Heterogeneity in effective size across the

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# genome: effects on the Inverse Instantaneous Coalescence Rate (IICR) and implications for demographic inference under linked selection Simon Boitard<sup>\*</sup>, Armando Arredondo<sup>†</sup>, Camille Noûs<sup>‡</sup>, 5 Lounès Chikhi<sup>§,\*\*</sup>, Olivier Mazet<sup>†</sup> 6 \*: CBGP, Université de Montpellier, CIRAD, INRAE, Institut Agro, IRD, 7 Montpellier, France. <sup>†</sup>: Université de Toulouse, Institut National des Sciences Appliquées, Institut de Mathématiques de Toulouse, Toulouse, France. 10 <sup>‡</sup>: Laboratoire Cogitamus, Toulouse, France. <sup>§</sup>: Instituto Gulbenkian de Ciência, Oeiras, Portugal 12 \*\*: Laboratoire Évolution & Diversité Biologique (EDB UMR 5174), CNRS, IRD, UPS, Université de Toulouse Midi-Pyrénées, Toulouse, France

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## <sup>26</sup> Abstract

The relative contribution of selection and neutrality in shaping species genetic diversity is 27 one of the most central and controversial questions in evolutionary theory. Genomic data 28 provide growing evidence that linked selection, i.e. the modification of genetic diversity 29 at neutral sites through linkage with selected sites, might be pervasive over the genome. 30 Several studies proposed that linked selection could be modelled as first approximation 31 by a local reduction (e.g. purifying selection, selective sweeps) or increase (e.g. balancing 32 selection) of effective population size  $(N_e)$ . At the genome-wide scale, this leads to a large 33 variance of  $N_e$  from one region to another, reflecting the heterogeneity of selective con-34 straints and recombination rates between regions. We investigate here the consequences 35 of this variation of  $N_e$  on the genome-wide distribution of coalescence times. The underly-36 ing motivation concerns the impact of linked selection on demographic inference, because 37 the distribution of coalescence times is at the heart of several important demographic 38 inference approaches. Using the concept of Inverse Instantaneous Coalescence Rate, we 39 demonstrate that in a panmictic population, linked selection always results in a spurious 40 apparent decrease of  $N_e$  along time. Balancing selection has a particularly large effect, 41 even when it concerns a very small part of the genome. We quantify the expected mag-42 nitude of the spurious decrease of  $N_e$  in humans and Drosophila melanogaster, based on 43  $N_e$  distributions inferred from real data in these species. We also find that the effect of 44 linked selection can be significantly reduced by that of population structure. 45

## 46 Introduction

47 One of the greatest challenges of evolutionary biology is to understand how natural se48 lection, mutation, recombination and genetic drift have shaped and are still shaping the

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patterns of genomic diversity of species living today (Charlesworth, 2010, Lewontin, 1974, 49 Walsh and Lynch, 2018). In the last decade genomic data have become increasingly avail-50 able for both model and non-model species. It is expected that by analysing these genomic 51 data we will be able to better understand the respective roles of mutation and recombi-52 nation and characterize the relative importance of drift and selection in evolutionary 53 processes (Charlesworth, 2010, Lewontin, 1974). In particular, it is believed that we will 54 be able to identify the regions that have been shaped by selection, and those that may be 55 more neutral (Johri et al., 2020, Pouvet et al., 2018). The relative importance of selection 56 and neutrality in generating the genomic patterns of diversity we see today has been at 57 the heart of many evolutionary debates and controversies over the last decades (Kimura, 58 1983, Lewontin, 1974, Ohta, 1992) and recent studies suggest that it still is (Comeron, 59 2017, Jensen et al., 2019, Kern and Hahn, 2018). 60

The concept of effective size  $(N_e)$  is central to these debates (Charlesworth, 2009) 61 because selection is expected to be more efficient when  $N_e$  is large, and genetic drift to 62 be the main driver of evolutionary change when  $N_e$  is small (Ohta, 1992). For instance, 63 Charlesworth (2009) notes that it is expected that an autosomal locus under positive 64 selection will behave neutrally when  $s < 1/4N_e$ , where s is the selection intensity at this 65 locus. At the same time it is commonly assumed that selection will itself imply a variation 66 of  $N_e$  across the genome (Charlesworth, 2009, Gossmann et al., 2011, Jiménez-Mena et al., 67 2016b). For instance, Gossmann et al. (2011) write that "The effective population size 68 is expected to vary across the genome as a consequence of genetic hitchhiking (Smith and 69 Haigh, 1974) and background selection (Charlesworth et al., 1993)". They add that "The 70 action of both positive and negative natural selection, is expected to reduce the effective 71 population size leading to lower levels of genetic diversity and reduced effectiveness of 72 selection." They also stress that "The evidence that there is variation in  $N_e$  within a 73

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genome comes from three sources. First, it has been shown that levels of neutral genetic 74 diversity are correlated to rates of recombination in Drosophila [...], humans [...], and 75 some plant species...". In his 2009 review on the concept of  $N_e$  Charlesworth (2009) 76 made a similar comment: " $N_e$  may also vary across different locations in the genome of a 77 species [...] because of the effects of selection at one site in the genome on the behaviour of 78 variants at nearby sites". More recently, Jiménez-Mena et al. (2016a) stated that "recent 79 studies [...] suggest that different segments of the genome might undergo different rates 80 of genetic drift, potentially challenging the idea that a single  $N_e$  can account for 81 the evolution of the genome" (emphasis ours). 82

Under these explicit or implicit modelling frameworks, genomic regions with limited 83 genetic diversity are thus seen as regions of low  $N_e$  as a result of selective sweeps (Smith 84 and Haigh, 1974) or background selection (Charlesworth et al., 1993), whereas regions 85 with very high levels of genetic diversity may be seen as regions of large  $N_e$  and could 86 be explained by balancing selection (Charlesworth, 2009) (see also Hill and Robertson 87 (1966)). Following that rationale, Jiménez-Mena et al. (2016b) suggested that different 88 species might thus differ in the statistical distribution of  $N_e$  across the genome and they 89 presented such distributions for eleven species. 90

Given the central role played by the  $N_e$  concept to detect, identify, and even *conceptual*-91 *ize* selection, it may be important, perhaps even enlightening, to explore the consequences 92 of the ideas presented above with the concept of IICR (inverse instantaneous coalescence 93 rate) recently introduced by Mazet et al. (2016). Indeed, the IICR is equivalent to the 94 past temporal trajectory of  $N_e$ , previously defined as the coalescent  $N_e$  (Sjödin et al., 95 2005), in a pannictic population under neutrality, and it is the quantity estimated by the 96 popular PSMC method of Li and Durbin (2011). The IICR was first defined by Mazet 97 et al. (2016) for a sample size of two and its properties were studied under several models 98

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of population structure (Chikhi et al., 2018, Grusea et al., 2018, Rodríguez et al., 2018) 99 and it has been shown that it can be used for demographic inference under neutrality 100 and models of population structure Arredondo et al. (2021), Chikhi et al. (2018). These 101 studies showed that the IICR will significantly change over time when populations are 102 structured, even when population size is actually constant. They also outlined that the 103 IICR not only depends on the model of population structure but also on the sampling 104 scheme, which questions the notion that an  $N_e$  can be easily associated to (or is a property 105 of) the model of interest when the model is structured (Chikhi et al., 2018, Rodríguez 106 et al., 2018). The reason for this dependency is that the IICR is by definition a function 107 of the distribution of coalescence times for two genes  $(T_2)$ , which is itself a function of 108 both the evolutionary model and the location (in time and space) of the sampled genes. 109

One important assumption of the IICR studies mentioned above is that this distri-110 bution of  $T_2$  is homogeneous along the genome. The IICR, as defined and computed in 111 previous studies, is thus a genomic average assuming that all loci follow a single Wright-112 Fisher model with or without population structure but with the same number of haploid 113 genes. Whichever definition of  $N_e$  one assumes, the underlying model assumes that  $N_e$  is 114 constant along the genome. If we now assume that there is an  $N_e$  that varies across the 115 genome as a consequence of selection (even as an approximation) then the IICR should 116 be a function of the underlying distribution of these  $N_e$  values across the sampled genes. 117 Genomic regions under different selection regimes might then exhibit specific signatures 118 leading to differing IICR curves for each region. Alternatively, these regions might not be 119 easy to identify but they might still influence the average genomic IICR estimated from 120 sequenced genomes. In the present study we thus wish to explore ideas related to drift, 121 selection and patterns of genomic diversity by studying the consequences of this putative 122 genomic variation of  $N_e$  on the IICR. 123

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We first study the IICR under panmixia and constant population size but assuming 124 that  $N_e$  can vary across the genome, using hypothetical distributions of  $N_e$  and distribu-125 tions inferred from genomic data. We then generalise the model to integrate population 126 structure or population size variation through time. In particular we consider a structured 127 model in which we allow several classes of genomic regions to evolve under different n-128 island models each characterized by a specific deme size. We also apply this approach to a 129 structured model inferred for humans, which includes temporal variations of the migration 130 rate between demes. Finally, we consider temporal variations of the genomic  $N_e$  to model 131 possible transitory effects of selection under panmixia. Altogether, we advocate the use 132 of the IICR as a concept that may help clarify what  $N_e$  means and as one way, among 133 others, to improve our understanding of the recent and ancient evolutionary history of 134 species. 135

## <sup>136</sup> The IICR under panmixia with several classes of (con-<sup>137</sup> stant size) $N_e$ along the genome

## $_{138}$ Model

We assume that the genome can be divided in K independent classes, each of them characterized by a different  $N_e$  that is constant over time. To model these differences of  $N_e$ , we consider that each class i (i = 1...K) evolves under a constant size Wright-Fisher (WF) model (*i.e.* panmictic with non-overlapping generations) with diploid population size  $\lambda_i N$  (2  $\lambda_i N$  haploids), for some reference population size N corresponding to the actual number of diploids. Note that 2N represents an actual number of haploid genomes and that under the WF model, there is no ambiguity and N represents the  $N_e$  under

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neutrality. Thus,  $\lambda_i$  reflects the ratio of effective population size  $N_e$  in class i relative to 146 N and for convenience we may sometimes refer to  $\lambda_i$  as the effective population size in 147 class *i*. Assuming that N is large (i.e. that all  $\lambda_i N$  are large), we rescale time by units 148 of 2N generations and study the coalescence process resulting from this model. If we 149 sample in the present (at time t = 0) k genes for a locus from the  $i^{th}$  class of the genome, 150 the genealogy of this sample will follow a standard coalescent model with coalescence 151 rate  $\mu_i = \frac{1}{\lambda_i}$  between any pair of sequences. This model is associated to the successive 152 coalescence times  $T_j^i$ ,  $j = k \dots 2$ , where  $T_j^i$  is the coalescence time of j lineages sampled 153 in the class i. 154

We will study the properties of the IICR under this model. As a reminder, the IICR was originally defined for a sample of size k = 2 by Mazet et al. (2016), who showed how it could be computed for any model for which  $T_2$  values could be generated (*i.e.* any model under the coalescent possibly involving complex population structure and population size changes).

