

## Online Supplementary Information

### *A. Simulating different environments*

We created 4 different types of environments:

1. **Constant and homogeneous environment across habitat patches:** Under this type of environment, the  $E$  values in all habitat patches are set to 0.5 and do not change over time.
2. **Constant and heterogeneous environment across habitat patches:** Under this type of environment, the  $E$  value in each of the habitat patches is independently drawn from a normal distribution with  $\mu = 0.5$  and  $\sigma = 0.2$ , and bounded between 0 and 1. The  $E$  values do not change over time. Supplementary Figure S1 shows 10 independent samples of this type of environment.

Examples of Static and Heterogeneous Environment

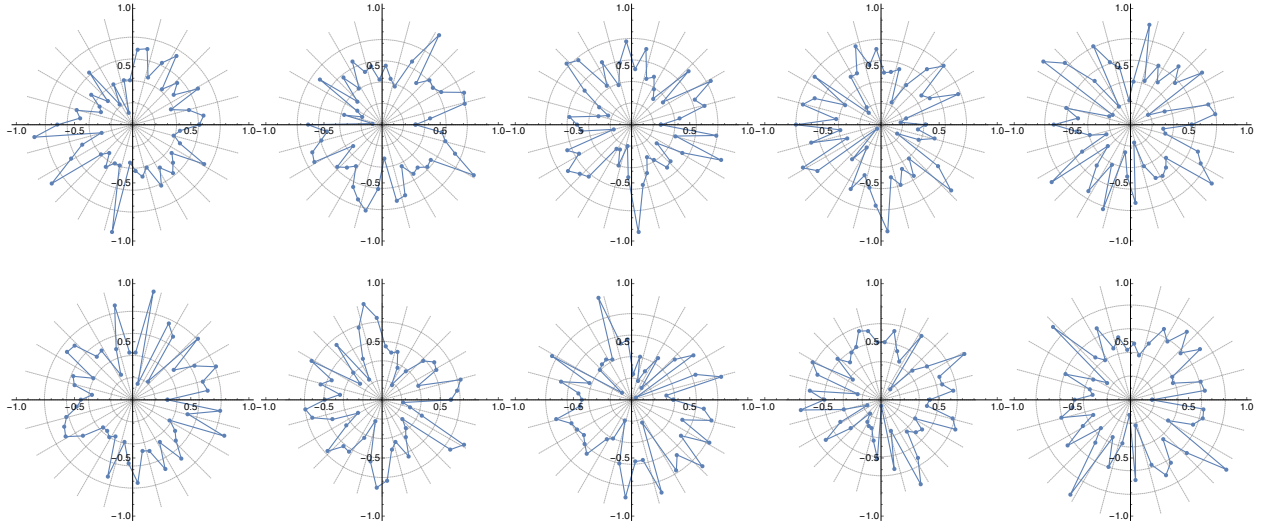


Figure S1: Independent examples of the environmental states ( $E$  values) across the 50 habitat patches (shown as radially-arranged points) under the static but spatially heterogeneous environment.

3. **Heterogeneous and mildly fluctuating environment**, and

4. **Heterogeneous and strongly fluctuating environment**: When simulating these two types of environment, we assume that the  $E$  values are spatially autocorrelated across space so that nearby patches tend to have similar values. In addition, we allow  $E$  to change over time within each patch, with temporal autocorrelation. The environmental state  $E$  on patch  $j$  at generation  $t$ ,  $E_j(t)$ , is determined first by calculating its spatial component  $E_j^s(t) = p_s \langle E_j(t-1) \rangle + (1 - p_s) \zeta$ , in which  $p_s$  ranges between 0 and 1, adjusting the degree of spatial autocorrelation,  $\langle E_j(t-1) \rangle$  is the mean environment condition on patch  $j$  and its two closest neighbours at the previous generation, and  $\zeta \in (0, 1)$  is a uniformly-distributed random number. After the spatial component, temporal autocorrelation is incorporated to update  $E_j(t)$ , so that  $E_j(t) = p_t E_j(t-1) + (1 - p_t) E_j^s(t)$ , where  $p_t$  also ranges between 0 and 1, adjusting the degree of temporal autocorrelation.

