right) m_{j 1}+\sum_{h=2}^{N} \frac{\left(1-\varepsilon_{j h}\right)}{\left(1-\varepsilon_{1 h}\right)} m_{j h}-\sum_{h=2}^{N} \frac{\left(1-\varepsilon_{h j}\right)}{\left(1-\varepsilon_{1 j}\right)} m_{h j} \frac{P_{h}^{*}}{P_{j}^{* *}} . \tag{A8}
\end{equation*}
$$

Dividing equation (A8) by $P_{1}^{*} / P_{j}^{*}$, we have

$$
\begin{equation*}
m_{1 j}=\left(1-\varepsilon_{j 1}\right) m_{j 1} \frac{P_{j}^{*}}{P_{1}^{* *}}+\sum_{h=2}^{N} \frac{\left(1-\varepsilon_{j h}\right)}{\left(1-\varepsilon_{1 h}\right)} m_{j h} \frac{P_{j}^{*}}{P_{1}^{*}}-\sum_{h=2}^{N} \frac{\left(1-\varepsilon_{h j}\right)}{\left(1-\varepsilon_{1 j}\right)} m_{h j} \frac{P_{h}^{*}}{P_{1}^{* *}} \tag{A9}
\end{equation*}
$$

This completes the proof of part (a), theorem 1.
Lemma 3. For the movement strategy given by equation (A3), the immigration and emigration flux for patch 1 is balanced; that is, if $\left(m_{12}, \ldots, m_{1 N}\right)=\left(m_{12, \text { opt }}, \ldots, m_{1 N, \text { opt }}\right)$, then

$$
\begin{equation*}
\sum_{j}\left(1-\varepsilon_{j 1}\right) m_{j 1} P_{j}^{*}=\left(\sum_{j} m_{1 j, \mathrm{opt}}\right) P_{1}^{*} ; \tag{A10}
\end{equation*}
$$

or equivalently, the resident species at equilibrium (with invader absent) has zero fitness in patch 1 :

$$
\begin{equation*}
b_{1} a_{1} R_{1}^{*}-d_{1}-f_{1} M_{1}^{*}=0 . \tag{A11}
\end{equation*}
$$

Proof. Multiplying equation (A3) by $P_{1}^{*}$ and summing up for $2 \leq i \leq N$, we have

$$
\begin{aligned}
\left(\sum_{i=2}^{N} m_{1 i, \mathrm{opt}}\right) P_{1}^{*} & =\sum_{i=2}^{N}\left(1-\varepsilon_{i 1}\right) m_{i 1} P_{i}^{*}+\sum_{i, h=2}^{N}\left[\frac{\left(1-\varepsilon_{i h}\right)}{\left(1-\varepsilon_{1 h}\right)} m_{i h} P_{i}^{*}-\frac{\left(1-\varepsilon_{h i}\right)}{\left(1-\varepsilon_{1 i}\right)} m_{h i} P_{h}^{*}\right] \\
& =\sum_{i=2}^{N}\left(1-\varepsilon_{i 1}\right) m_{i 1} P_{i}^{*}
\end{aligned}
$$

which implies that equation (A10) holds since we assume that $m_{11}=0$. Clearly, equation (A11) follows from equation (A10) and equation (9b) for $P_{1}^{*}$.

Lemma 4. If $\left(m_{12}, \ldots, m_{1 N}\right)=\left(m_{12, \text { opt }}, \ldots, m_{1 N, o p t}\right)$, then for every patch $i \geq 2$, the resident species at equilibrium has fitness

$$
b_{i} a_{i} R_{i}^{*}-d_{i}-f_{i} M_{i}^{*}= \begin{cases}0 & i=1  \tag{A12}\\ {\left[1-\left(1-\varepsilon_{1 i}\right)\left(1-\varepsilon_{i 1}\right)\right] m_{i 1}+\sum_{h=2}^{N} m_{i h}\left[1-\left(1-\varepsilon_{i h}\right) \frac{\left(1-\varepsilon_{1 i}\right)}{\left(1-\varepsilon_{1 h}\right)}\right]} & i \geq 2\end{cases}
$$