One important assumption of the previous IICR studies was that the coalescence times obtained along the genome are sampled from the same distribution (under neutrality). Here this distribution will depend on class *i*. More precisely, the distribution of  $T_2^i$  is the exponential distribution with parameter  $\mu_i = \frac{1}{\lambda_i}$ , whose probability density function (pdf) is

$$f_i(t) = \mu_i e^{-\mu_i t}, i = 1 \dots K.$$

If the sampled loci are uniformly distributed along the genome and represent an unbiased sample of the genomic  $\lambda_i$  values, and if we denote by  $a_i$  the proportion of the genome corresponding to class *i*, we will then infer a genomic distribution of coalescence time with

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168 pdf

$$f(t) = \sum_{i=1}^{K} a_i f_i(t) = \sum_{i=1}^{K} a_i \mu_i e^{-\mu_i t}.$$
 (1)

## <sup>169</sup> IICR expression and main properties

Denoting F the cumulative distribution function of  $T_2$  and f(t) = F'(t) its pdf, the IICR can be defined Mazet et al. (2016) in the most general case as:

$$\mathrm{IICR}(t) = \frac{R(t)}{f(t)}$$

172 where

$$R(t) = \mathbb{P}(T_2 \ge t) = 1 - F(t).$$

For our model with K different  $\lambda_i$ , we then have from equation (1):

$$\mathrm{IICR}(t) = -\frac{R(t)}{R'(t)} = \frac{\sum_{i=1}^{K} a_i e^{-\mu_i t}}{\sum_{i=1}^{K} a_i \mu_i e^{-\mu_i t}}.$$
(2)

Thus, the first result on the IICR is that, despite the panmixia and constant size of the population, it is straightforward to see that the IICR is not constant as soon as there are at least two different values of  $\lambda_i$  with non null proportion  $a_i$  across the genome. In other words, the assumption that there is more than one  $N_e$  in the genome means that the IICR will change with time. Classical interpretations of PSMC plots under panmixia will thus lead to the conclusion that the population size changed through time.

To be more specific on the nature of these changes, we now obtain the derivative of the IICR as a function of time (backward from present):

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IICR'(t) = 
$$\frac{R(t)R''(t) - R'(t)^2}{R'(t)^2}$$

<sup>182</sup> which has the sign of

$$\begin{aligned} R(t)R''(t) - R'(t)^2 &= \sum_{i=1}^{K} a_i e^{-\mu_i t} \sum_{j=1}^{K} a_j \mu_j^2 e^{-\mu_j t} - \sum_{i=1}^{K} a_i \mu_i e^{-\mu_i t} \sum_{j=1}^{K} a_j \mu_j e^{-\mu_j t} \\ &= \sum_{i=1}^{K} \sum_{j \neq i} a_i e^{-\mu_i t} a_j e^{-\mu_j t} \mu_j^2 - \sum_{i=1}^{K} \sum_{j \neq i} a_i e^{-\mu_i t} a_j e^{-\mu_j t} \mu_i \mu_j \\ &= \sum_{i=1}^{K} \sum_{j > i} a_i e^{-\mu_i t} a_j e^{-\mu_j t} (\mu_i^2 + \mu_j^2 - \mu_i \mu_j - \mu_j \mu_i) \\ &= \sum_{i=1}^{K} \sum_{j > i} a_i e^{-\mu_i t} a_j e^{-\mu_j t} (\mu_i - \mu_j)^2 \end{aligned}$$

This quantity is always positive so we can conclude that the IICR is always increasing from t = 0 to  $t = +\infty$  (*i.e.* backward in time). In a stationary pannictic population, the fact that there are at least two  $N_e$  across the genome  $(\lambda_i, i > 1)$  means that we will always infer a decreasing IICR (forward in time) typically interpreted as an apparent but spurious population size decrease. Interestingly, it could also be interpreted as the spurious presence of population structure since population structure can also generate similar changes in the IICR.

## <sup>190</sup> Detailed results with a two-class model

These properties can be observed in Figure 1 where we represent the simplest case with K = 2 classes of genomic regions. In this figure we present the IICRs for  $\lambda_1 = 0.1$ 

and  $\lambda_2 = 1$ , for proportions of  $\lambda_2$  (represented by the parameter  $a_2$ ) varying from 0 to 1. Consistent with the choice made in most studies inferring past population size changes, time is plotted in log10 scale in this Figure and all others shown in the main text. Equivalent figures with time plotted in natural scale are provided in the Supplementary Material, because they may sometimes lead to slightly different interpretations.



Figure 1: IICR curves for a panmictic model with K = 2 classes of genomic regions with constant size. Genomic regions of class i (i = 1, 2) have a constant population size  $\lambda_i N$ , with  $\lambda_1 = 0.1$  and  $\lambda_2 = 1$ . Their frequencies are  $a_1$  and  $a_2$ , respectively, with  $a_1 + a_2 = 1$ . The IICR curves are represented for  $a_2$  values (representing neutrality, see main text) varying between zero and one. Time is plotted in log10 scale.

To simplify the interpretation of our results, we consider (by convention) throughout this manuscript that  $\lambda_i = 1$  corresponds to the neutral regions of the genome, whether  $a_i$ , their relative proportion in the genome, is large or not. We thus do not necessarily

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consider that most of the genome is neutral in that sense. In this setting and in Figure 1, where  $\lambda_1 = 0.1$  and  $\lambda_2 = 1$ ,  $a_1$  can be interpreted as the fraction of the genome showing reduced  $N_e$  by a multiplicative factor  $\lambda_1 = 0.1$  as a consequence of positive or background selection.

Figure 1 thus shows that for small values of  $a_2$  (*i.e.* when most of the genome is under 205  $N_e$ -reducing selection) the IICR is S-shaped, slowly increasing backward from  $\lambda_1 = 0.1$ 206 in the recent past to a plateau at  $\lambda_2 = 1$  in the ancient past. For increasing  $a_2$  values 207 the IICR curves are becoming flatter as their left-most section flattens upward. When 208 using a natural time scale (Figure S1) the curves simply seem to be shifted to the left for 209 increasing  $a_2$  values, the S shape being lost due to the truncation of the leftmost part of 210 the curve. In other words, these curves start (in recent times) at increasing IICR values 211 above  $\lambda_1 = 0.1$  when the value of  $a_2$  increases, but the curves always reach the same 212 plateau at  $\lambda_2 = 1$ . However, and this is an important point, this plateau is reached earlier 213 as  $a_2$  increases. When  $a_2=1$ , only the plateau remains and the IICR is flat at  $\lambda_2=1$  and 214 when  $a_2 = 0$ , it is a flat at  $\lambda_1 = 0.1$ . Thus, when there is only one  $\lambda_i$  over the genome, 215 the IICR is constant over time and equal to that value, as expected for a population with 216 constant size  $\lambda_i N$ . 217

If we now assume that the only type of selection present in the genome increases the 218 effective size by an order of magnitude, with  $a_1$  and  $a_2$  corresponding to  $\lambda_1 = 1$  and 219  $\lambda_2 = 10$ , we obtain exactly the same figure with the only difference that it is rescaled 220 (see Discussion and Figure S2). This figure now shows that even if most of the genome is 221 neutral, tiny amounts of  $N_e$ -increasing selection strongly influence the IICR, as it always 222 grows backward towards the plateau corresponding to the largest of the two  $\lambda_i$  values. It 223 also shows that the recent IICR values can also be significantly greater than one, expected 224 under neutrality. 225

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Altogether Figures 1 and S2 suggest that there is a strong asymmetry between selection reducing (background and positive) or increasing (balancing)  $N_e$  in the genome in the way they affect IICR shapes. Balancing selection generates an ancient and high plateau at the level of  $\lambda_2$ , even for small proportions of  $a_2$  (Figure S2), whereas positive and background selection generate a recent and relatively more modest decrease of the IICR for small values of  $a_1$ , even assuming, as in Figure 1, that these generate a ten-fold decrease in  $N_e$ (Figure 1).

### 233 Extension to more classes

<sup>234</sup> While these observations are limited to the simplest case where there are only two  $\lambda_i$ <sup>235</sup> values, it is straightforward to show that they hold for any number of classes. Indeed, the <sup>236</sup> starting value of the IICR in a model with  $K \lambda_i$  values is

$$IICR(0) = \frac{1}{\sum_{i=1}^{K} a_i \mu_i} = \frac{1}{\sum_{i=1}^{K} \frac{a_i}{\lambda_i}}$$
(3)

237 and the limit value when  $t \to +\infty$  is equal to

$$\frac{1}{\mu_{i_0}} = \lambda_{i_0} = \max_{i=1\dots K} (\lambda_i).$$

The initial value IICR(0) is thus necessarily between the smallest and largest  $\lambda_i$ , as it is the harmonic mean of the  $\lambda_i$ s weighted by their respective proportions  $a_i$ . The asymptotic value IICR(+ $\infty$ ) will always be the largest  $\lambda_i$  found in the genome, *independent* of its proportion. In other words, even if a minute proportion of the genome is under balancing selection, under panmixia the IICR should necessarily plateau in the ancient past to a value corresponding to that  $\lambda_i$ . One intuitive explanation for the IICR growing (backward in time) towards the largest  $\lambda_i$  is that the genes that are characterized by a large  $N_e$ 

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have much larger coalescence times than the rest of the genome. They thus contribute
proportionately more to most ancient part of the IICR curve.