We initialise the environment by first setting  $E$  to 0 or 1 with equal probability for each patch, and then letting the environment update for 500 generations, ensuring the environment has reached a dynamic equilibrium (corresponding to the specified levels of spatial and temporal autocorrelation) before introducing the population. We set  $p_s = p_t = 0.7$  for simulating the heterogeneous and mildly fluctuating environment, and set  $p_s = p_t = 0.5$  for simulating the heterogeneous and strongly fluctuating environment.

Note that the method we use here for simulating spatially and temporally autocorrelated environmental fluctuation means that the spatial and temporal autocorrelations are not independent of each other; this method was chosen for computational efficiency (a theoretically better method would be to use a 2D Gaussian field with space and time on each axis, but this would necessitate constructing and calculating the singular value decomposition of matrices of size  $(5 \times 10^5) \times (5 \times 10^5)$  for simulating the environmental states on 50 patches for  $10^4$  generations, which is computationally not feasible). Because of this limitation, we did not vary  $p_s$  and  $p_t$  independently of each other, and simply examined a pair of high

values and a pair of lower values. Supplementary Figure S2 shows a sample series of the environmental states across habitats through 10 consecutive generations for each of the high/low environmental fluctuation regimes.

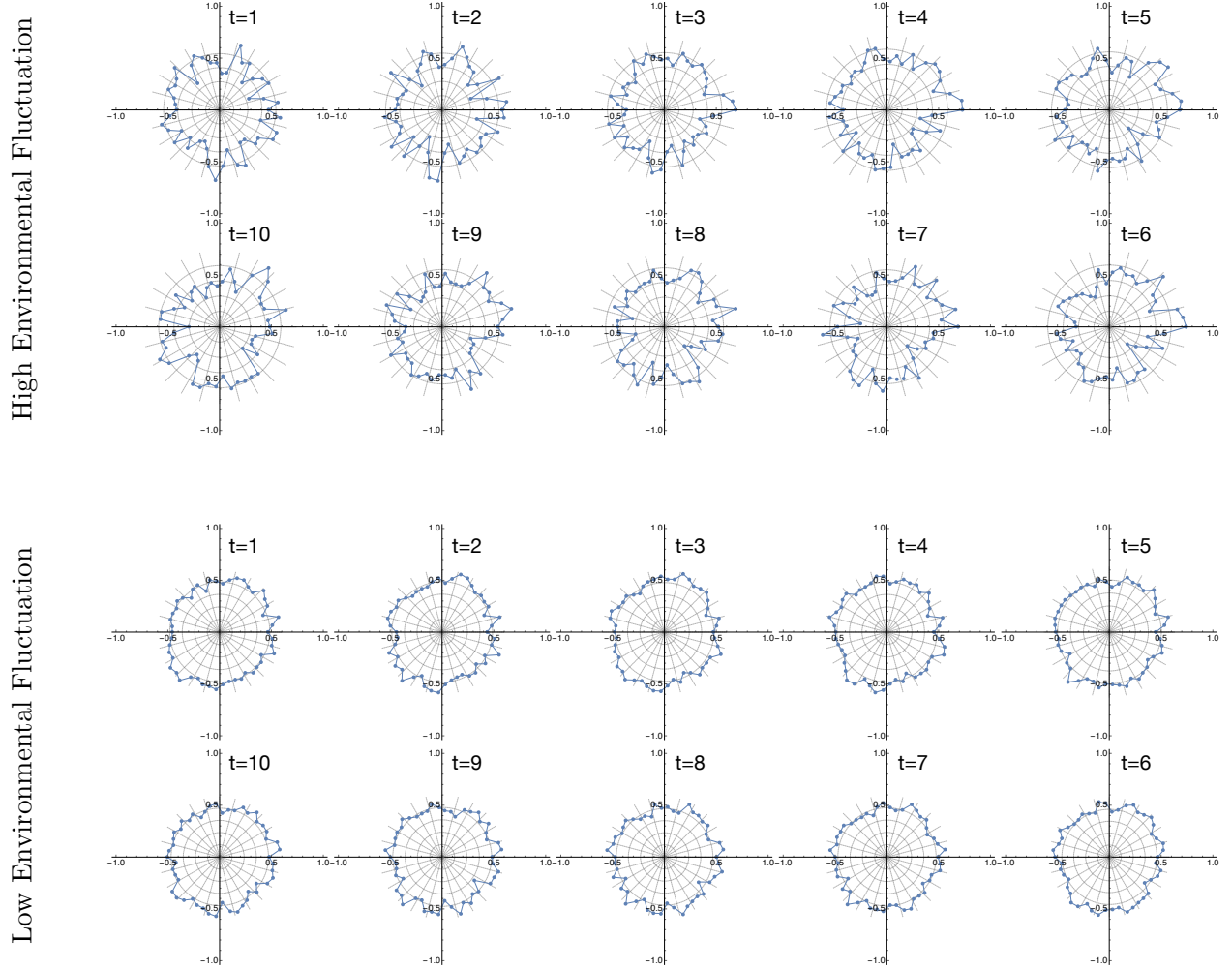


Figure S2: The environmental states ( $E$  values) of the 50 habitat patches (shown as radially-arranged points), under strong or mild environmental fluctuations ( $p_s = p_t = 0.7$  or  $p_s = p_t = 0.5$  respectively).

When sexual conflict arises from different environmental optima between males and females, we generate another environmental state  $E'$  to determine the environmental component of indi-

