

Some Thoughts on Ford et al. (2018)  
by Bill Menke, May 16, 2018

Professional scientists and graduate students submit abstracts to sessions at the American Geophysical Union’s annual meeting. Each session has a lead convener, a scientist who presides over it. A convener selects a small number of “invited” abstracts, which are highlighted as especially important. Figure 3A of Ford et al. (2018) (reproduced below) builds the case for gender bias in the invitation process: a lower percentage of female-authored abstracts are invited by male conveners than by female conveners; furthermore, the percentage is lower than the proportion of female-authored submissions.

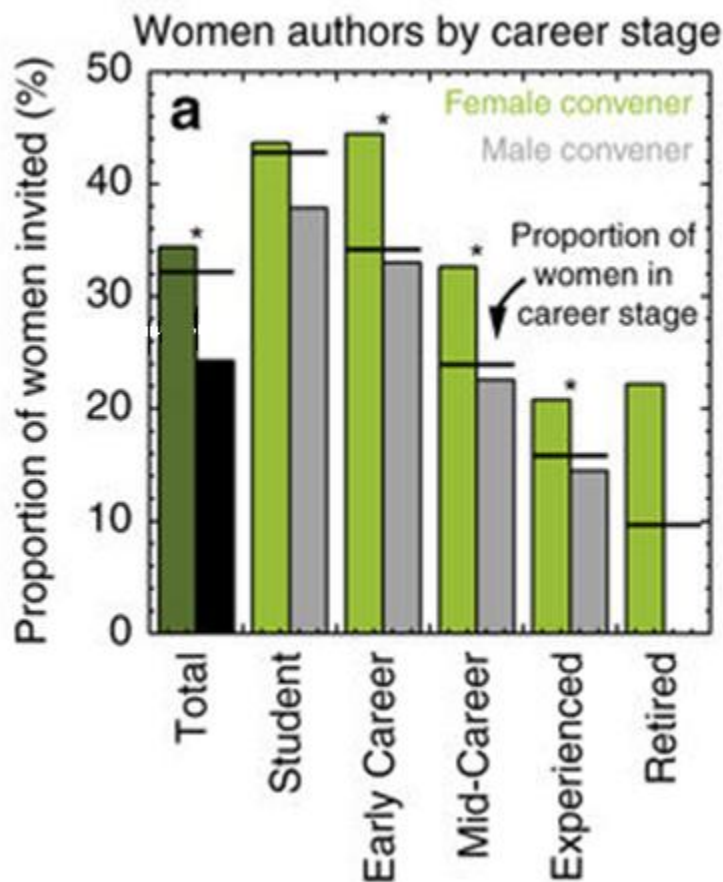


Figure 1. This is Figure 3A of Ford et al. (2018)

**Simple rate model of invitation.** I analyze these data in terms of a simple rate model:

$$\begin{array}{l}
 N(i, j) \\
 \text{number of} \\
 \text{invitees of} \\
 \text{gender } i \text{ by} \\
 \text{conveners of} \\
 \text{gender } j
 \end{array}
 =
 \begin{array}{l}
 \text{invitations} \\
 \text{per} \\
 \text{convener} \\
 \text{per abstract}
 \end{array}
 \times
 \begin{array}{l}
 \text{number of} \\
 \text{abstracts with} \\
 \text{gender } i
 \end{array}
 \times
 \begin{array}{l}
 \text{number of} \\
 \text{conveners with} \\
 \text{gender } j
 \end{array}$$

or, for genders  $F$  (female) and  $M$  (male):

$$N(F, F) = r (1 + \Delta_F) \times f_A N_A \times f_C N_C$$

$$N(M, F) = r (1 - \Delta_F) \times (1 - f_A) N_A \times f_C N_C$$

$$N(F, M) = r (1 + \Delta_M) \times f_A N_A \times (1 - f_C) N_C$$

$$N(M, M) = r (1 - \Delta_M) \times (1 - f_A) N_A \times (1 - f_C) N_C$$

Here  $r$  is an overall invitation rate. The factor  $(1 \pm \Delta_F)$  represents bias of female conveners in inviting females (+) and males (-), and the factor of  $(1 \pm \Delta_M)$  represents bias of male conveners in inviting females (+) and males (-).  $N_A$  is the number of submitted abstracts and  $f_A$  and  $(1 - f_A)$  are the fractions of female and male abstracts, respectively. Similarly,  $N_C$  is the number of conveners and  $f_C$  and  $(1 - f_C)$  are the fractions of female and male conveners, respectively. Because the patterns of the Early Career, Mid-Career and Experiences Categories in Figure 3A are very similar to one another, I have aggregated them into a single “Professional” category. I used numerical data from Ford et al.’s (2018) Supplementary Tables 1 and 4 in Table 1, below.