To further explore the influence of both types of selection (reducing and increasing 247  $N_e$ , we considered a model with 3 classes such that  $\lambda_1 < 1$ ,  $\lambda_2 = 1$  and  $\lambda_3 > 1$  (Figure 2). 248 In this Figure we set the three  $\lambda_i$  as  $(\lambda_1, \lambda_2, \lambda_3) = (0.1, 1, 3)$ . As above,  $\lambda_1 < 1$  corresponds 249 to genomic regions under linked positive or background selection,  $\lambda_2 = 1$  corresponds to 250 the neutral part of the genome and  $\lambda_3 = 3$  to genomic regions under linked balancing 251 selection. In the left panel, we considered a fixed small proportion of balancing selection 252  $(a_3 = 0.01)$ , and allowed the proportions of neutral and positive or background selection 253 to vary  $(a_1 \text{ varied from } 0 \text{ to } 0.8, \text{ and thus } a_2 \text{ from } 0.99 \text{ to } 0.19)$ . In the right panel, we 254 considered a fixed and large proportion of positive or background selection  $(a_1 = 0.5)$  and 255 varied the proportion of regions under balancing selection ( $a_3$  from 0 to  $10^{-1}$ ), and thus 256 the proportion of neutral regions too  $(a_2 \text{ between } 0.5 \text{ and } 0.4)$ . 257

Figure 2 shows similarities with Figure 1. Specifically, both figures suggest that regions 258 reducing  $N_e$  impact the IICR curves in the recent past whereas regions increasing  $N_e$ 259 impact the IICR in the ancient past. This is worth stressing given that our model assumes 260 that  $N_e$  is reduced (in class 1) or increased (in class 3) in a stationary way throughout the 261 genealogical history of the sampled genes. Also, small proportions of balancing selection 262 seem to generate much bigger changes than small proportions of positive or background 263 selection, as shown by the comparison of the IICRs obtained for  $a_1 = 0.01$  vs  $a_1 = 0$  on 264 one hand (left panel) and for  $a_3 = 0.01$  vs  $a_3 = 0$  on the other hand (right panel). 265

There are however differences between Figure 2 and Figure 1. The simple fact that we consider both  $N_e$ -reducing and  $N_e$ -increasing forms of selection and thus variable proportions of neutral genomic regions generates complex IICR curves, in which both forms of selection directly or indirectly impact the whole IICR curves. When neutral

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regions are frequent enough ( $a_1 \leq 0.5$  and  $a_3 \leq 0.01$ ), the IICR exhibits a plateau or a 270 flattening at  $\lambda_2$  in its middle section, but for larger values of either  $a_1$  (left panel,  $a_1 = 0.8$ ) 271 or  $a_3$  (right panel,  $a_3 = 0.1$ ) the proportion of neutral genomic regions decreases and the 272 IICR curve only exhibits a short inflexion corresponding to  $\lambda_2 = 1$  before increasing 273 backwards towards  $\lambda_3$ . An interesting pattern related to this intermediate plateau is 274 observed on the left panel when  $a_3$  is fixed: the IICR in the ancient past increases more 275 and quicker (backward in time) for  $a_1 = 0.8$  than for lower values of  $a_1$ , although  $a_1$ 276 models the proportion of low  $N_e$  regions in the region. This counterintuitive result likely 277 comes from the fact that the proportion of neutral regions decreases when  $a_1$  increases, so 278 that the IICR directly increases to its highest possible value ( $\lambda_3 = 3$ ). 279

Despite this complex interplay, Figure 2 provides some insights about our capacity 280 to detect or quantify either type of selection based on the IICR. The left panel suggests 281 that the proportion of the genome under positive or background selection can be assessed 282 from this curve: for large values of  $a_1$ , there is a quick decline of the IICR (forward in 283 time) followed by a low plateau around  $\lambda_1$ , whereas lower  $a_1$  values see a more recent and 284 gradual decrease of the IICR without any clear recent plateau. However, this distinction 285 is far less visible when plotting on a natural scale (Figure S3), in which case  $a_1$  values as 286 different as 0.1 and 0.5 lead to quite similar IICRs. Besides, results on the importance 287 of  $a_1$  are likely exaggerated by the small value of  $\lambda_1$  used in Figure 2, which implies a 288 10-fold reduction of  $N_e$ . In comparison, our choice of  $\lambda_3$  only implies a 3-fold increase of 289  $N_e$  in Figure 2. 290

While the value of  $\lambda_3$  (more generally of the highest  $\lambda_i$ ) determines the plateau of the IICR, the proportion of this class  $(a_3)$  appears to determine to a large extent the speed of convergence (backward) to this ancient plateau (right panel). For the smallest  $a_3$  values (0.1 or 0.01%), this ancient plateau is not reached within the figure (for  $t \leq 10$ ) whereas

a plateau corresponding to the neutral regions ( $\lambda_2 = 1$ ) is observed for quite long periods. For the largest  $a_3$  values considered here (1 or 10%), the convergence backward to the ancient plateau is so fast that the IICR does not exhibit the middle plateau around the neutral value, as already mentioned.



Figure 2: IICR for a panmictic model with  $K = 3 \lambda_i$  values such that  $\lambda_1 < 1$ ,  $\lambda_2 = 1$  and  $\lambda_3 > 1$ . The first class (or type) of genomic regions ( $\lambda_1 < 1$ ) is meant to represent regions of the genome under (linked) positive or purifying selection and is modelled by a constant population size  $\lambda_1 N$  with  $\lambda_1 = 0.1$ . Genomic regions of class 2 are meant to represent neutrality and they have a constant population size  $\lambda_2 N$  where  $\lambda_2 = 1$ . Regions of class 3 are meant to represent genomic regions under (linked) balancing selection, they have a constant population size  $\lambda_2 N$  where  $\lambda_2 = 1$ . Regions of class 4 are meant to represent genomic regions under (linked) balancing selection, they have a constant population size  $\lambda_3 N$  with  $\lambda_3 = 3$ . Left panel: the frequency of class 3 is fixed at  $a_3 = 0.01$  and the frequencies of classes 1 and 2 are allowed to vary. The frequency  $a_1$  is given by the legend. Right panel: the frequency of class 1 is fixed at  $a_1 = 0.5$  and the frequency of classes 2 and 3 are allowed to vary. The frequency  $a_3$  is given by the legend.

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In any case, these results suggest that if selection can be seen as reducing or increasing 307  $N_e$  in a pannictic population, the strongest effect on the IICR seems to be dispropor-308 tionately the result of the largest  $N_e$ , even though it may in practice affect ancient parts 309 of the IICR curves that may not be easily reconstructed from real data. PSMC curves 310 obtained from real data show a sharp increase (backward in time) in the very ancient past 311 in several species, including humans and Neanderthals. While this ancient increase is usu-312 ally ignored or interpreted as a statistical artefact resulting from the very low number of 313 coalescence events dating back to this period. Figure 2 suggests that that it is possibly due 314 to divergent alleles maintained by balancing selection. But it could also result from other 315 factors of the ancient demographic history of species (Chikhi et al., 2018, Mazet et al., 316 2016). The interpretation of the IICRs represented in Figures 1 and 2 should indeed be 317 done with caution given that the model used in the present section is panmictic whereas 318 most species are likely to be structured. It is relevant to mention structure here because 319 models of population structure also suggest a decrease of  $N_e$  (forward in time), visually 320 similar to the model of selection considered here without structure. Models including both 321 population structure and selection will be considered in a next section. Before coming 322 to this we study a series of panmictic models inspired by research aiming at estimating 323 variation in  $N_e$  in the genome of *Drosophila melanogaster* and *Homo sapiens*. 324

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## $_{325}$ Towards realistic distributions of $N_e$

The above examples highlighted important and partly unexpected properties of the IICR when  $N_e$  is variable along the genome. However, they relied on arbitrary  $\lambda_i$  and  $a_i$  values. It is thus not clear to which extent they inform us on the impact of selection in real species. In this section we consider two model species for which variation in  $N_e$  has been documented or estimated, the fruit fly *Drosophila melanogaster* and humans (Figure 3).