vidual condition. The  $E'$  environment is of the same type (e.g. have the same degree of spatial and temporal variations) as  $E$  in the corresponding simulations, but generated independently.

### *B. Representing female preferences using the beta function*

Sexual selection models involving female choice typically assume that females either mate randomly or prefer mating with high-condition males if they are allowed to choose [1–3]. The assumption is appropriate if the relationship between genotype and fitness is concordant between the sexes. But when at least some loci have sexually antagonistic effects on fitness, choosy females must trade off the fitness of sons and daughters, and it becomes harder to differentiate males that are well-adapted to the environment from males that are simply well-adapted to being male. With this in mind, we sought to use a more flexible female preference function than in previous models, which would also allow the evolution of preferences for low- or intermediate-condition males, if such preferences were advantageous.

Therefore, we represent the preference for a male with condition  $\xi$  as  $\mathcal{B}(\xi; \alpha, \beta) = \Gamma(\alpha)\Gamma(\beta)/\Gamma(\alpha + \beta)$ . Supplementary Figure S3 illustrates the change of female relative preference as the two shape parameters  $\alpha$  and  $\beta$  vary. When  $\alpha$  is fixed, increasing  $\beta$  causes females to increase their preference for low-condition males while decreasing preference for high-condition males; when  $\beta$  is fixed, increasing  $\alpha$  causes females to increase preference for high-condition males and decrease preference for low-condition males. When  $\alpha = \beta = 1$ , females prefer males of all conditions equally, representing random mate choice.

Qualitatively, the female preference function is increasing (females prefer high-condition males over low-condition males) when  $\alpha \geq 1$  and  $\beta < 1$ , and decreasing (females prefer low-condition males over high-condition males) when  $\alpha < 1$  and  $\beta \geq 1$ .