Table 1. Aggregated Professional data.

$N_A$	45234
$f_A$	0.28
$(1 - f_A)$	0.72
$N(F, F)$	660
$N(M, F)$	1272
$N(F, M)$	1186
$N(M, M)$	3769

I have not been able to find values for  $N_C$  or  $f_C$ , as Ford et al. (2018) does not this information (as far as I can tell). However, they do state that when all categories (not just professional categories) are aggregated, “male conveners control 72% of the abstract pool”. I take that to mean that  $f_C^{all} = 0.28$  (“all” for all categories). I expect that nearly all conveners are from the professional categories, since only a very small percentage of students are conveners and the percentage of retirees is also very small. Hence, I would expect that  $f_C \approx f_C^{all}$ , in which case, I observe that  $f_C \approx f_A = 0.28$ . Consequently, I write  $f_C = \beta f_A$ , where both  $N_C$  and  $\beta$  are unknown and where  $\beta$  is close to unity. The rate model becomes:

$$N(F, F) = C \times (1 + \Delta_F) \times f_A \times \beta f_A$$

$$N(M, F) = C \times (1 - \Delta_F) \times (1 - f_A) \times \beta f_A$$

$$N(F, M) = C \times (1 + \Delta_M) \times f_A \times (1 - \beta f_A)$$

$$N(M, M) = C \times (1 - \Delta_M) \times (1 - f_A) \times (1 - \beta f_A)$$

where  $C \equiv rN_A N_C$ .

**Male conveners are biased towards male invitees.** The fraction  $X(F, M)$  of female invitees by male conveners is:

$$X(F, M) = \frac{N(F, M)}{N(F, M) + N(M, M)} = \frac{(1 + \Delta_M) f_A}{(1 + \Delta_M) f_A + (1 - \Delta_M) (1 - f_A)}$$

(which is independent of  $C$ ,  $\beta$  and  $\Delta_F$ ). Solving for  $\Delta_M$  yields:

$$\Delta_M = \frac{f_A - X(F, M)}{X(F, M)(2f_A - 1) - f_A}$$

(a formula that I have checked numerically). Note that  $\Delta_M = 0$  only when  $X(F, M) = f_A$ ; that is, the rate of inviting females matches the fraction of females in the pool. For the observed value of  $X(F, M) = 1186/(1186 + 3799) = 0.24$ , we find that  $\Delta_M = -0.11$ ; that is, male conveners are biased towards male invitees.

**Female conveners are biased towards female invitees.** The fraction  $X(F, M)$  of female invitees by female conveners is:

$$X(F, F) = \frac{N(F, F)}{N(F, F) + N(M, F)} = \frac{(1 + \Delta_F) f_A}{(1 + \Delta_F) f_A + (1 - \Delta_F) (1 - f_A)}$$

(which is independent of  $C$ ,  $\beta$  and  $\Delta_M$ ). Solving for  $\Delta_F$  yields:

$$\Delta_F = \frac{f_A - X(F, F)}{X(F, F)(2f_A - 1) - f_A}$$

(a formula that I have checked numerically). Note that  $\Delta_F = 0$  only when  $X(F, F) = f_A$ ; that is, the rate of inviting females matches the fraction of females in the pool. For the observed value of  $X(F, F) = 660/(660 + 1272) = 0.34$ , we find that  $\Delta_F = 0.14$ ; that is, female conveners are biased towards female invitees.

**Female conveners are a little over-represented among conveners.** The ratio  $R$  of male-invitees-by-female-conveners to female-invitees-by-male-conveners is:

$$R = \frac{N(M, F)}{N(F, M)} = \frac{(1 - \Delta_F)(1 - f_A)\beta f_A}{(1 + \Delta_M)f_A(1 - \beta f_A)} = D \frac{\beta f_A}{(1 - \beta f_A)} \quad \text{with} \quad D \equiv \frac{(1 - \Delta_F)(1 - f_A)}{(1 + \Delta_M)f_A}$$

Note that  $R = 1$  when  $\Delta_F = \Delta_M = 0$  (no bias in inviting) and  $\beta = 1$  (no under/over-representation of female conveners). Solving for  $\beta$  yields:

$$\beta = \frac{R/D}{f_A[1 + (R/D)]}$$

(a formula that I have checked numerically). For the observed value of  $R = 1272/1186 = 1.07$ , we find that  $\beta = 1.08$  and  $f_C \approx 0.30$  (which is larger than  $f_A \approx 0.28$ ). That is, female conveners are a little over-represented among conveners. (This model result could – and should – be tested against the actual fraction of professional-category women conveners, which is, in principal, available).