In the case of *Drosophila melanogaster*, we compared two different distributions of  $\lambda_i$ 331 over the genome. The first one was taken from the study of Elyashiv et al. (2016), who 332 developed a method for inferring the distribution of fitness effects in different classes of 333 functional annotations (UTRs, codons ...) for both beneficial and deleterious mutations. 334 This method requires polymorphism data from the focal species, divergence data with 335 closely related species and precise recombination and annotation maps allowing to assess 336 the selection constraints acting on each position in the genome. A by-product of their 337 analysis is that an estimation of  $N_e$  can be obtained for sliding windows along the genome. 338 Interestingly, these  $N_e$  values resulting from the strength of linked selection in each ge-339 nomic region are defined as the inverse of the coalescence rate between two sequences 340 and all computations rely on heterozygosity values observed between pairs of individuals. 341 This suggests that the  $N_e$  estimates should be directly comparable with our  $\lambda_i$  values, 342 which also correspond to the inverse of pairwise coalescence rates. The values of  $N_e$  esti-343 mated by Elyashiv et al. (2016) for 1Mb sliding windows in Drosophila melanoqaster were 344 downloaded at https://github.com/sellalab/LinkedSelectionMaps. Their distribution (top 345 left panel) was converted into a discrete distribution of  $\lambda_i$  values with K = 25 classes 346 using the hist() function of R. The IICR resulting from this distribution is shown in the 347 top middle and right panels. 348



Figure 3: IICRs for panmictic models with large numbers of classes. This figure represents genome-wide distributions of  $\lambda_i$  (left panels) and the associated IICRs until t = 10 (middle panels) or t = 500 (right panels). Top panels: IICR for *Drosophila melanogaster* based on the  $N_e$  distribution estimated by Elyashiv et al. (2016). Middle panels: IICR for *D. melanogaster* based on the  $N_e$  distribution estimated by Gossmann et al. (2011) assuming a lognormal distribution. To make the two IICRs comparable, the distribution estimated by Elyashiv et al. (2016) (top left) was re-scaled to have an average of one, as assumed in the analysis of Gossmann et al. (2011) (middle left). Bottom panels: IICR for humans based on the  $N_e$  distribution estimated by Gossmann et al. (2011) assuming a lognormal distribution estimated by Gossmann et al. (2011) assumed in the analysis of Gossmann et al. (2011) (middle left). Bottom panels: IICR for humans based on the  $N_e$  distribution estimated by Gossmann et al. (2011) assuming a lognormal distribution.

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The second distribution used for this species was that estimated by Gossmann et al. 349 (2011). While these authors also used polymorphism and divergence data, they focused on 350 exons and did not aim at modelling the distribution of fitness effects. They assumed a log-351 normal distribution of  $N_e$  with mean value of 1 and estimated the scale parameter of this 352 distribution from the observed data at several independent genes in the genome. Using the 353 parameter obtained by this approach for *Drosophila melanogaster* and no recombination 354 within genes (Table 1 of their study), we randomly sampled 100,000 values of  $N_e$  (or  $\lambda$ ) 355 under the log-normal distribution (middle left panel). A discrete distribution of the  $\lambda_i$ 's 356 and the associated IICR were then computed as explained above, filtering out large  $\lambda$ 357 values (we arbitrarily excluded values above five). Indeed, it is not clear whether such 358 large values would be realistic or statistical artifacts resulting from the use of a continuous 359 distribution estimated mainly from smaller  $\lambda$  values. Also, they represent less than 0.6% 360 of the distribution. As a comparison with another species, we also applied this second 361 approach with the scale parameter inferred by Gossmann et al. (2011) for humans (bottom 362 panels). 363

Figure 3 shows that, when focusing on times from 0 to 10 (middle column), the three IICRs produced by these analyses have similar shapes. The value of the IICR at t = 0is close to 0.5 for the three distributions. Interestingly, the two most similar IICRs were those based on the log-normal distribution estimated by Gossmann et al. (2011), despite the fact they correspond to two rather different species (fruit fly and humans).

The IICR resulting from the distribution of Elyashiv et al. (2016) for *Drosophila* differs from the other two on two aspects. First, it has a lower value at t = 10 (below two, whereas the others are close to three). One likely explanation is the smaller support of this distribution (up to  $\lambda_i = 2.5$ , versus  $\lambda_i = 5$  for the others), which implies a smaller plateau of the IICR as demonstrated in previous section. This effect becomes clear when

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considering more ancient times (back to t = 500, right columns), but IICRs at such 374 ancient times are unlikely to be observed from real data. Second, the IICR resulting from 375 the distribution of Elyashiv et al. (2016) top middle panel) includes an inflexion between 376 t = 0.1 and t = 1. This inflexion may be related to the mode observed for very low 377  $\lambda_i$  values with this approach (which probably results from the inclusion of regions with 378 very low recombination where the impact of linked selection is substantial) but not with 379 the approach of Gossmann et al. (2011). Indeed, a similar (although more pronounced) 380 inflexion was observed for models combining selection both reducing and increasing  $N_e$ 381 (Figure 2) but not for models with only one neutral and one selection class (Figure 1). 382 Consistent with this hypothesis, filtering out  $\lambda$  values below 0.25 from the distribution of 383 Elvashiv et al. (2016) lead to an IICR without inflexion (Figure S4). 384

Beyond these differences between the approaches of Gossmann et al. (2011) and 385 Elyashiv et al. (2016), we note again that they resulted in rather similar IICRs, at least 386 between t = 0 and t = 10. The magnitude of the decrease observed in these IICRs was 387 also comparable to that expected from Figure 2 for small values of  $a_1$  (e.g.  $a_1 = 0.1$ , 388 top right panel). Consequently, a long term 5 fold IICR decrease (from t = 10 to t = 0389 forward in time) could realistically be the result, in both humans and Drosophila, of a 390 moderate proportion of loci with very small  $N_e$  (Figure 2,  $a_1 = 0.1$ , Figure 3, top) or from 391 a larger proportion of loci with only slightly decreased  $N_e$  (Figure 3, middle and bottom), 392 all as a consequence of linked selection. 393

## <sup>394</sup> Generalisation to more complex models

We can generalise equation (2) to more complex models by still assuming that the genome is divided into K groups of loci each characterized by a different coalescence rate history.

However, instead of describing this history by assuming panmixia and constant popula-397 tion size  $(\lambda_i N)$ , we can study different demographic models with departures from these 398 assumptions, including models with population structure, models with panmixia and pop-399 ulation size changes, or models with transient changes in some of the  $\lambda_i$  values. In this 400 more general framework, let us denote by  $f_i(t)$  the pdf of the  $T_2$  corresponding to the 401 *i*-th class. If we keep the assumption that we can obtain a sufficiently large and unbiased 402 number of independent loci across the genome, and if we denote by  $a_i$  the proportion of 403 the genome described by  $f_i$ , then the IICR is: 404

$$\text{IICR}(t) = \frac{\sum_{i=1}^{K} a_i R_i(t)}{\sum_{i=1}^{K} a_i f_i(t)}.$$
(4)

405 where  $f_i(t) = -R'_i(t)$ .

#### <sup>406</sup> Models with population structure: the n-island model

One potential application of this general framework is to account for population structure 407 when modelling each genomic class. To illustrate this idea, we first considered a model 408 with K = 2,  $\lambda_1 = 0.1$  and  $\lambda_2 = 1$  as in Figure 1. Here we assumed that these two classes 409 evolved under a n-island model with the same number of demes (n = 10), the difference 410 in  $N_e$  being modelled through the use of different deme sizes in the two classes ( $\lambda_1 N$ 411 and  $\lambda_2 N$ ) We further assumed that selection did not affect migration, so that the *per* 412 generation migration rate m was the same for the two classes. In other words, selection 413 reducing  $N_e$  is assumed to operate after migration and thus only affects coalescence rates, 414 but not migration rates, of the two genomic regions. This implies that the scaled migration 415 rate M = 2Nm is identical in the two classes (time scale is still 2N here, but  $\lambda_i N$  now 416 refers to deme size rather than to the entire population size). One way of seeing this is 417

<sup>418</sup> by considering that there are 2N haploid genomes in each deme with scaled migration <sup>419</sup> rate 2Nm and that selection acts on the different genomic regions by changing drift by a <sup>420</sup> factor  $\lambda_i$ .

As already mentioned and exploited in previous studies on the IICR (Grusea et al., 2018, Mazet et al., 2016, Rodríguez et al., 2018), the distribution of coalescence times under a symmetrical n-island model can be derived analytically (Herbots, 1994). Extending these derivations to a model with general deme size  $\lambda_i N$ , instead of N in previous studies, we can show (see Appendix) that in this case we have

$$f_i(t) = p_i e^{-\alpha_i t} + \left(\frac{1}{\lambda_i} - p_i\right) e^{-\beta_i t}$$
(5)

426 with

$$\alpha_{i} = \frac{1}{2} \left( \frac{1}{\lambda_{i}} + n\gamma + \sqrt{\left(\frac{1}{\lambda_{i}} + n\gamma\right)^{2} - \frac{4}{\lambda_{i}}\gamma} \right),$$
$$\beta_{i} = \frac{1}{2} \left( \frac{1}{\lambda_{i}} + n\gamma - \sqrt{\left(\frac{1}{\lambda_{i}} + n\gamma\right)^{2} - \frac{4}{\lambda_{i}}\gamma} \right),$$
$$\gamma = \frac{M}{n-1}$$

427 and

$$p_i = \frac{\gamma - \alpha_i}{\lambda_i (\beta_i - \alpha_i)}.$$

<sup>428</sup> By setting  $\lambda_i = 1$  for all *i* we have the results of Mazet et al. (2016). The IICR of an <sup>429</sup> n-island model with two classes of deme size can be obtained by computing  $f_i(t)$  with <sup>430</sup> each  $\lambda_i$  using Equation (5) and inserting the results into Equation (4).



Figure 4: IICR curves for a symmetrical n-island model with n = 10 demes and K = 2classes of genomic regions. Regions of class 1 and 2 have a constant deme size  $2N\lambda_1$  and  $2N\lambda_2$  with  $\lambda_1 = 0.1$  and  $\lambda_2 = 1$ . Scaled migration rate M = 4Nm is the same for the two classes, each panel corresponding to a different value of this parameter. Frequencies  $a_1$  and  $a_2$  of the 2 classes are given by the legend (having in mind that  $a_1 + a_2 = 1$ ). For comparison with panmictic models (in particular those in Figure 1), time is scaled by the meta-population size 2Nn rather than by the deme size 2N as in Equation (5).

<sup>431</sup> IICR curves obtained for this two class n-island model are shown in Figure 4 for <sup>432</sup> different values of the scaled migration rate. For M = 5, they are similar to those shown <sup>433</sup> in Figure 1. This was expected given that an n-island model with high migration  $(M \gg 1)$ <sup>434</sup> should behave in a way that is similar to a panmictic model with population size 2Nn, <sup>435</sup> except in the recent past where the IICR of the n-island still reflects local deme size <sup>436</sup> (Mazet et al., 2016). For lower migration rates, the two extreme models with  $a_2 = 0$ 

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(red curve) or  $a_2 = 1$  (violet) show that a higher plateau of the IICR is observed as Mdecreases, which was again expected (Mazet et al., 2016).

