

# Variance of the stationary distribution for a first-order vector autoregressive model

Mark Scheuerell, NOAA Northwest Fisheries Science Center, Seattle, WA USA

## Background

There is growing interest in the use of first-order vector autoregressive, or VAR(1), models in ecology where they are often referred to as multivariate autoregressive, or MAR(1), models (*e.g.*, Ives *et al.* 2003 *Ecological Monographs* 73:301–330).

Assume a MAR(1) model of the general form

$$\mathbf{x}_t = \mathbf{a} + \mathbf{B}(\mathbf{x}_{t-1} - \mathbf{a}) + \mathbf{w}_t$$

where  $\mathbf{x}_t$  is an  $n \times 1$  vector of states at time  $t$ ,  $\mathbf{a}$  is an  $n \times 1$  vector of underlying levels (means) for each of the states,  $\mathbf{B}$  is an  $n \times n$  interaction matrix, and  $\mathbf{w}_t$  is an  $n \times 1$  vector of multivariate normal process errors;  $\mathbf{w}_t \sim \text{MVN}(\mathbf{0}, \mathbf{Q})$ .

I note here that MAR(1) models are often used for zero-mean processes, in which case  $\mathbf{a} = \mathbf{0}$ . Alternatively, MAR(1) models may be embedded within a state-space framework, which adds an observation model to account for noisy and/or missing data. In those so-called MARSS(1) models, any non-zero mean vector  $\mathbf{a}$  is typically incorporated into the model for the observed data  $\mathbf{y}_t$ , such that

$$\begin{aligned}\mathbf{x}_t &= \mathbf{B}\mathbf{x}_{t-1} + \mathbf{w}_t \\ \mathbf{y}_t &= \mathbf{a} + \mathbf{x}_t + \mathbf{v}_t,\end{aligned}$$

and the observation errors,  $\mathbf{v}_t$ , are distributed as a multivariate normal with mean  $\mathbf{0}$  and variance-covariance matrix  $\mathbf{R}$ .

## Variance of the stationary distribution

Regardless of the specific form, the discussion here is restricted to stationary process models wherein all of the eigenvalues of  $\mathbf{B}$  lie within the unit circle. One of the many appeals of stationary MAR(1) models is that the variance-covariance matrix of the stationary distribution for  $\mathbf{x}_t$  as  $t \rightarrow \infty$  gives an indication of the relative stability of the system.

Recognizing that  $t = t - 1$  as  $t \rightarrow \infty$ , we can write

$$\mathbf{x}_\infty = \mathbf{a} + \mathbf{B}(\mathbf{x}_\infty - \mathbf{a}) + \mathbf{w}_\infty,$$

where

$$\text{Var}(\mathbf{x}_\infty) = \text{Var}(\mathbf{a}) + \mathbf{B}(\text{Var}(\mathbf{x}_\infty) - \text{Var}(\mathbf{a}))\mathbf{B}^\top + \text{Var}(\mathbf{w}_\infty).$$

If we define  $\mathbf{\Omega} = \text{Var}(\mathbf{x}_\infty)$ , then

$$\begin{aligned}\boldsymbol{\Omega} &= \mathbf{0} + \mathbf{B}(\boldsymbol{\Omega} - \mathbf{0})\mathbf{B}^\top + \mathbf{Q} \\ &= \mathbf{B}\boldsymbol{\Omega}\mathbf{B}^\top + \mathbf{Q}.\end{aligned}$$

Unfortunately, however, there is no closed-form solution for  $\boldsymbol{\Omega}$  when written in this form.

## The *vec* operator

It turns out that we can use the *vec* operator to derive an explicit solution for  $\boldsymbol{\Omega}$ . The *vec* operator converts an  $i \times j$  matrix into an  $(ij) \times 1$  column vector. For example, if

$$\mathbf{M} = \begin{bmatrix} 1 & 3 \\ 2 & 4 \end{bmatrix},$$

then

$$\text{vec}(\mathbf{M}) = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix}.$$

## Solution

Thus, if  $\mathbf{I}$  is an  $n \times n$  identity matrix, and we define  $\mathcal{I} = (\mathbf{I} \otimes \mathbf{I})$  and  $\mathcal{B} = (\mathbf{B} \otimes \mathbf{B})$ , then

$$\text{vec}(\boldsymbol{\Omega}) = (\mathcal{I} - \mathcal{B})^{-1} \text{vec}(\mathbf{Q}).$$