Proof. This result follows by using equation (A3) in equation (9b) for $P_{i}^{*}$.
Proof of Theorem 1(b). By lemmas 3 and 4, we see that if $\left(m_{12}, \ldots, m_{1 N}\right)=\left(m_{12, \text { opt }}, \ldots, m_{1 N, \text { opt }}\right)$, then

$$
D_{i j}=\left\{\begin{array}{ll}
-\sum_{h=1}^{N} \hat{m}_{1 h} & i=j=1 \\
-\left(1-\varepsilon_{1 i}\right)\left(1-\varepsilon_{i 1}\right) m_{i 1}-\sum_{h=2}^{N} m_{i h}\left(1-\varepsilon_{i h}\right) \frac{\left(1-\varepsilon_{1 i}\right)}{\left(1-\varepsilon_{1 h}\right)} & i=j \geq 2 \\
\left(1-\varepsilon_{1 i}\right) \hat{m}_{1 i} & i \geq 2, j=1 \\
\left(1-\varepsilon_{j i}\right) m_{j i} & i \geq 1, j \geq 2, i \neq j
\end{array} .\right.
$$

Set

$$
V_{*}=\left(1, \frac{1}{1-\varepsilon_{12}}, \ldots, \frac{1}{1-\varepsilon_{1 N}}\right) .
$$

Then, $V_{*} D=(0, \ldots, 0)$. That is, the vector $V_{*}$ is the left eigenvector of $D$ corresponding to the eigenvalue 0 . Since all components of $V_{*}$ are positive, 0 must be the dominant eigenvalue of matrix $D$, and all other eigenvalues must have strictly negative real parts.

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## Scenario 1: Calculation of $\boldsymbol{m}_{i 1, \text { opt }}, \mathbf{2} \leq \boldsymbol{i} \leq \boldsymbol{N}$

Theorem 2. Suppose that $R_{i}^{*}>0$ and $M_{i}^{*} \geq 0$ for all $i=1, \ldots, N$ and that assumptions $\left(\mathrm{H}_{0}\right),\left(\mathrm{H}_{1}\right)$, and $\left(\mathrm{H}_{2}\right.$, scenario 1) hold.
a) If there exist $\left\{m_{i 1, \text { opt }}\right\}_{i=2}^{N}$ with $m_{i 1, \text { opt }}>0$ for $2 \leq i \leq N$ such that $\lambda_{1} \leq 0$ for $\left(m_{21}, \ldots, m_{N 1}\right)=$ $\left(m_{21, \mathrm{opt}}, \ldots, m_{N 1, \mathrm{opt}}\right)$ and all $\left(\hat{m}_{21}, \ldots, \hat{m}_{N 1}\right)$ in a neighborhood of $\left(m_{21, \mathrm{opt}}, \ldots, m_{N 1, \mathrm{opt}}\right)$, then for every $2 \leq i \leq N$,

$$
\begin{equation*}
m_{i 1, \mathrm{opt}}=\left(1-\varepsilon_{1 i}\right) m_{1 i} \frac{P_{1}^{*}}{P_{i}^{*}}+\frac{1}{P_{i}^{*}} \sum_{j=2}^{N}\left[\left(1-\varepsilon_{j i}\right) m_{j i} P_{j}^{*}-\frac{\left(1-\varepsilon_{i j}\right)\left(1-\varepsilon_{j 1}\right)}{\left(1-\varepsilon_{i 1}\right)} m_{i j} P_{i}^{*}\right] . \tag{A13}
\end{equation*}
$$

b) Suppose that $m_{i 1, \mathrm{opt}}$ is positive for every $i \geq 2$. If $\left(m_{21}, \ldots, m_{N 1}\right)=\left(m_{21, \mathrm{opt}}, \ldots, m_{N 1, \mathrm{opt}}\right)$, then $\lambda_{1} \equiv 0$ for any $\hat{m}_{j 1}, j \geq 2$.