For lower migration rates ( $M \leq 1$  in Figure 4), models with rather large values of  $a_1$ 439 are hard to distinguish from the model with  $a_1=0$  (no selection). For instance, the IICR 440 with  $a_2 = a_1 = 0.5$  is not very different from that with  $a_2 = 1$ , in contrast to Figure 1 441 where panmixia was assumed. This suggests that population structure may tend to mask 442 the effect of positive or negative selection as long as a moderate part of the genome is 443 under selection. On the other hand, the IICR with  $a_2 = 0.01$  is more similar to that with 444  $a_2 = 0$  than under panmixia. This suggests that, in the presence of population structure, 445 models with pervasive selection (99% of the genome with  $\lambda = 0.1$ ) may be interpreted as 446 neutral models with small effective size (100% of the genome with  $\lambda = 0.1$ ). 447

Another interesting observation from Figure 4 is the existence of a time window where 448 the IICR is lower when  $a_2$ , corresponding to the largest  $N_e$ , is largest, *i.e.* the IICR 449 is lower for models with a smaller part of their genome under selection reducing  $N_e$ . 450 This time window occurs in the recent past and is wider for lower migration rates. This 451 counter-intuitive result illustrates the limits of interpreting the IICR as a trajectory of 452 effective size, as already outlined for several other demographic scenarios (Chikhi et al., 453 2018, Mazet et al., 2016). Outside this period, the IICR curves seem to always reach 454 higher values when  $a_2$  is larger. This is in particular the case for t close to 0, which is 455 expected analytically (Equation (3)). 456

To check whether these conclusions may still hold for more realistic demographic scenarios, we next assume that each genomic class evolves under the non stationary n-island model estimated by Arredondo et al. (2021) to fit the observed PSMC of a modern human from Karitiana (Li and Durbin, 2011). This model includes 11 islands with symmetric migration and (diploid) deme size 1,380 and it assumes that these islands go through 4

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changes of connectivity in the past:  $M \approx 0.9 \ (m \approx 1.6e - 4)$  from present to 24,437 462 generations before present (BP),  $M \approx 17.7 \ (m \approx 3.2e - 3)$  from 24,437 to 82,969 gen-463 erations BP,  $M \approx 2.5~(m \approx 4.5e-4)$  from 82,969 to 107,338 generations BP,  $M \approx 0.7$ 464  $(m \approx 1.3e - 4)$  from 107,338 to 179,666 generations BP and  $M \approx 1.1$   $(m \approx 2e - 4)$  in 465 more ancient times. We define K classes of genomic regions: one neutral region with 466 deme size N and K-1 other regions under selection with deme size  $\lambda_i N$ , for  $\lambda_i$  either 467 smaller or larger than 1. Two different options are considered to model the heterogeneity 468 of effective size along the genome: (i) the hypothetical three class model of Figure 2 with 469 one class corresponding to positive or negative selection and one other corresponding to 470 balancing selection (top panels), and (ii) the 25 class model of Figure 3 estimated from 471 Gossmann et al. (2011)'s analysis of human real data (bottom panel). 472

We find that large values of  $a_1$  could have a significant impact on the IICR in the 473 period ranging from 10,000 to 30,000 generations ago (corresponding to 200-300,000 to 474 600-900,000 years ago). For instance with  $a_1 = 0.8$ , the IICR is around 17 in the most 475 recent hump and around 5 in the most recent bump, versus 22 and 12 without selection 476 (top left panel). However, this effect is very moderate when considering the  $\lambda_i$  distribu-477 tion estimated by Gossmann et al. (2011) (bottom panel). Much more dramatic is the 478 effect observed in the ancient past above 100,000 generations ( $\approx 2-3$  million years) before 479 present, where the IICR with selection is significantly larger than the neutral IICR. This 480 difference is driven by the part of the genome with large effective size (i.e. under balancing 481 selection) and is found (with varying magnitude) in all scenarios. 482



Figure 5: IICRs for demographic models combining population structure and linked selection in humans. The neutral part of the genome evolves under the non stationary n-island model estimated by Arredondo et al. (2021) to fit the observed PSMC of a modern human from Karitiana (Li and Durbin, 2011) **Good ref?**. This model includes 11 islands with (diploid) deme size N = 1380, whose connectivity varied along time according to a 3 step process (see the text for details). To account for selection, this neutral class only represents a fraction of the genome and other classes with lower or higher  $N_e$  are also considered. The number of these classes, their proportions and deme sizes (relative to the neutral class) are taken either from Figure 2 (top, where  $a_3$  is fixed to 0.01 in the left panel, and  $a_1$  fixed to 0.5 in the right one) or from Figure 3 (bottom, red line). The black curve on all panels depicts the IICR for this demographic scenario but without selection. Time is shown in generations and in log10 scale.

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## <sup>483</sup> Panmictic models with transient selection

We finally apply this general framework to model the transient effect of recent selec-484 tive sweeps, rather than the effect of recurrent positive, negative or balancing selection 485 considered until now. For this analysis we consider a panmictic population. A similar 486 question was tackled by Schrider et al. (2016), who showed in their Figure 5 the esti-487 mations obtained when applying the PSMC to a 15Mb genomic region that experienced 488 one or several recent selective sweeps. We focus here on a scenario similar to theirs, with 489 one single selective sweep and propose a model with different classes of  $\lambda_i$  that are time-490 dependent, which allows to approximate the resulting IICR. Although this model is built 491 based on the expected variations of effective size (or coalescence rate) in a 15Mb region, 492 we note that it also applies to a whole genome having experienced on average one recent 493 selective sweep per 15 Mb region. In other words, our aim here is not to switch from 494 the analysis of global to local IICRs, but rather to explore the local and implicitly global 495 effects in a relatively realistic example. 496

To approximate the IICR resulting from a recent selective sweep, we assume that the effect of this sweep can be modelled by a reduction of effective population size that is limited both in time (from the emergence of the derived favorable allele to its eventual fixation in the population) and in "genomic space" (*i.e.* in a genomic neighborhood of this selected variant). More precisely, we consider that the region affected by the sweep on one side of the selected locus is of size

$$L = -\log(0.05)\frac{\alpha}{8Nr\log(\alpha)}$$

with N the diploid population size, r the per site recombination rate and  $\alpha = 2Ns$ the scaled selection intensity (s being the fitness advantage of homozygotes carrying the

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selected mutation). This quantity corresponds to the distance in base pairs (bp) from 505 the selected site such that heterozygosity is reduced by only 5% at the end of the sweep 506 (Walsh and Lynch, 2018, chap. 8). To capture the fact that the reduction of effective 507 size caused by the sweep depends on the physical distance to the selected site, we divide 508 this affected region in 10 classes of same size  $2\frac{L}{10}$  with increasing distance from the sweep, 509 where the factor two results from the sweep extending on both sides of the selected site. 510 To quantify the reduction of effective size in a given class, we consider the genealogy 511 at a neutral locus located d bp away from the selected site. This process can be modelled 512 using a structured coalescent where lineages are either in the 'derived' or 'ancestral' back-513 ground, depending on which allele at the selected locus they are associated with (to avoid 514 any confusion, we remind here that this structure is a modelling facility and has nothing to 515 do with the island structure considered in previous section. In this framework, ancestral 516 recombination events creating or breaking the association with the derived allele can be 517 seen as migration events from one background to the other (Kaplan et al., 1988). In the 518 case of a complete selective sweep, lineages sampled at present all belong to the derived 519 background, because the derived allele is then fixed in the population. Following previous 520 studies on this topic, e.g. (Nielsen et al., 2005), we further assume a "star-like" model 521 where these lineages can either (i) escape this derived background through recombination 522 and stay in the ancestral background until the end of the sweep phase (i.e. at the time 523 when the derived allele appeared, as we go backward in time) or (ii) coalesce all together 524 at the end of the sweep phase. Actually, we slightly relax this second hypothesis and 525 simply assume that their average coalescence time corresponds to the end of the sweep 526 phase. The probability for each lineage to escape the sweep is approximately 527

$$a = 1 - e^{-4drN\log(\alpha)/\alpha}$$

Because lineages can only coalesce if they are in the same background (derived with probability  $(1-q)^2$  or ancestral with probability  $q^2$ ), we assume that the average coalescence rate during the sweep is

$$\mu_{sweep} = (1-q)^2 \frac{1}{\tau} + q^2 \frac{1}{2N}$$

531 where

$$\tau = 8N \log(\alpha) / \alpha$$

is the duration of the sweep (in generations). In this formula,  $\frac{1}{\tau}$  approximates the average coalescence rate for two lineages not escaping the sweep, which follows from our assumption that the average coalescence time is  $\tau$ , and  $\frac{1}{2N}$  is the standard neutral coalescence rate which applies to two lineages having escaped the sweep.

In summary, the relative effective population size in a given genomic class affected by the sweep is equal to 1 before and after the sweep and to

$$\lambda_{sweep} = \frac{1/\mu_{sweep}}{2N}$$

during the  $\tau$  generations of the sweep. A neutral class (with  $\lambda = 1$  at all times) is also included to account for positions within the 15Mb segment but with physical distance to the selected site greater than L.