**Check of consistency of the model.** Solving the  $N(F, F)$  rate equation for  $C$ , we find:

$$C = \frac{N(F, F)}{(1 + \Delta_F)\beta f_A^2} \approx 6797$$

(a formula that I have checked numerically). The predicted values of  $\Delta_F$ ,  $\Delta_M$ ,  $\beta$  and  $C$  reproduce the data in Table 1 exactly, as shown in the figure, below:

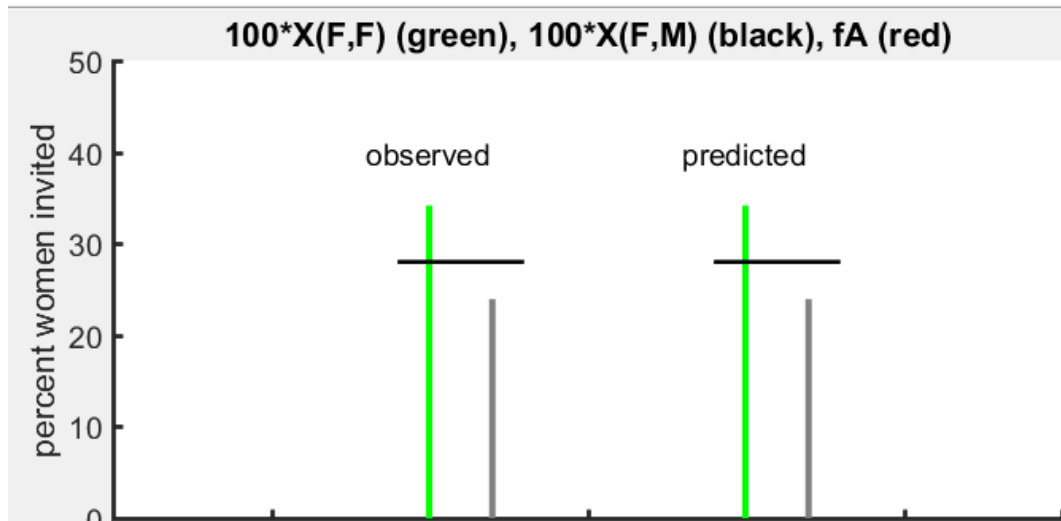


Figure 2. Observed and predicted rate data.

**Discussion.** We are now in a position to discuss the main features of Ford et al.’s (2018) Figure 3A (reproduced here as Figure 1) and in my corresponding figure of the aggregated data (Figure 2).

The percent of females invited by male conveners (grey vertical bars) is *below* the percent of women who submitted abstracts (black horizontal bar) because male conveners are inviting females at a rate that is lower than for males. In the aggregated professional data, male convener’s bias is about  $\pm 11\%$ , meaning that for every 111 males who are invited only 89 females are invited. A similar bias is observed in Ford et al.’s (2018) data and holds for all categories.

The percent of females invited by female conveners (green vertical bars) is *above* the percent of women who submitted abstracts (black horizontal bar) because female conveners are inviting females at a rate that is higher than for males. In the aggregated data, their bias is about  $\pm 14\%$ , meaning that for every 114 females who are invited only 86 males are invited. A similar bias is also observed in Ford et al.’s (2018) data and holds for all categories.

Ford et al. (2018) speaks of the dual biases as having a compensatory effect:

“Male conveners offered fewer invited abstracts and speaking opportunities to women; this implies the reason AGU has gender parity when controlling for career stage is because women disproportionately invite other women. This suggests the underrepresented gender is doing the burden of gender parity efforts.”

This pattern is true of the aggregated professional category we well, where the fraction of female invitees is:

$$(660 + 1186)/(660 + 1186 + 1272 + 3769) = 0.27$$

which is close to the abstract pool  $f_A = 0.28$ . As Ford et al.'s (2018) says, “the underrepresented gender is doing the burden of gender parity efforts”.

