

This Maple worksheet is denoted sirs2c.

It is used to study an SIRS model with demography, for $R_0 > 1$ and α_1 large.

The deterministic version of the model then shows damped oscillations toward an endemic infection level.

The particular model dealt with here has a state space with 2 variables: S and I.

This means that the variable R is approximated by $N - S - I$.

Furthermore, the infection rate is "conventional": the denominator $S + I + R - 1$ of the proper infection rate is replaced by N.

Two things are done here:

I) We derive an expression for the angular frequency of the deterministic model oscillations; and

II) We give a derivation of the moments of the stationary distribution of a diffusion approximation.

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```
> restart;
with(LinearAlgebra,Transpose,Eigenvalues,
CharacteristicPolynomial);
with(VectorCalculus,Jacobian);
interface(imaginaryunit=II);
      [Transpose, Eigenvalues, CharacteristicPolynomial]
      [Jacobian]
      /
```

(1)

The reason for changing the notation used for the imaginary unit is that "I" will be used below to denote the number of infected individuals.

The original transition rates are stored in the table transA:

```
> transA:=table([[1,0]=mu*N+delta*(N-S-I),[-1,1]=beta*S*I/N,[-1,
0]=mu*S,[0,-1]=(mu+gamma)*I]):
```

After scaling: $x_1 = \frac{S}{N}$, $x_2 = \frac{I}{N}$, and reparametrization $R_0 = \frac{\beta}{\gamma + \mu}$, $\alpha_1 = \frac{\gamma + \mu}{\mu}$, $\alpha_2 = \frac{\delta + \mu}{\mu}$,

we get: $S = x_1 \cdot N$, $I = x_2 \cdot N$, $\beta = \mu \cdot \alpha_1 \cdot R_0$, $\gamma = \mu \cdot (\alpha_1 - 1)$, $\delta = \mu \cdot (\alpha_2 - 1)$.

The Maple procedure "scale" is used to change the transition rates accordingly:

```
> scale:=proc(tab)
  local xA,n,xB,xC;
  xA:=op(2,eval(tab));
  n:=nops(xA);
  xB:=subs(S=x1*N,I=x2*N,beta=mu*alpha1*R0,gamma=mu*(alpha1-1),
delta=mu*(alpha2-1),xA);
  xC:=[seq(lhs(op(i,xB))=simplify(rhs(op(i,xB)/N)),i=1..n)];
  table(xC);
end proc:
```

We apply the scaling and reparametrization mentioned above to get the table of transition rates "trans":

```
> trans:=scale(transA);
trans:=table([[0,-1]=mu*alpha1*x2,[-1,0]=mu*x1,[-1,1]=mu*alpha1*R0*x1*x2,[1,0]=
-mu*(-alpha2+alpha2*x1+alpha2*x2-x1-x2)])
```

(2)

Next is a procedure that determines the right-hand sides of the deterministic ODEs for the scaled variables x_1 and x_2 from the table of transition rates:

```
> equ:=proc(i,tab)
  local x,n;
  x:=op(2,eval(tab));
  add(lhs(x[n])[i]*rhs(x[n]),n=1..nops(x));
end proc;
```

The right-hand sides of the ODEs for the variables x_1 and x_2 are found to be:

```
> eq1:=simplify(equ(1,trans));
eq2:=simplify(equ(2,trans));
eq1:= -μ α1 R0 x1 x2 + μ α2 - μ α2 x1 - μ α2 x2 + μ x2
eq2:= -μ α1 x2 + μ α1 R0 x1 x2
```

(3)

Now determine the critical points of these two ODEs:

```
> crit:=solve({eq1,eq2},{x1,x2});
crit:= {x1 = 1, x2 = 0}, {x1 = 1/R0, x2 = α2(R0-1)/(R0(α1+α2-1))}
```

(4)

The point corresponding to an endemic infection level is termed (x_{10}, x_{20}) :

```
> x10:=rhs(crit[2][1]);
x20:=rhs(crit[2][2]);
x10:= 1/R0
x20:= α2(R0-1)/(R0(α1+α2-1))
```

(5)

The Jacobian of the system of ODEs is denoted B_x :

```
> Bx:=Jacobian([eq1,eq2],[x1,x2]);
Bx:= [ -μ α1 x2 R0 - μ α2    -μ α1 R0 x1 - μ α2 + μ
       μ α1 x2 R0            -μ α1 + μ α1 R0 x1 ]
```

(6)

Evaluate the Jacobian at the critical point:

```
> B:=simplify(subs(x1=x10,x2=x20,Bx));
B:= [ - μ α2 (α1 R0 + α2 - 1) / (α1 + α2 - 1)    -μ α1 - μ α2 + μ
      μ α1 α2 (R0 - 1) / (α1 + α2 - 1)            0 ]
```

(7)

We proceed to determine the eigenvalues of the matrix B .

The command "CharacteristicPolynomial" gives