Figure 6: IICRs for a 15Mb region experiencing a single recent selective sweep. Parameter values were chosen to reproduce those in Figure 5 of Schrider et al. (2016): N = 10000(diploid size),  $r = 10^{-8}$  (per site recombination rate) and  $t_0 = 4000$  generations before present (time where the derived allele got fixed). Times are given in generations and are shown in log10 scale. Top: Expected IICRs when modelling selection using a panmictic model with K = 11 classes of regions. Class 11 represents the neutral part of the region (unaffected by the sweep), with relative population size  $\lambda_{11} = 1$ . Class j  $(1 \le j \le 10)$ represents a part of the region affected by the sweep, with a given physical distance from the selected site (which increases with j). Relative population size is equal to  $\lambda_j = 1$  before and after the sweep and is decreased during the sweep to match the larger coalescence rate (see the text for more details). The proportion of each selected class j > 10 is L/5, where L is the size of the region affected by the sweep on either side of the selected site. Scaled selection intensity  $\alpha = 2Ns$  was equal to 200, 1000 or 10000 (see the legend). Bottom: Empirical IICRs based on coalescence times simulated with the software msms, for  $\alpha = 1000$ . Two hundreds independent 15Mb regions were simulated. Colored lines show the IICRs for 5 of these regions (taken at random) and thus represent typical local IICRs. Black lines show the IICRs obtained when merging coalescence times from all regions, they thus correspond to genome-wide IICRs obtained for a 3Gb genome (200  $\times$ 15Mb) with one selective sweep every 15Mb. The number of time windows considered (i.e. of distinct estimated IICR values) was equal to 25 (left) or 200 (right) and the length of these windows was increasing exponentially backward in time, as in the PSMC approach.

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As shown in Figure 6, top panel, the resulting IICR for  $\alpha = 200$  (corresponding to 541 s = 0.01 for N = 10,000) is very close to that of a neutral scenario. The IICR for 542  $\alpha = 1000$  (corresponding to s = 0.05 for N = 10,000) shows a reduction of about one half 543 at sweep time, similar to the average PSMC plot in Figure 6B of Schrider et al. (2016). 544 The IICR for  $\alpha = 10000$  (corresponding to s = 0.5 for N = 10,000 or to s = 0.05 for 545 N = 100,000) shows a much stronger decline, down to almost zero. However, the IICR 546 decline in our analysis is very localized in time, while the PSMC decline in (Schrider et al., 547 2016) extends for a longer period. Another important difference is that the PSMC plot 548 in the simulations of Schrider et al. (2016) not only recovers the neutral value after the 549 sweep but increases up to more than twice this value in the recent past. To understand 550 these differences, we simulated coalescence times along a 15Mb region under the same 551 sweep scenario, with  $\alpha = 1000$ , using the software msms (Ewing and Hermisson, 2010) 552 and estimated the resulting empirical IICR as in Chikhi et al. (2018). 553

Similar to PSMC estimations, these empirical IICR estimations depend on the number 554 of time windows considered, the assumption being that  $N_e$  is constant within each time 555 window but may vary between time windows. In the bottom left panel of Figure 6, we 556 consider 25 time windows, which corresponds to the order of magnitude used in most 557 PSMC studies. The resulting IICR, averaged over 200 replicates, is transiently reduced 558 around the sweep time and shows no increase above 1 in the recent past, similar to our 559 theoretical prediction (top panel). However, the reduction of  $N_e$  is both longer and of 560 lower magnitude than in our prediction, as in the PSMC plots of Schrider et al. (2016). 561 In the bottom right panel, we consider 200 time windows and obtain an average IICR 562 in which the magnitude and duration of the decrease is much more consistent with our 563 theoretical prediction. IICRs from single replicates also correctly capture this reduction 564 around the sweep time but are very noisy outside this period as a side effect of the 565

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finer time discretization. Altogether, these results show that modelling selective sweeps 566 by local transient changes of population size leads to a reasonable approximation of the 567 IICR (or equivalently of the genome-wide distribution of  $T_2$ ) but that discretizing time 568 using a limited number of time windows may lead to soften the true sweep signature by 569 an averaging effect. The IICR increase following the sweep observed with the PSMC plots 570 produced by Schrider et al. (2016) but not in our results (even when simulating sweeps) 571 also outlines that the genome-wide distribution of  $T_2$  may not be sufficient to characterize 572 the genomic patterns left by selective sweeps in the data (some of them being exploited 573 by PSMC). We come back to this point in the Discussion section. 574

## 575 Discussion

## 576 Effects of linked selection on the IICR

A now classical hypothesis in population genetics considers that linked selection can be 577 modelled as a first approximation by a local change in effective population size (Hill 578 and Robertson, 1966). Background selection and selective sweeps, which tend to reduce 579 genetic diversity locally Charlesworth et al. (1993), Smith and Haigh (1974), are then seen 580 as resulting in lower  $N_e$  values, whereas genomic regions under balancing selection are in 581 contrast interpreted in terms of higher  $N_e$  values. In both cases, the impact of selection on 582 genetic diversity or  $N_e$  is stronger for regions with lower recombination or higher selective 583 constraints (number of selected sites, selection intensity) Charlesworth (2009). At the 584 genome-wide level, linked selection appears thus to generate an apparent heterogeneity of 585  $N_e$  among genomic regions, reflecting the variations of the mode (increasing or decreasing 586  $N_e$ ) and the intensity of linked selection (Gossmann et al., 2011, Jiménez-Mena et al., 587 2016a). Following this simplifying assumption, we described in this study the distribution 588

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of the coalescence time between two sequences  $(T_2)$  for models including variable classes 589 of  $N_e$  along the genome. More precisely, we characterized the Inverse Instantaneous 590 Coalescence Rate (IICR) (Mazet et al., 2016) of such models, a quantity that is equivalent 591 to the  $T_2$  distribution and corresponds to the output of the popular PSMC approach (Li 592 and Durbin, 2011), which is generally (and in some cases at least wrongly) interpreted 593 as the past temporal trajectory of  $N_e$  of the population or species under study. This 594 analysis allowed us to predict the expected effects of linked selection on PSMC or related 595 demographic inference approaches Schiffels and Durbin (2013). 596

One of the main conclusions of our work is that, under panmixia and constant popula-597 tion size, the existence of several classes of  $N_e$  (induced by linked selection) always results 598 in a spurious signal of population size decline: the IICR of such models is a decreasing 599 function (forward in time) whose highest value (reached in the ancient past) corresponds 600 to the largest genomic  $N_e$  and lowest value (reached in the most recent past) to the har-601 monic mean of genomic  $N_e$  values weighted by their relative proportion in the genome 602 (Figure 1, Equation 3). Specifically, we found that selection reducing  $N_e$  (background 603 selection or sweeps) has a stronger effect on the IICR in the recent past, while selection 604 increasing  $N_e$  (balancing selection) mainly influences the IICR in the intermediate and 605 ancient past (Figure 2). There is a striking asymmetry between the two forms of selection: 606 because the IICR plateau is determined by the class with the largest  $N_e$  independently 607 of the proportion of this class, even a minute proportion of balancing selection can have 608 a large effect on the IICR, whereas higher proportions of background selection or sweeps 609 are necessary to generate significant and detectable effects on the IICR (Figure 2). Com-610 bining the two forms of selection by considering  $N_e$  distributions inferred from real data 611 (Elyashiv et al., 2016, Gossmann et al., 2011) we found that linked selection is expected 612 to cause a long term apparent five-fold decrease of the IICR in organisms such as humans 613

or *Drosophila melanogaster* (Figure 3). However, we stress that these results assumed
 panmixia and constant population size.

Another important conclusion of our work is indeed that the effects of linked selection 616 on the IICR mentioned above may be largely hidden by those of population structure. 617 Considering a symmetrical n-island model, we observed for instance that even when a 618 large proportion of the genome is influenced by selection reducing  $N_e$  the effect on the 619 IICR could be difficult to see for models with reduced migration rates between islands 620 (Figure 4). Focusing on humans we also considered a simple but reasonable demographic 621 scenario of variable population structure Arredondo et al. (2021) together with a realistic 622 genomic  $N_e$  distribution for this species Gossmann et al. (2011). We found that the 623 largest and most visible effect of linked selection on the IICR was an ancient population 624 size increase (backward in time) related to the presence of balancing selection (Figure 5, 625 bottom). 626

The predominant influence of balancing selection outlined by our results may need to 627 be toned down in more practical or realistic settings. Depending on the proportion of the 628 genome under balancing selection, this effect may or may not be visible on real PSMC 629 plots. For instance in humans, estimated PSMC plots extend to a few million years before 630 present. Under the common assumptions of a diploid effective population size of 10,000 631 (under panmixia) and a generation time of about 20-30 years, one million years would 632 correspond to a scaled time of five. Thus, human PSMC curves would fit within the 633 panels represented in Figure 2, but the effect of balancing selection would not be easily 634 detectable if  $a_3 \leq 0.01$ . For  $a_3 \geq 0.01$ , it might only be detected as a rapid backward 635 increase in the most ancient parts of the PSMC curves, as also suggested when considering 636 more realistic demographic and selection models (Figure 5). Such ancient increases are 637 indeed observed in humans and a number of other species, but a further complication 638

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is that these patterns may also arise due to the low number of informative coalescence 639 events available to PSMC in this ancient time period. PSMC analyses of genomic data 640 simulated under realistic demographic scenarios, with and without balancing selection, 641 will be necessary to investigate whether these ancient signatures of balancing selection 642 can be disentangled from statistical artifacts. As a simple test we carried out additional 643 simulations under an n-island model, generating genomic data under the demographic 644 model of Figure 5 with a single genomic  $N_e$  (i.e. no selection). We applied PSMC to 645 these data and found no ancient increase in the estimated trajectory compared to the 646 expected IICR (Figure S5). These admittedly limited results suggest that the PSMC is 647 not necessarily *statistically* biased in the ancient past, and that the signals observed in 648 several species including humans and chimpanzees might be due to balancing selection or 649 other forms of selection maintaining high levels of diversity over very long periods. One 650 possible strategy to limit the influence of regions submitted to such forms of selection 651 would be to first detect them and filter them out from the PSMC analysis. For the 652 demographic scenario of Figure 5, we found that this would reduce the biases observed in 653 the ancient past without affecting significantly other parts of the IICR (Figure S6). 654