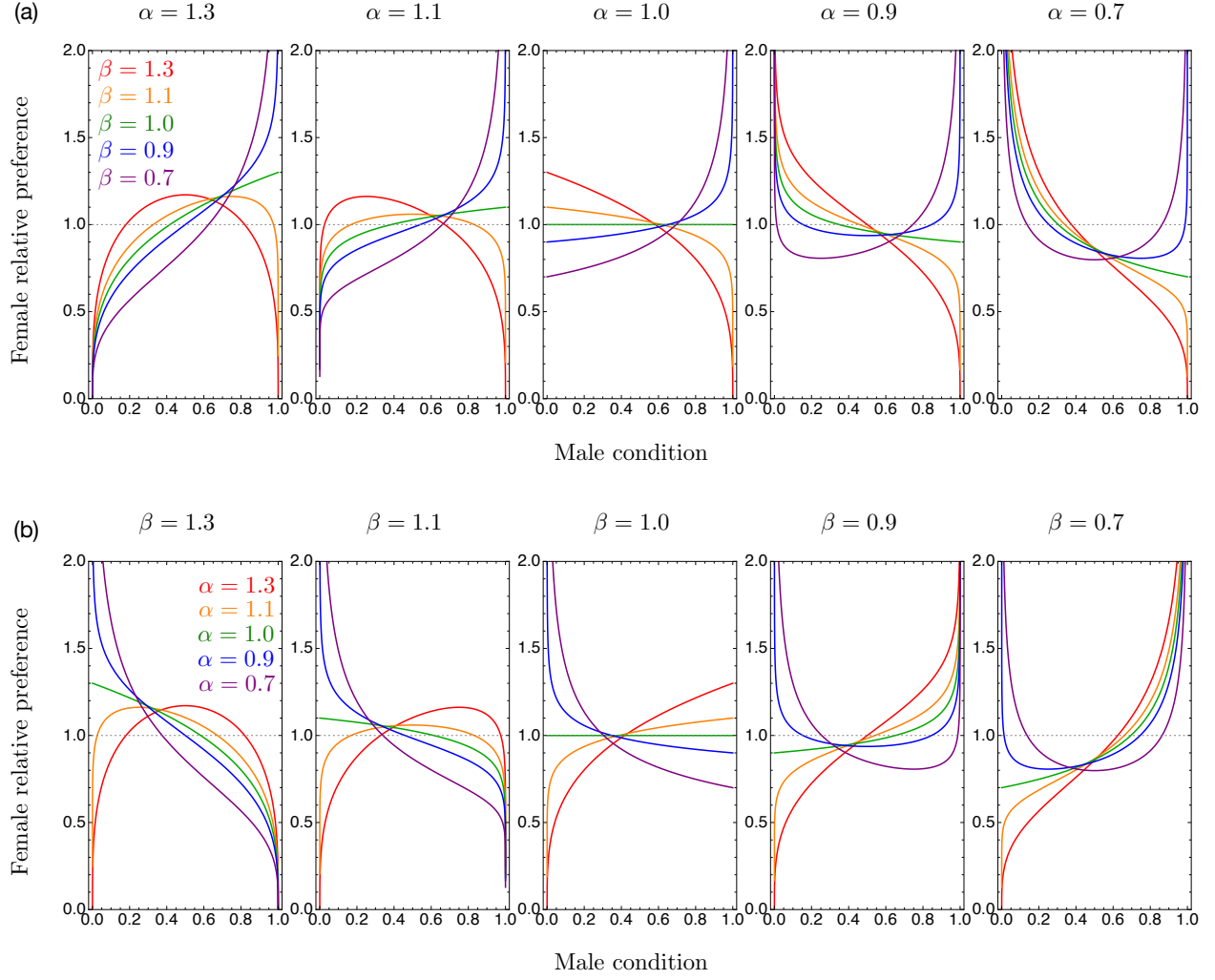


Figure S3: Examples of female relative preference as a function of male condition  $\zeta$  modelled by the beta distribution function as the values of  $\alpha$  and  $\beta$  vary. By allowing the loci controlling  $\alpha$  and  $\beta$  to evolve, our model potentially allows the evolution of a wide range of monotonic and non-monotonic female preference functions.

### C. Additional results

#### *Evolved dispersal probability under different types of environments*

In Figure 2 of the main text, we showed the evolved dispersal probability of males and females at equilibrium under static and homogeneous environment across habitat patches. The results are similar under the other 3 types of environment, as shown in Figure S4. The sex-specific equilibrium dispersal probability is featured with a male-bias under small  $k_{LA}$  values throughout all cases.