However, more works needs to be done to establish that the female *conveners* are responsible for these efforts. An alternative possibility that cannot be excluded based on these data alone is that females are preferentially submitting abstracts to sessions convened by females (perhaps in anticipation of unbiased treatment). This possibility could be tested by examining whether the percentage of females-submitting-to-sessions-convened-by-females is higher than the percentage of females-submitting-to-sessions-convened-by-males.

If it is found to be the case that female conveners are working towards gender parity, then understanding the nature of their efforts becomes vitally important, because they might provide widely-applicable strategies for reducing bias. Are female conveners doing a better job at identifying high-profile female-authored abstracts that have been submitted to their session? Or are they actively *recruiting* high-profile female authors to their sessions? Questions like these can probably not be answered by analysis of AGU's abstract database. However, they probably could be addresses by post-facto questionnaires of invitees.

## **Reference**

Heather L. Ford, Cameron Brick, Karine Blaufuss & Petra S. Dekens, Gender inequity in speaking opportunities at the American Geophysical Union Fall Meeting, *Nature Communications* 9, Article number: 1358 (2018), doi:10.1038/s41467-018-03809-5.

## Supplementary Information

Part 1

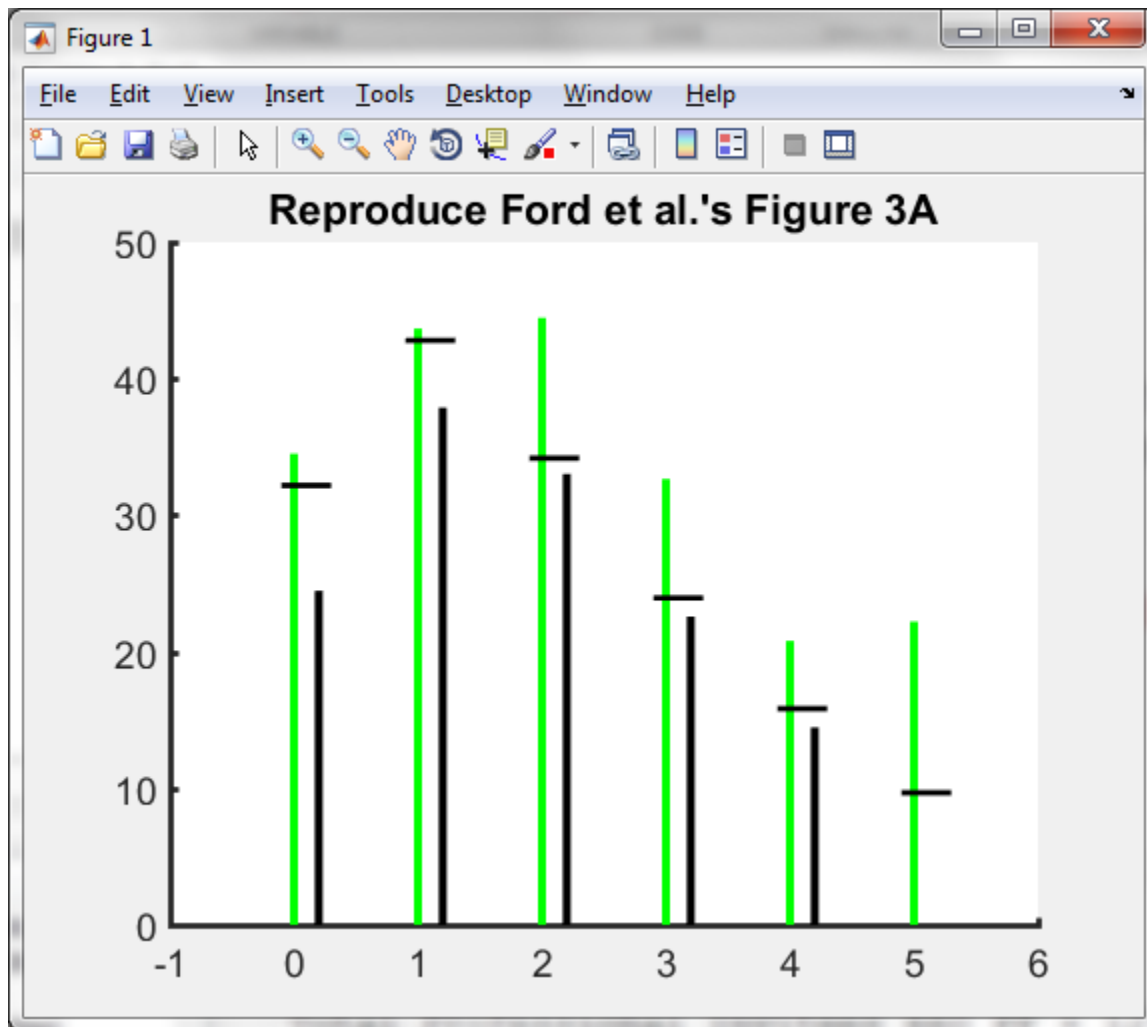
Total Professional Abstracts 12605 F + 32629 M = 45234