## <sup>655</sup> The intriguing signature of background selection on the IICR

The framework developed in this study makes no particular distinction between positive and background selection, which are both modelled as leading to a reduction of  $N_e$ . Thus, one possible interpretation of our results would be that unaccounted background selection leads to a spurious signal of population decline. This conclusion is at odds with several previous studies, which concluded that unaccounted background selection may actually lead to a spurious signature of recent population expansion. For instance, Zeng and Charlesworth (2011) and Walczak et al. (2012) developed theoretical approximations

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of the genealogical process at a neutral locus linked to a site under negative selection and 663 showed that this process shared many properties with that of an expanding population. 664 The former study accounted for intra-locus recombination, whereas the latter ignored it. 665 Several recent studies have applied demographic inference methods to genomic data simu-666 lated with and without linked background selection (Ewing and Jensen, 2016, Johri et al., 667 2021, Lapierre et al., 2016, Pouvet et al., 2018) and observed a signal of recent popula-668 tion expansion in the scenarios including selection. Finally, Johri et al. (2020) analyzed 669 real data from an African population of Drosophila melanogaster with a new ABC demo-670 graphic inference approach accounting for background selection. They estimated that the 671 size of this population has been relatively constant for a few millions generations, while 672 several previous studies on this or other related populations, which ignored background 673 selection, estimated a strong recent population size increase. 674

Two main reasons may resolve this apparent paradox between these previous results 675 and ours. First, we assume that linked selection can be modelled by a local change of 676  $N_e$  without any temporal dynamics (except in Figure 6 and related text), whose focus is 677 specifically on recent selective sweeps). In particular, our results do not hold for demo-678 graphic inference approaches based on the Site Frequency Spectrum (SFS), because weak 679 background selection is expected to produce an excess of low frequency alleles, in partic-680 ular singletons, which cannot be mimicked by just assuming a smaller  $N_e$ . Such an excess 681 of rare alleles is also a classical signature of expanding populations, which may explain 682 the conclusions of several of the studies mentioned above (Ewing and Jensen, 2016, Johri 683 et al., 2020, Lapierre et al., 2016, Pouvet et al., 2018). 684

Second, even when focusing on pairwise statistics such as heterozygosity or  $T_2$ , the signature of population decline predicted by the IICR can only be observed if the data considered exhibit some heterogeneity in  $N_e$ . As it can easily be seen from Figure 1,

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panmictic models with either no  $(a_2 = 1)$  or only  $(a_2 = 0)$  selection do not show declining 688 but constant IICRs. Consequently, a decline signature is not necessarily expected when 689 analyzing a single locus under selection as in Zeng and Charlesworth (2011) or Walczak 690 et al. (2012). It is also not necessarily expected when analyzing genome-wide data with 691 homogeneous selective constraints along the genome. For instance, Johri et al. (2021) 692 simulated genome-wide sequences including background selection by considering a regular 693 alternance of functional (selected) and intergenic (neutral) regions of fixed and relatively 694 small sizes: depending on the scenario, the size of a single 'unit' including one functional 695 and one intergenic region ranged from  $\approx 13$  to 55 kb. The PSMC analyses of these 696 sequences suggested a population under constant size or slight recent expansion. We 697 believe that some of the results obtained by these (and possibly other) authors could 698 be due to the fact that the data simulated with this approach do not exhibit enough 699 heterogeneity in population sizes among (short) sliding windows over the genome. Such a 700 regularity is at odds with observations made in different organisms (Elyashiv et al., 2016, 701 Gossmann et al., 2011). 702

## <sup>703</sup> IICR predictions and PSMC estimations

Understanding the difference between our results and those of Johri et al. (2021) also leads 704 to the fundamental question of the link between a PSMC curve and the IICR. As outlined 705 in Mazet et al. (2016) and several subsequent studies, the IICR is a theoretical function 706 associated to a given evolutionary model (and sampling scheme), while the PSMC is an 707 estimation of this theoretical quantity. When population size history is homogeneous 708 along the genome (i.e. K = 1 class), PSMC provides a very good estimation of the IICR 709 (Mazet et al., 2016). But when population size history is heterogeneous along the genome, 710 as considered here to approximate the effects of selection, the answer may depend on the 711

scale (10kb? 100kb? 1Mb?) at which this heterogeneity is detectable. In other words, for
a fixed proportion of genomic positions with reduced effective size due to linked selection,
PSMC results may depend on the spatial clustering of these positions along the genome,
while the IICR does not.

To explore this question, we tested whether genomic data including genome-wide het-716 erogeneity of  $N_e$  at different scales could generate PSMC plots consistent with our IICR 717 predictions. To do this we carried out a limited number of additional simulations in which, 718 using the genomic sizes  $\lambda_1 = 1$  and  $\lambda_2 = 10$ , we varied the lengths  $L_1$  and  $L_2$  of con-719 tiguous DNA chunks belonging to a given class, while keeping constant the proportions 720  $a_1$  and  $a_2 = 1 - a_1$  at which these classes are represented. We tested three values for 721 the frequency  $a_1$  (0.5, 0.9 and 0.99), and for each combination of these parameters we 722 simulated two independent genomes of length  $10^9$  base pairs, where the two size classes 723 were evenly spaced in the form: 724

$$(L_1, L_2, L_1, L_2, \ldots, L_1, L_2).$$

The lengths  $L_2$  for the chunks of class 2 were chosen to be  $10^6$ ,  $10^5$  and  $10^4$  base pairs, and the lengths for the chunks of class 1 follow from the proportions  $a_1$  and  $a_2$ . We found that PSMC estimations fit well our predictions for large chunks ( $10^6$  and  $10^5$ ), but may highlight more complex and unpredicted patterns for smaller ones (Figure S7). This may explain the poor fit of our predictions with the PSMC results of Johri et al. (2021), where the heterogeneity of  $N_e$  was detectable only at very small scale ( $\leq 55$ kb).

The recent selective sweep scenario considered in Figure 6 also nicely illustrates the potential difference between PSMC estimations and IICR predictions in the case of genomic heterogeneity. Simulating *genome sequences* in a single 15Mb region experiencing

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one recent selective sweep, Schrider et al. (2016) found that PSMC applied to these se-734 quences would infer a bottleneck around the time of the sweep completion, generally 735 followed by a more recent expansion exceeding the 'neutral' effective size. Simulating 736 coalescence times under the same selective sweep scenario and estimating the IICR from 737 these simulated values, we observed a similar bottleneck but no recent expansion. This 738 difference likely results from the fact that short coalescence times are mostly clustered 739 around the selected site in the real data, while for IICR estimation only their proportion 740 over the 15Mb region matters. Including a transient change of  $N_e$  into our model with 741 heterogeneous effective size along the genome, we can reproduce the main characteristics 742 of the IICR with selection, but not completely of the PSMC with selection. 743

Overall, the results discussed in this section suggest that, although our study allows to describe the expected effects of linked selection on the overall distribution of coalescence times, specific simulations based on precise genomic annotations (positions and lengths of genes, local recombination rates ...) may be necessary to really assess potential PSMC biases in a given species.

## 749 Perspectives

The above discussion illustrates that the effects of linked selection on demographic in-750 ference are complex, as they not only depend on the type and intensity of selection but 751 also on the inference approach applied and how data are summarized (SFS or  $T_2$  based 752 for instance) or the scale at which selection constraints vary along the genome. If the 753 future confirms that linked selection is pervasive in the genome as claimed for several 754 model species (Elyashiv et al., 2016, Pouyet et al., 2018) new demographic inference ap-755 proaches accounting for linked selection and population structure will be needed. One way 756 of achieving this objective is to jointly estimate demographic and selection parameters, 757

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as proposed in two recent studies relying on simulation based approaches, deep learning 758 (Sheehan and Song, 2016) and Approximate Bayesian Computation (ABC) (Johri et al., 759 2020). These studies focused on relatively simple models, considering pannictic popula-760 tions with a single population size change and only some types of selection (background 761 selection in one study, sweeps and balancing selection in the other). To integrate more 762 complex demographic scenarios, several recent studies considered interesting approaches, 763 by assuming demographic models including two classes of  $N_e$  along the genome, one for 764 neutral loci and one for loci under linked selection. The proportion of the two classes and 765 the ratio of  $N_e$  between them were estimated together with other parameters of the demo-766 graphic model, using either ABC (Rougemont and Bernatchez, 2018, Roux et al., 2016) or 767 a modification (Rougemont et al., 2020, Rougeux et al., 2017) of the diffusion approach 768 implemented in the software  $\partial a \partial i$  (Gutenkunst et al., 2009). The models described in 769 the present study propose another direction for the development of demographic infer-770 ence methods by accounting for linked selection through variable classes of  $N_e$  along the 771 genome, and using the IICR as summary statistic. An IICR-based inference framework 772 was recently proposed for the estimation of non stationary n-island models and provided 773 very encouraging results (Arredondo et al., 2021). Given the strong impact of linked se-774 lection on the IICR under panmixia, as described in the present study, we believe that a 775 similar approach could allow to jointly infer parameters related to demographic history 776 and to the  $N_e$  distribution. However, the results obtained under models of population 777 structure suggest that it may be necessary to use the IICR in addition to other summaries 778 of genomic diversity to overcome identifiability issues. Also, we should stress that sepa-779 rating the effects of population size change, selection and population structure is likely to 780 be one of the major challenges of population genetics in the future. 781

Whether the objective is to predict potential effects of linked selection or to estimate

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linked selection parameters from real data, two nice features, and possible advantages of 783 an IICR-based approach such as the one considered here are flexibility and speed of com-784 putation. Our approach allows to simultaneously include different forms of selection and 785 to combine linked selection with arbitrary demographic models. The examples considered 786 here included stationary pannictic and n-island models (Figure 2 and 4) and non station-787 ary island models (Figure 5). We also considered different distributions of  $\lambda_i$  and temporal 788 variation of  $\lambda_i$ . Our approach can easily be extended to more general structured models 789 including temporal population size variations. In the case of structured models, variable 790 migration rates along the genome may be considered, to mimic variation in introgression 791 rates. Indeed, we could either decreasing M in the linked selection class to account for 792 possible effects of selection on migration success or introduce new classes with lower M793 values in order to model possible barriers to gene flow (Roux et al., 2016). As outlined 794 in Figure 6, transient selection can be modelled by including population size changes in 795 one class, and this approach could also be extended to model more complex fluctuating 796 selection effects. 797

Whatever the complexity of the model considered, the associated IICR can be com-798 puted exactly in a very small time using the rate matrix approach described in (Rodríguez 799 et al., 2018) or Arredondo et al. (2021), which allows to efficiently explore a very large 800 number of scenarios or parameter values. As previously mentioned, the main limitation 801 of the IICR approach described in this study is that it focuses on pairs of sequences. 802 It provides information that is complementary to that provided by the SFS, as we have 803 noted elsewhere Arredondo et al. (2021), Chikhi et al. (2018) This means that some ef-804 fects of weak background selection or selective sweeps may be visible on the SFS but 805 not on the IICR. Currently we have mainly focused on the IICR as defined for a pair of 806 sequences, but extensions to multiple sequences might provide additional information on 807

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the distribution of higher order coalescence times  $(T_3, T_4, \ldots)$ , hence allowing a finer characterization of selective and neutral processes.