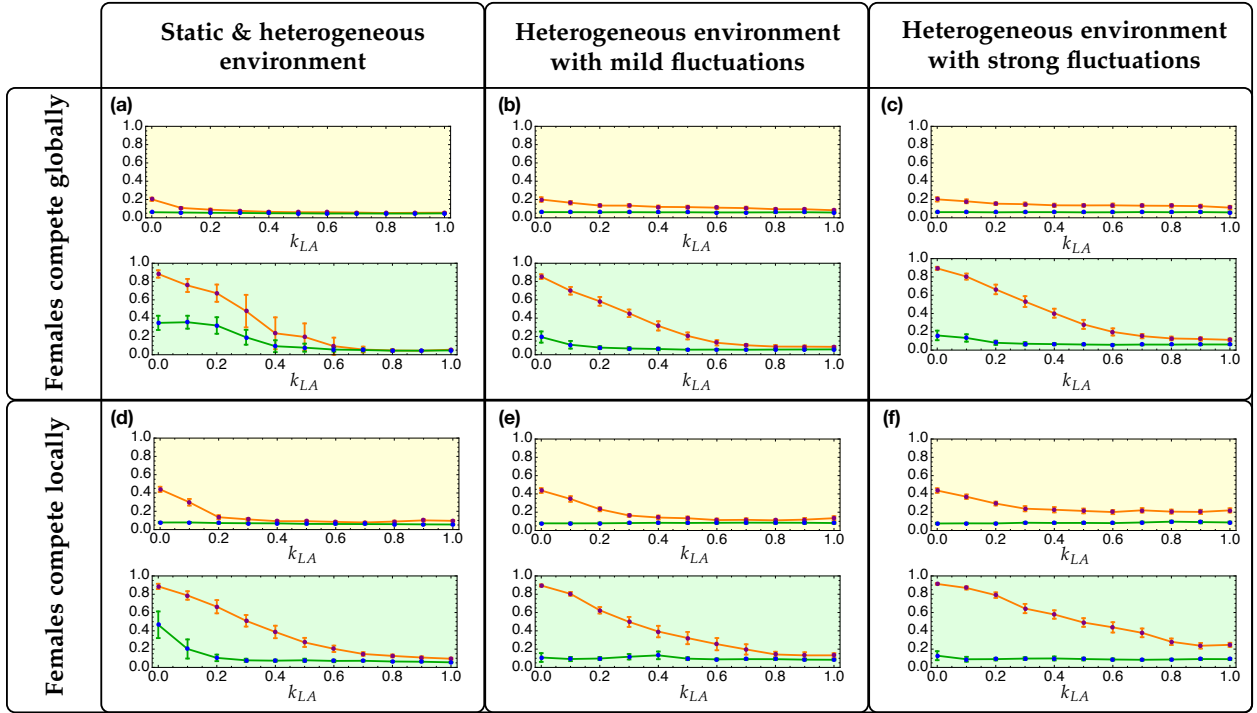


Figure S4: Equilibrium dispersal probability of males (orange) and females (green) under different intensity of sexual conflict, when females compete either globally or locally. Panels with yellow background represent the cases where sexual conflict arises from IASC, and panels with green background represent the cases where males and females have different environmental optima. The error bar plots show the mean and standard deviation of 30 independent simulation realisations.

## Effect of female choice on individual condition under different environment types

In Figure 4 of the main text, we showed the effect of female choice on individual conditions when the environment is static but heterogeneous across habitat patches. Here we show in Figure S5 that qualitatively similar results also hold under different types of environment.