Under assumption $\left(H_{2}\right)$ (scenario 1 ), the matrix $D$ has components

$$
D_{i j}=\left\{\begin{array}{ll}
b_{1} a_{1} R_{1}^{*}-d_{1}-f_{1} M_{1}^{*}-\sum_{h=1}^{N} m_{1 h} & i=j=1 \\
b_{i} a_{i} R_{i}^{*}-d_{i}-f_{i} M_{i}^{*}-\hat{m}_{i 1}-\sum_{h \geq 2} m_{i h} & i=j \geq 2 \\
\left(1-\varepsilon_{j 1}\right) \hat{m}_{j 1} & i=1, j \geq 2 \\
\left(1-\varepsilon_{j i}\right) m_{j i} & i \geq 2, j \geq 1, i \neq j
\end{array} .\right.
$$

By a similar argument as for scenario 2,

$$
\begin{equation*}
\left.\lambda_{1}\right|_{\left(\hat{m}_{21}, \ldots, \hat{m}_{n 1}\right)=\left(m_{21}, \ldots, m_{N_{1}}\right)}=0 \tag{A14}
\end{equation*}
$$

Proof of Theorem 2(a). If there exist some ( $m_{21}, \ldots, m_{N 1}$ ) with $m_{i 1}>0$ for every $2 \leq i \leq N$ such that $\lambda_{1} \leq 0$ for all $\left(\hat{m}_{21}, \ldots, \hat{m}_{N 1}\right)$ in a neighborhood of $\left(m_{21}, \ldots, m_{N 1}\right)$, then

$$
\begin{equation*}
\left.\frac{\partial \lambda_{1}}{\partial \hat{m}_{i 1}}\right|_{\left(\hat{m}_{21}, \ldots, \hat{m}_{N 1}\right)=\left(m_{21}, \ldots, m_{N 1}\right)}=0 \tag{A15}
\end{equation*}
$$

for every $i \geq 2$.
Under the assumption $\left(H_{2}\right.$, scenario 1$)$, the matrix $D-\lambda_{1} I_{N}$ has components

$$
\left(D-\lambda_{1} I_{N}\right)_{i j}= \begin{cases}b_{1} a_{1} R_{1}^{*}-d_{1}-f_{1} M_{1}^{*}-\sum_{h=1}^{N} m_{1 h}-\lambda_{1} & i=j=1 \\ b_{i} a_{i} R_{i}^{*}-d_{i}-f_{i} M_{i}^{*}-\hat{m}_{i 1}-\sum_{h \geq 2}^{N} m_{i h}-\lambda_{1} & i=j \geq 2 \\ \left(1-\varepsilon_{j 1}\right) \hat{m}_{j 1} & i=1, j \geq 2 \\ \left(1-\varepsilon_{j i}\right) m_{j i} & i \geq 2, j \geq 1, i \neq j\end{cases}
$$

By direct calculation, we find that for every $2 \leq k \leq N$,

$$
\left.\frac{\partial\left|D-\lambda_{1} I_{N}\right|}{\partial \hat{m}_{k 1}}\right|_{\left(\hat{m}_{21}, \ldots, \hat{m}_{11}\right)=\left(m_{21}, \ldots, m_{N 1}\right)}=0
$$

is equivalent to $\left|D_{1}\right|=0$, where matrix $D_{1}$ is given by

$$
\left(D_{1}\right)_{i j}= \begin{cases}b_{i} a_{i} R_{i}^{*}-d_{i}-f_{i} M_{i}^{*}-\sum_{h=1}^{N} m_{i h} & i=j \geq 1, i \neq k \\ \left(1-\varepsilon_{k 1}\right) & i=1, j=k \\ -1 & i=j=k \\ 0 & i \geq 2, i \neq k, j=k \\ \left(1-\varepsilon_{j i}\right) m_{j i} & i \geq 1, j \geq 1, i \neq j, j \neq k\end{cases}
$$