Rate females 0.28 yields 12605

Total Professional Invitees 660 FF + 1272 MF + 1186 FM + 3769 MM  
=

Total Professional Invitees 1932 AF + 4955 AM =

Total Professional Invitees 6887



```
% Part 1: Enter Ford et at.'s (2018) numerical data and create  
% aggregated professional category
```

```
clear all;
```

```

F=1;
M=2;
C=5;

% Supplementary Table 1, Total Abstracts
A=[ 8042, 7900, 3548, 1157, 18;
    10747, 15212, 11267, 6150, 168 ];
AT = sum(A,2);

% AT is (20665, 43544) but total is (20900, 44347)
% Perhaps some are uncategorized?

ATT = sum(AT);
% ATT is 64209 but total is 65247

% Supplementary Table 1, Invited authors
I=[ 124, 862, 725, 281, 2;
    192, 1501, 2134, 1477, 22];

IT = sum(I,2);
% IT is (1994, 5326) but total is (2040, 5499)

ITT = sum(IT);
% ITT is 7320 but total is 7539

% V(category, invitee, convener)
V(:,F,F) = [38, 309, 258, 93, 2];
V(:,M,F) = [49, 386, 532, 354, 7];
V(:,F,M) = [86, 542, 458, 186, 0];
V(:,M,M) = [141, 1099, 1570, 1100, 15];

VTF = sum( squeeze(V(:,1:2,F)) , 1 );
% VTF is (700, 1328) but Total is (716, 1365)

VTM = sum( squeeze(V(:,1:2,M)) , 1 );
% VTM is (1272, 3925) but Total is (1302, 4059)

VTT = sum(V(:));
% VTT is 7225 but Total is 7442

figure(1);
clf;
set(gca, 'LineWidth',2);
set(gca, 'FontSize',14);
hold on;
axis( [-1, 6, 0, 50] );
title('Reproduce Ford et al.'s Figure 3A');
for ic = [1:5]
    p=100*V(ic,F,F)/(V(ic,F,F)+V(ic,M,F));
    plot( [ic,ic]', [0,p]', 'g-', 'LineWidth', 3 );

    p=100*V(ic,F,M)/(V(ic,F,M)+V(ic,M,M));
    plot( [ic,ic]'+0.2, [0,p]', 'k-', 'LineWidth', 3 );

    p = 100*A(F,ic)/(A(F,ic)+A(M,ic));
    plot( [ic-0.1,ic+0.3]', [p,p]', 'k-', 'LineWidth', 2 );
end

```



```

ic=0;
p=100*sum(squeeze(V(:,F,F)))/(sum(squeeze(V(:,F,F)))+
sum(squeeze(V(:,M,F)))));
plot([ic,ic]',[0,p]','g-', 'LineWidth', 3);

p=100*sum(squeeze(V(:,F,M)))/(sum(squeeze(V(:,F,M)))+
sum(squeeze(V(:,M,M)))));
plot([ic,ic]'+0.2,[0,p]','k-', 'LineWidth', 3);

p = 100*AT(F)/(AT(F)+AT(M));
plot([ic-0.1,ic+0.3]',[p,p]','k-', 'LineWidth', 2);

% professional cartegories 2:4

AP = squeeze(sum(A(:,2:4),2));
fAPF = AP(F)/(AP(F)+AP(M));
fAPM = AP(M)/(AP(F)+AP(M));
pAPF = 100*fAPF;
pAPM = 100*fAPM;
APT = sum(AP(:));

VP = squeeze(sum(V(2:4,:,:),1));
fVPPF = VP(F,F)/(VP(F,F)+VP(M,F));
fVPPM = VP(F,M)/(VP(F,M)+VP(M,M));
fVPMF = VP(M,F)/(VP(F,F)+VP(M,F));
fVPMM = VP(M,M)/(VP(F,M)+VP(M,M));
pVPPF = 100*fVPPF;
pVPPM = 100*fVPPM;
VPT = sum(VP(:));
fVPPFA = (VP(F,F)+VP(F,M))/VPT;
fVPPMA = (VP(M,F)+VP(M,M))/VPT;
pVPPFA = 100*fVPPFA;

fprintf('Part 1\n');
fprintf('Total Professional Abstracts %.0f F + %.0f M = %.0f\n', AP(F),
AP(M), APT);
fAPF;
fprintf('Rate females %.2f yields %.0f\n', fAPF, fAPF*APT);
fprintf('\n');

fprintf('Total Professional Invitees %.0f FF + %.0f MF + %.0f FM + %.0f MM
=\n', VP(F,F), VP(M,F), VP(F,M), VP(M,M));
fprintf('Total Professional Invitees %.0f AF + %.0f AM
=\n', VP(F,F)+VP(M,F), VP(F,M)+VP(M,M));
fprintf('Total Professional Invitees
%.0f\n', VP(F,F)+VP(M,F)+VP(F,M)+VP(M,M));