```
> p:=CharacteristicPolynomial(B,lambda);
p:= λ2 + μ α2 (α1 R0 + α2 - 1) λ / (α1 + α2 - 1) + (R0 - 1) α2 α1 μ2
```

(8)

The eigenvalues are found as solutions of the characteristic equation $p=0$ or $\lambda^2 + a \cdot \lambda$

+ b = 0.

They can be written $-\frac{a}{2} \pm i\Omega$, with $\Omega = \sqrt{b - \left(\frac{a}{2}\right)^2} =$

$\mu \cdot \sqrt{\alpha_1 \cdot \alpha_2 \cdot (R_0 - 1) - \left(\alpha_2 \cdot \frac{R_1}{2}\right)^2}$, and where $R_1 = \frac{\alpha_1 \cdot R_0 + \alpha_2 - 1}{\alpha_1 + \alpha_2 - 1}$.

Now proceed to determine approximations of the covariances of the diffusion approximation.

Covariances of $x[i]x[j]$ are determined by cov1:

```
> cov1:=proc(i,j,tab)
  local x,n;
  x:=op(2,eval(tab));
  add(lhs(x[n])[i]*lhs(x[n])[j]*rhs(x[n]),n=1..nops(x));
end proc;
```

The local covariance matrix S is determined by the procedure "cov":

```
> cov:=proc(tab)
  local i,j,d,S;
  d:=nops(lhs(op(2,eval(tab))[1]));
  for i from 1 to d do
    for j from 1 to d do
      S[i,j]:=cov1(i,j,tab);
    od;
  od;
  S:=Matrix(2,S);
end proc;
```

By using the table of transition rates in "trans", we get

```
> Sx:=simplify(cov(trans));
```

Sx:=

$$\begin{bmatrix} [2\mu x_1 + \mu \alpha_1 R_0 x_1 x_2 + \mu \alpha_2 - \mu \alpha_2 x_1 - \mu \alpha_2 x_2 + \mu x_2, \\ -\mu \alpha_1 R_0 x_1 x_2], \\ [-\mu \alpha_1 R_0 x_1 x_2, \mu \alpha_1 x_2 + \mu \alpha_1 R_0 x_1 x_2] \end{bmatrix}$$

(9)

Evaluate the local covariance matrix at the critical point:

```
> S:=simplify(subs(x1=x10,x2=x20,Sx));
```

$$S := \begin{bmatrix} \frac{2\mu(\alpha_1 + \alpha_2 - 1 + \alpha_1 \alpha_2 R_0 - \alpha_1 \alpha_2)}{R_0(\alpha_1 + \alpha_2 - 1)} & -\frac{\mu \alpha_1 \alpha_2 (R_0 - 1)}{R_0(\alpha_1 + \alpha_2 - 1)} \\ -\frac{\mu \alpha_1 \alpha_2 (R_0 - 1)}{R_0(\alpha_1 + \alpha_2 - 1)} & \frac{2\mu \alpha_1 \alpha_2 (R_0 - 1)}{R_0(\alpha_1 + \alpha_2 - 1)} \end{bmatrix}$$

(10)

Now proceed to solve $A = -S$, where $A = B \cdot \text{SIG} + \text{SIG} \cdot B^T$, and where $B^T = \text{Transpose}(B)$.

First introduce notation for the elements of the matrix SIG:

```
> SIG:=Matrix(2,[s11,s12,s21,s22]);
```

$$\text{SIG} := \begin{bmatrix} s11 & s12 \\ s21 & s22 \end{bmatrix}$$

(11)

Next, determine the matrix A:

```
> A:=Matrix(evalm(B&*SIG+SIG&*Transpose(B)));
```

$$A := \begin{bmatrix} -\frac{2\mu\alpha_2(\alpha_1 R_0 + \alpha_2 - 1)s_{11}}{\alpha_1 + \alpha_2 - 1} + (-\mu\alpha_1 - \mu\alpha_2 + \mu)s_{21} + s_{12}(-\mu\alpha_1 - \mu\alpha_2 + \mu) & -\frac{\mu\alpha_2(\alpha_1 R_0 + \alpha_2 - 1)s_{12}}{\alpha_1 + \alpha_2 - 1} + (-\mu\alpha_1 - \mu\alpha_2 + \mu)s_{22} \\ \frac{\mu\alpha_1\alpha_2(R_0 - 1)s_{11}}{\alpha_1 + \alpha_2 - 1} & \frac{\mu\alpha_1\alpha_2(R_0 - 1)s_{12}}{\alpha_1 + \alpha_2 - 1} - \frac{s_{21}\mu\alpha_2(\alpha_1 R_0 + \alpha_2 - 1)}{\alpha_1 + \alpha_2 - 1} + (-\mu\alpha_1 - \mu\alpha_2 + \mu)s_{22} \\ \frac{\mu\alpha_1\alpha_2(R_0 - 1)s_{12}}{\alpha_1 + \alpha_2 - 1} + \frac{s_{21}\mu\alpha_1\alpha_2(R_0 - 1)}{\alpha_1 + \alpha_2 - 1} & \end{bmatrix} \quad (12)$$

Solve the 4 scalar equations gotten from the matrix equation $A+S=0$ for the 4 unknowns in the matrix Σ :