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Since $E^{*}$ is an equilibrium point, by equation (9b),

$$
b_{i} a_{i} R_{i}^{*}-d_{i}-f_{i} M_{i}^{*}-\sum_{h \geq 1} m_{i h}=-\sum_{h \geq 1}\left(1-\varepsilon_{h i}\right) m_{h i} \frac{P_{h}^{*}}{P_{i}^{*}}
$$

for every $1 \leq i \leq N$. It follows that $\left|D_{1}\right|=0$ is equivalent to $\left|D_{2}\right|=0$, where matrix $D_{2}$ is given by

$$
\left(D_{2}\right)_{i j}=\left\{\begin{array}{ll}
-\sum_{h=1}^{N} m_{h j}\left(1-\varepsilon_{h j}\right) \frac{P_{h}^{*}}{P_{j}^{*}} & i=j \geq 1, i \neq k \\
\left(1-\varepsilon_{k 1}\right) & i=1, j=k \\
-1 & i=j=k \\
0 & i \geq 2, i \neq k, j=k \\
\left(1-\varepsilon_{j i}\right) m_{j i} & i \geq 1, j \geq 1, i \neq j, j \neq k
\end{array} .\right.
$$

Multiplying the $j$ th column of $D_{2}$ by $P_{j}^{*}$ for every $j \neq k,\left|D_{2}\right|=0$ is equivalent to $\left|D_{3}\right|=0$, where matrix $D_{3}$ is given by

$$
\left(D_{3}\right)_{i j}= \begin{cases}-\sum_{h=1}^{N}\left(1-\varepsilon_{h j}\right) m_{h j} P_{h}^{*} & i=j \geq 1, i \neq k \\ \left(1-\varepsilon_{k 1}\right) & i=1, j=k \\ -1 & i=j=k \\ 0 & i \geq 2, i \neq k, j=k \\ \left(1-\varepsilon_{j i}\right) m_{j i} P_{j}^{*} & i \geq 1, j \geq 1, i \neq j, j \neq k\end{cases}
$$

Multiplying the $i$ th row of $D_{3}$ by $\left(1-\varepsilon_{i 1}\right)$ for each $2 \leq i \leq N$ and adding the results to the first row, $\left|D_{3}\right|=0$ is equivalent to $\left|D_{4}\right|=0$, where matrix $D_{4}$ is given by

$$
\begin{aligned}
\left\{D_{4}\right)_{i j}= \begin{cases}A_{j} & i=1, j \geq 1, j \neq k \\
-\sum_{h=1}^{N}\left(1-\varepsilon_{h j}\right) m_{h j} P_{h}^{*} & i=j \geq 2, i \neq k \\
0 & i=1, j=k \\
-1 & i=j=k \\
0 & i \geq 2, i \neq k, j=k \\
\left(1-\varepsilon_{j i}\right) m_{j i} P_{j}^{*} & i \geq 1, j \geq 1, i \neq j, j \neq k\end{cases}
\end{aligned}
$$

where $A_{1}$ is defined as

$$
A_{1}=\sum_{j=1}^{N}\left(1-\varepsilon_{1 j}\right)\left(1-\varepsilon_{j 1}\right) m_{1 j} P_{1}^{*}-\sum_{j=1}^{N}\left(1-\varepsilon_{j 1}\right) m_{j 1} P_{j}^{*},
$$

and for $i \geq 2, A_{i}$ is defined by

$$
A_{i}=\left(1-\varepsilon_{i 1}\right)\left[m_{i 1} P_{i}^{*}-\left(1-\varepsilon_{1 i}\right) m_{1 i} P_{1}^{*}\right]+\sum_{h=2}^{N}\left[\left(1-\varepsilon_{i h}\right)\left(1-\varepsilon_{h 1}\right) m_{i h} P_{i}^{*}-\left(1-\varepsilon_{h i}\right)\left(1-\varepsilon_{i 1}\right) m_{h i} P_{h}^{*}\right]
$$