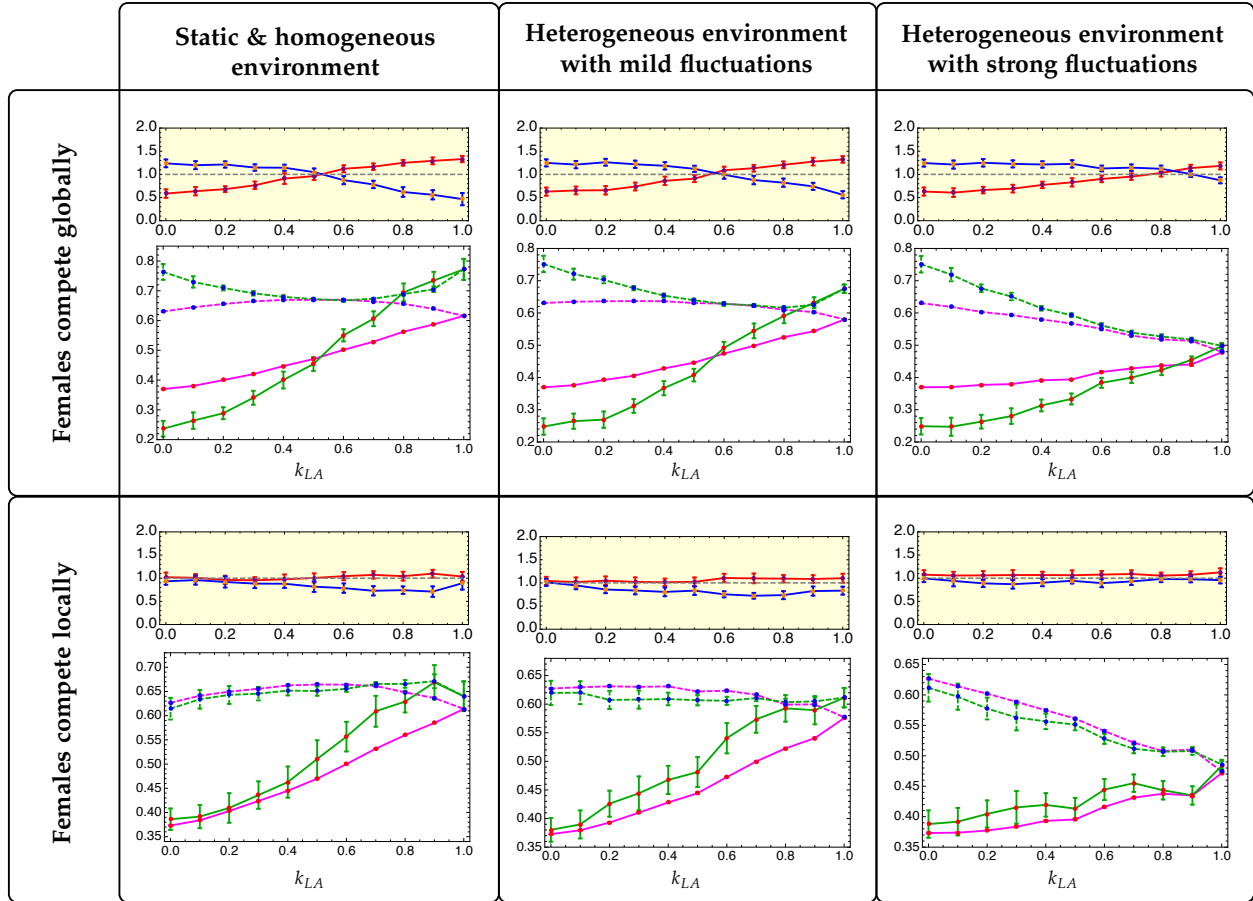


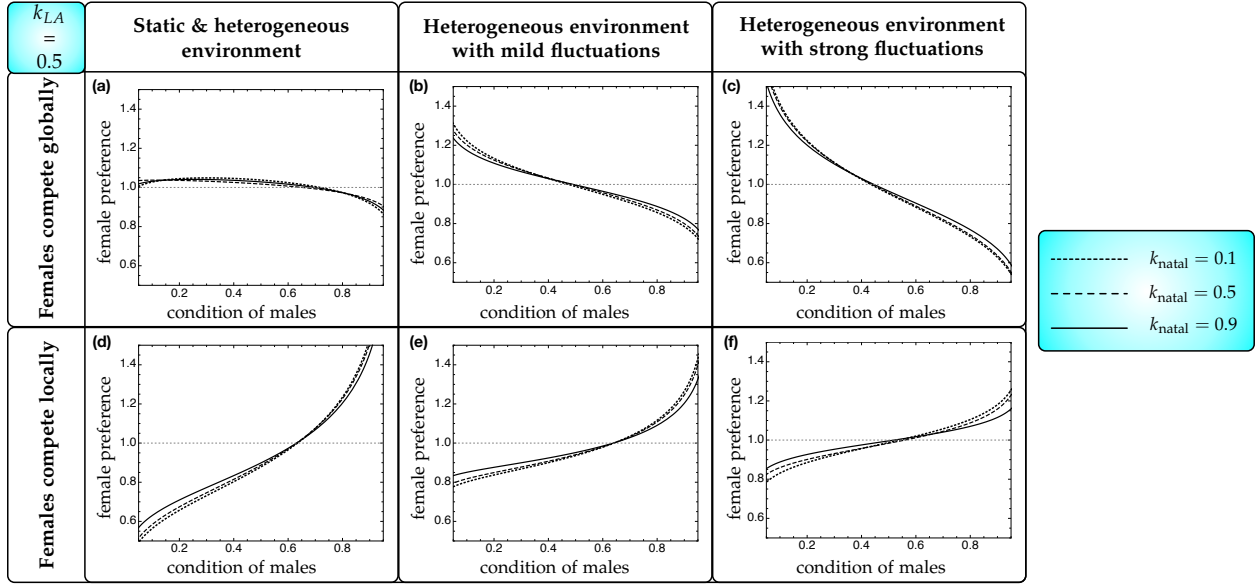
Figure S5: Evolved  $\alpha$  (red) and  $\beta$  (blue) values and corresponding equilibrium condition of males (solid line and red marker) and females (dashed line and blue marker) when female choice is either allowed (green) or prevented intentionally (magenta), when females compete either globally or locally under 4 different types of environment. Each data point in the error plots and represents the mean and standard deviation of 30 independent simulations. Sexual conflict arises from IASC.

As illustrated in Figure S5, under global competition (hard selection), choosy females always have higher or equal condition than females that are forced to mate randomly. But when selection is soft, choosy females can be trapped in a “tragedy of the commons” scenario due to competition for producing attractive sons (via mating with high-condition males) when sexual conflict is strong ( $k_{LA}$  is small).