```
> solve(convert(S+A,set),convert(SIG,set));
```

$$\left\{ s_{11} = \frac{-\alpha_1 - \alpha_2 + \alpha_2^2 + \alpha_1^2 + \alpha_1\alpha_2 + \alpha_1\alpha_2 R_0}{\alpha_2 R_0 (\alpha_1 R_0 + \alpha_2 - 1)}, s_{12} = -\frac{1}{R_0}, s_{21} = -\frac{1}{R_0}, s_{22} = \frac{(-R_0\alpha_1^2 + \alpha_2 + \alpha_1^2 + \alpha_1^2 R_0^2 \alpha_2 + \alpha_1^2 R_0 \alpha_2 - 2\alpha_2^2 + \alpha_2^3 - 2\alpha_1\alpha_2 R_0 - \alpha_1^2 \alpha_2 - \alpha_1^3 + \alpha_1^3 R_0 + 2\alpha_1\alpha_2^2 R_0)}{(R_0(-4\alpha_1\alpha_2 + 2\alpha_1^2 R_0 \alpha_2 + \alpha_1\alpha_2^2 R_0 - 2\alpha_1\alpha_2 R_0 + \alpha_1^2 \alpha_2 + 2\alpha_1\alpha_2^2 - 1 - \alpha_1^2 + 2\alpha_1 - 3\alpha_2^2 + 3\alpha_2 + \alpha_1^3 R_0 - 2R_0\alpha_1^2 + \alpha_1 R_0 + \alpha_2^3))} \right\} \quad (13)$$

```
> assign(%);
```

In simplified expressions below, we use two parameters α and R_1 as follows:

```
> alpha=alpha1+alpha2-1;
R1=(alpha1*R0+alpha2-1)/alpha;
```

$$\alpha = \alpha_1 + \alpha_2 - 1$$

$$R_1 = \frac{\alpha_1 R_0 + \alpha_2 - 1}{\alpha} \quad (14)$$

Next, we give alternate and simplified exact expressions for the two variances s_{11} and s_{22} .

These expressions have been derived "by hand". We use Maple only to check that $s_{11alt}=s_{11}$ and that $s_{22alt}=s_{22}$.

```
> s11alt:=1/R0+alpha1/(alpha2*R0*R1);
simplify(subs(R1=(alpha1*R0+alpha2-1)/(alpha1+alpha2-1),s11-s11alt));
```

$$s_{11alt} := \frac{1}{R_0} + \frac{\alpha_1}{\alpha_2 R_0 R_1} \quad (15)$$

```
> s22alt:=alpha1^2*(R0-1)/(alpha^2*R0*R1) + alpha2*R1/(alpha*R0);
simplify(subs(R1=(alpha1*R0+alpha2-1)/alpha,alpha=alpha1+alpha2-1,s22-s22alt));
```

$$s22alt := \frac{\alpha_1^2 (R_0 - 1)}{\alpha^2 R_0 R_1} + \frac{\alpha_2 R_1}{\alpha R_0}$$

(16)

The covariances s_{12} and s_{21} are seen above to be simple.

We give them below, and also the one-term asymptotic approximations of the variances s_{11} and s_{22} for large α_1 .

```
> s11a:=op(1,asympt(s11,alpha1));
s12:=s12;
s21:=s21;
s22a:=op(1,asympt(s22,alpha1));
```

$$s11a := \frac{\alpha_1}{\alpha_2 R_0^2}$$

$$s12 := -\frac{1}{R_0}$$

$$s21 := -\frac{1}{R_0}$$

$$s22a := \frac{R_0 - 1}{R_0^2}$$

(17)

$\mu_I = x_{20} * N$ divided by $\sigma_I = \sqrt{N * s_{22}}$ is called ρ_I .

We determine an approximation of ρ_I for large α_1 :

```
> x20;
x20a:=op(1,asympt(x20,alpha1));
rhoI:=simplify(x20a*N/sqrt(s22a*N)) assuming R0>1;
```

$$\frac{\alpha_2 (R_0 - 1)}{R_0 (\alpha_1 + \alpha_2 - 1)}$$

$$x20a := \frac{\alpha_2 (R_0 - 1)}{R_0 \alpha_1}$$

$$\rho_I := \frac{\alpha_2 \sqrt{R_0 - 1} \sqrt{N}}{\alpha_1}$$

(18)

$\mu_S = x_{10} * N$ divided by $\sigma_S = \sqrt{N * s_{11}}$ is called ρ_S .

We determine an approximation of ρ_S for large α_1 .

```
> x10;
simplify(x10*N/sqrt(N*s11a)) assuming R0>1,alpha1>0,alpha2>0;
```

$$\frac{1}{R_0}$$

(19)

$$\frac{\sqrt{N} \sqrt{\alpha_2}}{\sqrt{\alpha_1}}$$

(19)