It is easy to check that $\sum_{i=1}^{N} A_{i}=0$ (note that $m_{11}=0$ ). Since all of the entries in the $k$ th column of $D_{4}$ are 0 except $\left(D_{4}\right)_{k k}$, we see that $\left|D_{4}\right|=0$ is equivalent to $\left|D_{5}\right|=0$, where the $(N-1) \times(N-1)$ matrix $D_{5}$ is given

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by

$$
\begin{gathered}
\left\{\begin{array}{ll}
A_{j} & i=1,1 \leq j<k \\
\left(D_{5}\right)_{i j}= & i=1, k \leq j \leq N-1 \\
A_{j+1} & 2 \leq i=j<k \\
-\sum_{h=1}^{N-1}\left(1-\varepsilon_{h j}\right) m_{h j} P_{h}^{*} & 2 \leq \sum_{h=1}^{N-1}\left(1-\varepsilon_{h, j+1}\right) m_{h, j+1} P_{h}^{*} \\
-k \leq i=j \leq N-1 \\
\left(1-\varepsilon_{j, i}\right) m_{j, i} P_{j}^{*} & 2 \leq i<k, 1 \leq j<k, i \neq j \\
\left(1-\varepsilon_{j, i+1}\right) m_{j, i+1} P_{j}^{*} & k \leq i \leq N-1,1 \leq j<k \\
\left(1-\varepsilon_{j+1, i}\right) m_{j+1, i} P_{j+1}^{*} & 2 \leq i<k, k \leq j \leq N-1 \\
\left(1-\varepsilon_{j+1, i+1}\right) m_{j+1, i+1} P_{j+1}^{*} & k \leq i \leq N-1, k \leq j \leq N-1, i \neq j
\end{array} .\right.
\end{gathered} .
$$

Since $\sum_{i=1}^{N} A_{i}=0$, adding the $j$ th column to the first column for every $j$ with $j \geq 2$, we see that $\left|D_{5}\right|=0$ is equivalent to $\left|D_{6}\right|=0$, where the $(N-1) \times(N-1)$ matrix $D_{6}$ is given by

$$
\begin{gathered}
\begin{cases}-A_{k} & i=j=1 \\
A_{j} & i=1,2 \leq j<k \\
A_{j+1} & i=1, k \leq j \leq N-1 \\
-\sum_{h=1}^{N-1}\left(1-\varepsilon_{h j}\right) m_{h j} P_{h}^{*} & 2 \leq i=j<k \\
-\sum_{h=1}^{N-1}\left(1-\varepsilon_{h, j+1}\right) m_{h, j+1} P_{h}^{*} & k \leq i=j \leq N-1 \\
-\left(1-\varepsilon_{k i}\right) m_{k i} P_{k}^{*} & 2 \leq i<k, j=1 \\
-\left(1-\varepsilon_{k, i+1}\right) m_{k, i+1} P_{k}^{*} & k \leq i \leq N-1, j=1 \\
\left(1-\varepsilon_{j i}\right) m_{j i} P_{j}^{*} & 2 \leq i<k, 2 \leq j<k, i \neq j \\
\left(1-\varepsilon_{j, i+1}\right) m_{j, i+1} P_{j}^{*} & k \leq i \leq N-1,2 \leq j<k \\
\left(1-\varepsilon_{j+1, i}\right) m_{j+1, i} P_{j+1}^{*} & 2 \leq i<k, k \leq j \leq N-1 \\
\left(1-\varepsilon_{j+1, i+1}\right) m_{j+1, i+1} P_{j+1}^{*} & k \leq i \leq N-1, k \leq j \leq N-1, i \neq j\end{cases}
\end{gathered}
$$