***Does it matter whether condition is determined in the natal or breeding habitat?***

We find that slightly stronger female choice evolves when condition is determined primarily in the breeding patch rather than the natal patch (i.e. when  $k_{natal}$  is low), irrespective of whether high-condition or low-condition males are preferred (Figure S6). This result is intuitive because with low  $k_{natal}$ , females gain more information about adaptation to the environment of the breeding patch from male condition, which increases the benefit of condition-based choice, assuming that all else is equal and that most offspring remain in the breeding patch. As expected, the effect of  $k_{natal}$  on female preference is larger when local adaptation, rather than IASC, is the main determinant of condition. As shown in Figure S6, the impact of  $k_{natal}$  is slightly larger when local adaptation plays a major role in determining individual condition ( $k_{LA} = 0.9$ ) than when local adaptation and sexual conflict are equally important ( $k_{LA} = 0.5$ ).

**Local adaptation and sexual conflict are equally important in determining individual condition**



**Local adaptation is strong and sexual conflict is weak**

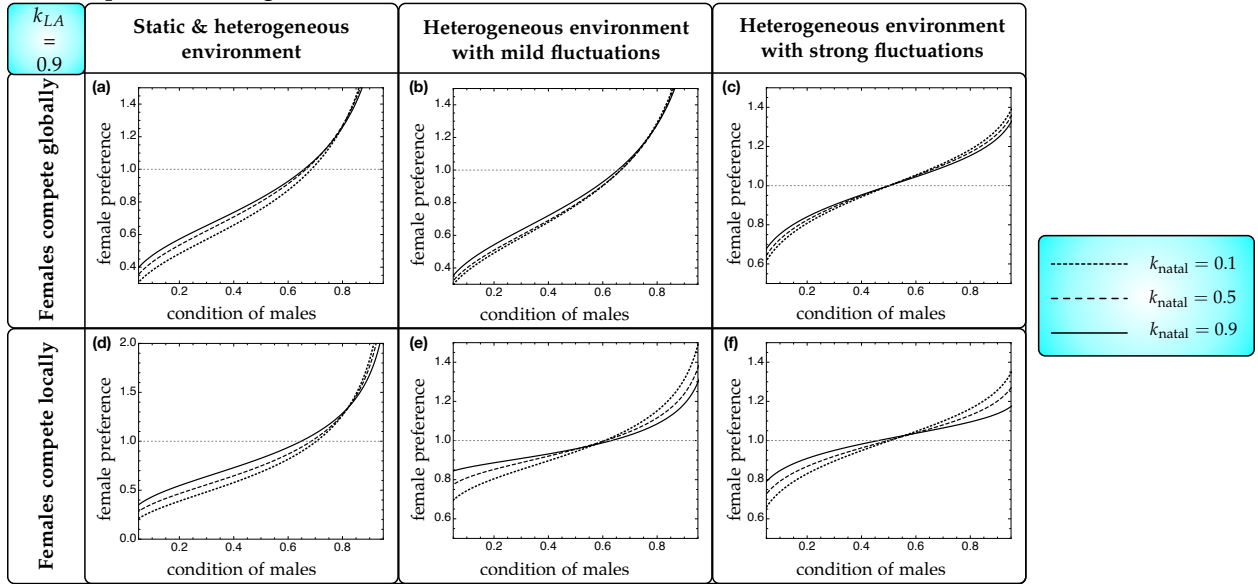


Figure S6: The effect of the relative weight of the natal habitat in determining individual condition ( $k_{natal}$ ) on female preference under different environments and different scale of female competition. Each curve is plotted using the mean  $\alpha$  and  $\beta$  values calculated from the last 2000 generations of 30 independent realisations. In all simulations, sexual conflict arises from the IASC locus, and the sex-specific dispersal probabilities can coevolve with female choice.

## References

- [1] Hanna Kokko, Robert Brooks, John M McNamara, and Alasdair I Houston. The sexual selection continuum. *Proceedings of the Royal Society of London B: Biological Sciences*, 269:1331–1340, 2002.
- [2] Klaus Reinhold. Modeling a version of the good-genes hypothesis: Female choice of locally adapted males. *Organisms Diversity & Evolution*, 4:157–163, 2004.
- [3] Luke Holman and Hanna Kokko. Local adaptation and the evolution of female choice. In *Genotype-by-Environment Interactions and Sexual Selection*, pages 41–62. John Wiley & Sons, 2014.