To conclude we have used the IICR as a way to explore important ideas that are 810 central to population genetics such as the notion of effective size (see also Chikhi et al. 811 (2018), Mazet et al. (2016) for discussions on these questions), drift and selection. We 812 wished to re-open discussions regarding the influence of selective and neutral processes on 813 genetic diversity, some of them general and theoretical, others more specific and practical: 814 Can selection be modelled as a genomic variation in  $N_e$ ? What are the limits of such 815 an approximation? How robust is it? Does an IICR perspective provide interesting 816 outcomes? Can  $N_e$  variation along the genome be detected in real genomes by applying 817 the PSMC method of (Li and Durbin, 2011) or related approaches? Can we infer the 818 presence of linked selection in humans from the PSMC plots or SFS histograms observed 819 in this and other species? These are exciting questions to ask and the recent years have 820 shown that they are at the heart of modern population genetics. 821

## <sup>822</sup> Data availability statement

<sup>823</sup> Code used to generate the exact and simulated IICRs shown in this study can be found <sup>824</sup> at https://github.com/sboitard/IICR\_selection.

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## <sup>837</sup> Supplementary Material

## Big Derivation of the pdf of $T_2$ in a *n*-island model

We derive here the pdf density of  $T_2$ , the coalescence time of two lineages sampled in the 839 same deme (resp. different deme), in an *n*-island model. We follow the identity by descent 840 approach used in Durrett's process (Durrett, 2008, p. 150). The size of each deme is  $\lambda N$ , 841 the probability of each lineage to migrate from a deme to another each generation is m, 842 and the per locus mutation rate is u. Define the rescaled mutation and migration rates 843 by  $\theta = 4Nu$  and M = 4Nm. Note that two lineages coalesce at rate  $c = \frac{1}{\lambda}$  when they 844 are in the same deme, migrate at rate  $2m \cdot 2N = M$  and experience mutations at rate 845  $2u.2N = \theta.$ 846

Let  $p_s(\theta)$  and  $p_d(\theta)$  be the probabilities that two lineages are identical by descent when they are chosen in the same or different demes. Following back two lineages from the same deme, three different events can occur: a coalescence with probability  $\frac{c}{c+\theta+M}$ , a migration with probability  $\frac{M}{c+\theta+M}$  and a mutation with probability  $\frac{\theta}{c+\theta+M}$ . If lineages are in different demes, the only possible events are mutation, with probability  $\frac{\theta}{\theta+M}$  and

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migration. In this second case lineages arrive in the same deme with probability  $\frac{1}{n-1}$  and stay in different ones with probability  $\frac{n-2}{n-1}$ . Hence we have the two coupled equations:

$$p_s(\theta) = \frac{c}{c+M+\theta} \cdot 1 + \frac{M}{c+M+\theta} \cdot p_d(\theta),$$

854 and

$$p_d(\theta) = \frac{M/(n-1)}{M+\theta} \cdot p_s(\theta) + \frac{M(n-2)/(n-1)}{M+\theta} \cdot p_d(\theta).$$

855 The second equation gives

$$\left(1 - \frac{M(n-2)}{(n-1)(M+\theta)}\right)p_d(\theta) = \frac{M}{(n-1)(M+\theta)}p_s(\theta)$$
$$\Leftrightarrow \frac{\theta(n-1) + M}{(n-1)(M+\theta)}p_d(\theta) = \frac{M}{(n-1)(M+\theta)}p_s(\theta)$$
$$\Leftrightarrow p_d(\theta) = \frac{M}{\theta(n-1) + M}p_s(\theta).$$

<sup>856</sup> We then inject in the first equation:

$$p_s(\theta) = \frac{c}{c+M+\theta} + \frac{M}{c+M+\theta} \frac{M}{\theta(n-1)+M} p_s(\theta)$$

<sup>857</sup> hence

$$p_s\left(1 - \frac{M^2}{(c+M+\theta)(\theta(n-1)+M)}\right) = \frac{c}{c+M+\theta}$$

858 and since

$$(c + M + \theta)(\theta(n - 1) + M) - M^{2} = \theta^{2}(n - 1) + \theta(c(n - 1) + Mn) + cM,$$

859 we get

$$p_s = \frac{c(\theta(n-1)+M)}{\theta^2(n-1)+\theta(c(n-1)+Mn)+cM} = \frac{c(\theta+\gamma)}{\theta^2+\theta(c+n\gamma)+c\gamma}$$

860 and

$$p_d = \frac{cM}{\theta^2(n-1) + \theta(c(n-1) + Mn) + cM} = \frac{c\gamma}{\theta^2 + \theta(c+n\gamma) + c\gamma}$$

861 with

$$\gamma = \frac{M}{n-1}.$$

Let's now note that the probability  $p_s(\theta)$  that two lineages has reached their common ancestor without undergoing any mutation is also the expected value  $\mathbb{E}(e^{\theta T_2})$ . In other words,  $p_s$  is the Laplace transform of  $T_2$ . It can be inverted by looking for the roots of  $\theta^2 + \theta(c + n\gamma) + c\gamma$ . Let  $\Delta = (c + n\gamma)^2 - 4c\gamma$ , then

$$p_s(\theta) = \frac{c(\theta + \gamma)}{(\theta + \alpha)(\theta + \beta)} = \frac{a}{\theta + \alpha} + \frac{b}{\theta + \beta}$$

866 with

$$\alpha = \frac{1}{2} \left( c + n\gamma + \sqrt{\Delta} \right),$$
$$\beta = \frac{1}{2} \left( c + n\gamma - \sqrt{\Delta} \right),$$
$$a = \frac{c(\gamma - \alpha)}{\beta - \alpha}$$

867 and

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$$b = \frac{c(\gamma - \beta)}{\alpha - \beta} = c - a$$

Hence the probability density function of  $T_2$  is:

$$f_{T_2}(t) = ae^{-\alpha t} + (c-a)e^{-\beta t}.$$

Note that  $-\alpha$  and  $-\beta$  are the non zero eigenvalues of the Q-matrix,  $-\beta$  being the closest to 0, and we have the relationships  $\alpha + \beta = c + n\gamma$  and  $\alpha\beta = c\gamma$ . Note also that we could similarly obtain the pdf distribution of the coalescence time of two lineages sampled in different demes, as  $p_d$  is its Laplace transform as well.

## <sup>873</sup> Supplementary figures



Figure S1: IICR curves for a panmictic model with K = 2 classes of genomic regions with constant size. Same as Figure 1 except that time is plotted in natural scale.



Figure S2: IICR curves for a pannictic model with K = 2 classes of genomic regions with constant size. Same as Figure 1 with  $\lambda_1 = 1$ ,  $\lambda_2 = 10$  and time from 0 to 100 (in log10 scale)



Figure S3: IICR for a pannictic model with  $K = 3 \lambda_i$  values such that  $\lambda_1 < 1$ ,  $\lambda_2 = 1$  and  $\lambda_3 > 1$ . Same as Figure 2 except that time is plotted in natural scale.

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Figure S4: IICR obtained when removing low  $N_e$  values from the distribution estimated by Elyashiv et al. (2016). This truncated distribution (rescaled to have a mean of 1 as the others) is shown on the left panel. The associated IICR is shown until t = 10 (middle panel) or t = 500 (right panel), in log10 scale.



Figure S5: PSMC curves of simulated data under a non-stationary n-island model. We show in black the exact IICR corresponding to an inferred n-island model for a Karitiana individual in Arredondo et al. (2021). In color, we show various PSMC curves obtained by independently simulating genomic sequences under this structured model. The real PSMC curve for this Karitiana individual is represented by the dashed plot (Prado-Martinez et al., 2013). The horizontal axis is scaled in years, with a generation time of 25 years.



Figure S6: IICRs for demographic models combining population structure and linked selection in humans. Same as Figure 5, bottom panel, except that  $\lambda$  values greater than 2 (left) or 3 (right) were filtered out from the distribution in order to mimic a situation were loci under balancing selection could be detected and removed before computing the IICR. The resulting truncated distribution was rescaled.





Figure S7: Comparison between theoretical IICR and inferred PSMC. For each frequency distribution  $(a_1, a_2)$  of the two size classes  $\lambda_1 = 1$  and  $\lambda_2 = 10$  we show the corresponding theoretical IICR (black) and two independent PSMC simulations for three variations of the chunk length  $L_2$ . In each case,  $L_1 = \frac{a_1}{a_2} L_2$ ; the simulated sequence has a total length of  $10^9$ base pairs and the two class chunks are evenly alternated in the form  $(L_1, L_2, L_1, \ldots, L_2)$ . The effective size  $N_1$  was chosen as 1000. The horizontal axis is scaled in years, with a generation time of 25 years.

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