Multiply the first column of $D_{6}$ by -1 and move it to become the $(k-1)$ th column, and then move the first row to become the $(k-1)$ th row. We obtain a new matrix, denoted by $D_{7}$. We see that $\left|D_{6}\right|=0$ is equivalent to $\left|D_{7}\right|=0$. To characterize $D_{7}$, define the $(N-1) \times(N-1)$ matrix $D_{8}$ as

$$
\left(D_{8}\right)_{i j}= \begin{cases}-\sum_{h=1}^{N-1}\left(1-\varepsilon_{h, j+1}\right) m_{h, j+1} P_{h}^{*} & 1 \leq i=j \leq N-1 \\ \left(1-\varepsilon_{j+1, i+1}\right) m_{j+1, i+1} P_{j+1}^{*} & 1 \leq i, j \leq N-1, i \neq j\end{cases}
$$

and let $V_{i}$ denote the $(i-1)$ th row of the matrix $D_{8}$ for every $2 \leq i \leq N$. By the definition of $D_{8}$, we see that the $(N-1) \times(N-1)$ matrix $D_{7}$ can be obtained by replacing the $(k-1)$ th row of $D_{8}$ by the $1 \times(N-1)$ vector

$$
V_{0}=\left(A_{2}, \ldots, A_{N}\right)
$$

Since $\left|D_{7}\right|=0, V_{2}, \ldots, V_{k-1}, V_{0}, V_{k+1}, \ldots, V_{N}$ are linearly dependent for any $2 \leq k \leq N$. By lemma 1 , we see that

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$V_{2}, \ldots, V_{N}$ are linearly independent and thus form a basis of $\mathbb{R}^{N-1}$. By lemma 2 , we see that $V_{0}$ is the zero vector in $\mathbb{R}^{N-1}$. Hence, $A_{i}=0$ for every $i \geq 2$ and $A_{1}=0$. As $A_{i}=0$ directly yields equation (A13), this completes the proof of part (b), theorem 2.

As a direct consequence of equation (A13), we have
Lemma 5. For the movement strategy given by equation (A13), the expected fitness of the resident species at equilibrium (with invader absent) is given by

$$
b_{i} a_{i} R_{i}^{*}-d_{i}-f_{i} M_{i}^{*}=\left\{\begin{array}{l}
\sum_{j=2}^{N}\left[1-\left(1-\varepsilon_{1 j}\right)\left(1-\varepsilon_{j 1}\right)\right] m_{1 j} \quad i=1  \tag{A16}\\
\sum_{j=2}^{N}\left[1-\frac{\left(1-\varepsilon_{i j}\right)\left(1-\varepsilon_{j 1}\right)}{\left(1-\varepsilon_{i 1}\right)}\right] m_{i j} i \geq 2
\end{array} .\right.
$$

Proof of Theorem 2(b). By lemma 5, we see that if $\left(m_{21}, \ldots, m_{N 1}\right)=\left(m_{21, \text { opt }}, \ldots, m_{N 1, \text { opt }}\right)$, then

$$
D_{i j}= \begin{cases}-\sum_{h=2}^{N}\left(1-\varepsilon_{1 h}\right)\left(1-\varepsilon_{h 1}\right) m_{1 h} & i=j=1 \\ -\hat{m}_{1 h}-\frac{1}{\left(1-\varepsilon_{i 1}\right)} \sum_{h=2}^{N}\left(1-\varepsilon_{i h}\right)\left(1-\varepsilon_{h 1}\right) m_{i h} & i=j \geq 2 \\ \left(1-\varepsilon_{j 1}\right) \hat{m}_{j 1} & i=1, j \geq 2 \\ \left(1-\varepsilon_{j i}\right) m_{j i} & i \geq 2, j \geq 1, i \neq j\end{cases}
$$

Set $V_{*}=\left(1,1-\varepsilon_{21}, \ldots, 1-\varepsilon_{N 1}\right)$. Then, $V_{*} D=(0, \ldots, 0)$. That is, the vector $V_{*}$ is the left eigenvector of $D$ corresponding to the eigenvalue 0 . Since all components of $V_{*}$ are positive, 0 must be the dominant eigenvalue of matrix $D$, and all other eigenvalues must have strictly negative real parts.

## Literature Cited Only in Appendix A

Horn, R. A., and C. R. Johnson. 1999. Matrix analysis. Cambridge University Press, Cambridge.