```

## Part 2

test of first two inversion formulas, Error = 0.000

XFFobs 0.341615 DFpre 0.143187

XFMobs 0.239354 DMpre -0.105487

D 2.463053

Robs 1.072513 bpre 1.083392 Rcheck 1.072513

C 6797.123016

Consistency check

NFF 660.0 660.0

NMF 1272.0 1272.0

NFM 1186.0 1186.0

NMM 3769.0 3769.0

```
% Part 2: Simple Rate Model
clear all;

fA = 0.28;
fprintf('Part 2\n');

% check of my first two inversion formulas
E = 0;
for i=[1:10]

    DF = random('Uniform',-0.10,0.10,1,1);
    DM = random('Uniform',-0.10,0.10,1,1);
    b=0.95;
    C=1;

    NFF = C*(1+DF)*fA*b*fA;
    NMF = C*(1-DF)*(1-fA)*b*fA;
    NFM = C*(1+DM)*fA*(1-b*fA);
    NMM = C*(1-DM)*(1-fA)*(1-b*fA);

    XFF = NFF/(NFF+NMF);
    XFM = NFM/(NFM+NMM);

    DFe = (fA-XFF)/(XFF*(2*fA-1)-fA);
    % fprintf('DF obs %.3f pre %.3f error %.3f\n', DF, DFe, DF-DFe );
    E = E + abs(DF-DFe);

    DMe = (fA-XFM)/(XFM*(2*fA-1)-fA);
    % fprintf('DM obs %.3f pre %f error %.3f\n', DM, DMe, DM-DMe );
    E = E + abs(DM-DMe);
end
fprintf('test of first two inversion formulas, Error = %.3f\n', E );

% inversion of professional category data

% Professional category data
fA = 0.28;
NFFobs = 660;
```

```

NMFobs = 1272;
NFMobs = 1186;
NMMobs = 3769;

XFFobs = NFFobs/(NFFobs+NMFobs);
DFpre = (fA-XFFobs)/(XFFobs*(2*fA-1)-fA);
fprintf('XFFobs %f DFpre %f\n', XFFobs, DFpre );

XFMobs = NFMobs/(NFMobs+NMMobs);
DMpre = (fA-XFMobs)/(XFMobs*(2*fA-1)-fA);
fprintf('XFMobs %f DMpre %f\n', XFMobs, DMpre );

D = ((1-DFpre)*(1-fA)) / ((1+DMpre)*fA);
fprintf('D %f\n', D );

Robs = NMFobs/NFMobs;
Q = Robs/D;
bpre = Q / (fA*(1+Q));
Rcheck = ((1-DFpre)*(1-fA)*bpre*fA) / ((1+DMpre)*fA*(1-bpre*fA));

fprintf('Robs %f bpre %f Rcheck %f\n', Robs, bpre, Rcheck);

Cpre = NFFobs / ( (1+DFpre)*bpre*fA*fA);
fprintf('C %f\n', Cpre );

NFFpre = Cpre*(1+DFpre)*fA*bpre*fA;
NMFpre = Cpre*(1-DFpre)*(1-fA)*bpre*fA;
NFMpre = Cpre*(1+DMpre)*fA*(1-bpre*fA);
NMMpre = Cpre*(1-DMpre)*(1-fA)*(1-bpre*fA);

fprintf('Consistency check\n');
fprintf('NFF %.1f %.1f\n', NFFobs, NFFpre );
fprintf('NMF %.1f %.1f\n', NMFobs, NMFpre );
fprintf('NFM %.1f %.1f\n', NFMobs, NFMpre );
fprintf('NMM %.1f %.1f\n', NMMobs, NMMpre );

```