# Appendix B from D. L. DeAngelis et al., "The Effect of Travel Loss on Evolutionarily Stable Distributions of Populations in Space" 

(Am. Nat., vol. 178, no. 1, p. 15)

## Interpretation of the Rates Given by Equation (17a) for the Three-Patch Tritrophic Case in Scenario 1

We describe a typical example in the three-patch case below. All parameters were fixed using the values given in table B 1 except the rates $m_{21}, m_{31}, \hat{m}_{21}$, and $\hat{m}_{31}$.

The rates given by formula (17a) were calculated (to machine accuracy) using Matlab: $m_{21, \mathrm{opt}}=$ 0.092409525773196 and $m_{31, \text { opt }}=0.335468571428571$. When the resident uses these rates, based on lemma 5, its fitness at the boundary equilibrium with the invader absent (shown here rounded to 3 decimal places, but calculated to 15 decimal places),

$$
\left(\hat{P}^{*}, P^{*}, R^{*}, M^{*}\right)=(0,0,0,30,22.727,31.818,32.941,43.402,19.727,22.476,26.115,49.65)
$$

on patch 1 is 0.02 , on patch 2 is -0.002 , and on patch 3 is 0 . It is interesting to note that as predicted by lemma 5, this is an example where the fitness on patch 2 is negative.

Recall that in the two-patch case, an optimal movement rate exists given by formula (14), and when the resident chooses this rate, no other genotype using a different rate can successfully invade. This is proved analytically in Y. Lou and C.-H. Wu (unpublished manuscript) and is illustrated in figure 4. In reality, it is impossible for a resident to choose the precise optimal movement rate, so the outcome of competition (exclusion of one genotype or the other, or coexistence) will in fact always be determined by the relative values of the movement rates as illustrated in figure $4 A, 4 C$. If the resident and the invader choose rates on opposite sides of the optimal rate, there is coexistence. Therefore, which rate is closer to the optimal rate matters only when either the resident and the invader both choose rates that are smaller or both choose rates that are larger than the optimal rate. Then, it is the population that chooses the rate closer to the optimal rates that wins, driving the other population to extinction.

This inability to select rates exactly equal to the optimal rates also occurs on a computer, due to round-off errors. This complicates numerical calculations in the immediate vicinity of the optimal rates. In particular, we do not know whether the rates we enter and think are the precise rates given by the formula are actually both slightly larger or both slightly smaller or whether one is larger and one is smaller than the precise rates. To complicate matters further, the invasion matrix has a zero eigenvalue if the precise rates are entered, making convergence very slow.

To test the predictions of our rates, we carried out a number of experiments using the AUTO interface in the software package XPPAUT (see Ermentrout 2002) to continue equilibrium solutions numerically and detect bifurcations, that is, detect changes in the stability and/or number of equilibrium solutions as the value of a parameter, called the bifurcation parameter, is varied.

Experiment I. We chose the residents' movements rates $m_{21}$ and $m_{31}$, close to the optimal rates $m_{21, \text { opt }}$ and $m_{31, \mathrm{opt}}$, respectively, but both larger than the optimal rates; and we chose the invaders' movement rates $\hat{m}_{21}$ and $\hat{m}_{31}$, both even larger than the residents' movement rates. As expected, the resident outcompeted the invader, driving it to extinction. Then, using one of the invaders' movement rates, $\hat{m}_{21}$, as the bifurcation parameter, we allowed it to decrease. The resident continued to outcompete the invader until $\hat{m}_{21}$ reached a critical rate, $m_{1}^{*}<$ $m_{21, \mathrm{opt}}$, at which there was a transcritical bifurcation resulting in the stable coexistence of both the resident and the invader for values of $\hat{m}_{21}<m_{1}^{*}$.

Experiment II. We chose the residents' movements rates $m_{21}$ and $m_{31}$, close to the optimal rates $m_{21, \text { opt }}$ and $m_{31, \text { opt }}$, respectively, but both smaller than the optimal rates; and we chose the invaders' movement rates $\hat{m}_{21}$ and $\hat{m}_{31}$, both even smaller than the residents' movement rates. Again, as expected, the resident outcompeted the

## Appendix B from D. L. DeAngelis et al., Travel Loss and Population Distribution

invader, driving it to extinction. Then, using one of the invaders' movement rates, $\hat{m}_{21}$, as the bifurcation parameter, we allowed it to increase. The resident continued to outcompete the invader until $\hat{m}_{21}$ reached a critical rate, $m_{2}^{*}>m_{21, o p t}$, at which there was a transcritical bifurcation resulting in the stable coexistence of both the resident and the invader for values of $\hat{m}_{21}>m_{2}^{*}$.

Experiment III. We chose the residents' movements rates $\hat{m}_{21}>m_{21}>m_{21, \text { opt }}$ and $\hat{m}_{31}<m_{31}<m_{31, \text { opt }}$. Once more, as expected, the resident outcompeted the invader, driving it to extinction. Then, using the invaders' movement rates $\hat{m}_{31}$ as the bifurcation parameter, we allowed it to increase. The resident continued to outcompete the invader until $\hat{m}_{31}$ reached a critical rate, $m_{3}^{*}>m_{31, \mathrm{opt}}$, at which there was transcritical bifurcation resulting in the stable coexistence of both the resident and the invader for values of $\hat{m}_{31}>m_{3}^{*}$.

Experiment IV. We chose rates $m_{31}=\hat{m}_{31}=m_{31, \text { opt }}$ and $m_{21}<m_{21, \text { opt }}$ and allowed $\hat{m}_{21}$ to vary. As expected, the outcome was similar to that described by figure $4 A$ in the two-patch case, with the transcritical bifurcation resulting in coexistence occurring at the optimal rate $m_{21, \mathrm{opt}}$.

Experiment $V$. We chose rates $m_{31}=\hat{m}_{31}=m_{31, \text { opt }}$ and $m_{21}>m_{21, \text { opt }}$ and allowed $\hat{m}_{21}$ to vary. As expected, the outcome was similar to that described by figure $4 C$ in the two-patch case, with the transcritical bifurcation resulting in coexistence occurring at the optimal rate $m_{21, \mathrm{opt}}$.

Experiment VI. We entered the rates calculated using Matlab for both of the residents' rates, and we chose two nonoptimal rates for the invaders. Convergence was too slow for us to be able to distinguish whether the invader would die out completely or coexist with the resident. Starting AUTO from the boundary equilibrium with only the resident present, AUTO did not detect a bifurcation to a coexistence equilibrium, but because of the zero eigenvalue of the invasion matrix, AUTO had difficulty determining the stability of the boundary equilibrium. It is therefore difficult to say with any certainty that no such bifurcation occurs.

Table B1. Parameter values used to illustrate the three-patch model

| $a_{1}=.01$ | $b_{1}=.5$ | $c_{1}=.5$ | $d_{1}=.01$ | $r_{1}=1.7$ | $K_{1}=40$ | $d_{\mathrm{m} 1}=.09$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| $a_{2}=.009$ | $b_{2}=.55$ | $c_{2}=.55$ | $d_{2}=.008$ | $r_{2}=1.55$ | $K_{2}=50$ | $d_{\mathrm{m} 2}=.1$ |
| $a_{3}=.03$ | $b_{3}=.48$ | $c_{3}=.6$ | $d_{3}=.011$ | $r_{3}=1.8$ | $K_{3}=42$ | $d_{\mathrm{m} 3}=.105$ |
| $\varepsilon_{12}=.03$ | $\varepsilon_{21}=.03$ | $\varepsilon_{13}=.02$ | $\varepsilon_{31}=.01$ | $\varepsilon_{23}=.01$ | $f_{1}=.006$ |  |
| $m_{12}=.23$ | $m_{13}=.21$ | $m_{23}=.2$ | $m_{32}=.0$ |  | $f_{2}=.008$ |  |
| $\hat{m}_{12}=.23$ | $\hat{m}_{13}=.21$ | $\hat{m}_{23}=.2$ | $\hat{m}_{32}=0$ |  | $f_{3}=.0055$ |  |

