1 The demographic history of populations experiencing asymmetric

- 2 gene flow: combining simulated and empirical data.
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17 Keywords: source-sink dynamics, demographic change, fish, rivers, ABC

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- 27 **Running title:** Asymmetric gene flow and demographic inferences

# 29 Abstract

30 Population structure can significantly affect genetic-based demographic inferences, 31 generating spurious bottleneck-like signals. Previous studies have typically assumed island or 32 stepping-stone models, which are characterized by symmetric gene flow. However, many 33 organisms are characterized by asymmetric gene flow. Here, we combined simulated and 34 empirical data to test if asymmetric gene flow affects the inference of past demographic 35 changes. Through the analysis of simulated genetic data with three methods (i.e., 36 BOTTLENECK, M-ratio and MSVAR), we demonstrated that asymmetric gene flow biases 37 past demographic changes. Most biases were towards spurious signals of expansion, albeit 38 their strength depended on values of effective population size and migration rate. It is 39 noteworthy that the spurious signals of demographic changes also depended on the statistical 40 approach underlying each of the three methods. To some extent, biases induced by 41 asymmetric gene flow were confirmed in an empirical multi-specific dataset involving four 42 freshwater fish species (Squalius cephalus, Leuciscus burdigalensis, Gobio gobio, Phoxinus 43 *phoxinus*). Indeed, all species exhibited signals of bottlenecks across two rivers for two out of 44 the three methods. This suggests that, although potentially biased by asymmetric gene flow, 45 these methods were able to bypass this bias when a bottleneck actually occurred. Our results 46 show that population structure and dispersal patterns have to be considered for proper 47 inference of demographic changes from genetic data.

# 48 Introduction

49 Inferring the demographic history of populations such as changes in effective 50 population size (contractions, expansions) is of prime importance for basic research and 51 conservation issues (Chikhi & Bruford 2005; Leblois et al. 2006). Several indirect methods 52 based on the analysis of neutral genetic variation have been developed to that aim (Cornuet & 53 Luikart 1996; Garza & Williamson 2001; Beaumont 1999; Storz & Beaumont 2002). These 54 methods have been largely used to assess the impact of environmental or anthropogenic 55 changes on the demographic history of endangered populations (e.g., Goossens et al. 2006; 56 Sousa et al. 2008).

57 However, inferring the demographic history of wild populations remains challenging. 58 Indeed, most methods assume that populations can be approximated by simple models such as 59 the Wright-Fisher model (Cornuet & Luikart 1996; Leblois et al. 2006). However, wild 60 populations rarely match these assumptions, since most of them are either spatially structured, 61 affected by external gene flow and/or at a non-equilibrium state (Hanski 1998; Broquet et al. 62 2010; Chikhi et al. 2010). Consequently, any deviations from these simple models may lead 63 to misinterpretations or incorrect inferences (Nielsen & Beaumont 2009; Städler et al. 2009; 64 Chikhi et al. 2010). Given that the development of inference methods based on complex 65 demographic models poses problems of its own, it is crucial to explore how existing inference 66 methods are robust to deviations from simple models assumptions (Leblois et al. 2006; 67 Städler et al. 2009; Chikhi et al. 2010). Recent programs based on the coalescent framework 68 (Kingman 1982) allow the simulation of genetic data under a wide variety of population 69 models (Hoban et al. 2012). Thus, specific simulated genetic datasets can be analyzed to test 70 the potential effects of particular population characteristics on the genetic inference of 71 populations' demographic history. Accordingly, population structure (Nielsen & Beaumont

2009; Städler *et al.* 2009; Chikhi *et al.* 2010; Peter *et al.* 2010), sampling scheme (Städler *et al.* 2009; Chikhi *et al.* 2010), gene flow reductions (Broquet *et al.* 2010) and isolation-bydistance (Leblois *et al.* 2006) have been identified as generators of false signals of
demographic change, with biases towards bottlenecks (e.g., Broquet *et al.* 2010; Chikhi *et al.*2010) and, more rarely, towards expansions (e.g., Leblois *et al.* 2006).

77 A population characteristic that has rarely been considered to date in the context of 78 demographic history inferences is asymmetric gene flow. Differences in habitat quality, social 79 interactions or abiotic constraints (e.g., wind, oceanic currents, river flow or gravity) 80 frequently generate source-sink dynamics and impose asymmetric gene flow on natural 81 populations (Kawecki & Holt 2002). For instance, in riverine freshwater ecosystems, 82 organisms generally experience an inherent downstream-biased gene flow due to the 83 unidirectional water flow of rivers (Hänfling & Weetman 2006; Pollux et al. 2009). Such 84 asymmetry in gene flow drastically affects the genetic structure of wild riverine populations, 85 with, for instance, an accumulation of genetic diversity (e.g., number of alleles per locus) 86 downstream (i.e., sink populations, Kawecki & Holt 2002; Hänfling & Weetman 2006).

87 The demography of wild populations is dramatically affected by human pressures, and 88 notably by human-induced habitat fragmentation (Fahrig 2003; Henle et al. 2004). Freshwater 89 ecosystems are particularly affected by habitat fragmentation, either through the building of 90 hydroelectric dams or the presence of smaller obstacles like weirs (2 to 3 meters high, 91 Raeymaekers et al. 2008; Blanchet et al. 2010). In general, habitat fragmentation induces 92 changes in effective population size  $(N_e)$  that are theoretically inferable using the methods 93 described above. However, river fragmentation by dams and weirs may strongly affect the 94 movements of fishes, in both upstream and downstream directions. As a result, river 95 fragmentation can alter natural gene flow, either by exacerbating or, on the contrary, by

96 disrupting the natural asymmetric (i.e., downstream-biased) gene flow expected on such 97 ecosystems (Hänfling & Weetman 2006; Raeymaekers *et al.* 2008; but see Horreo *et al.* 98 2011). Although several studies have used coalescent- and frequency-based estimators of  $N_e$ 99 in fragmented rivers to infer effects of recent fragmentation (Alò & Turner 2005; Sousa *et al.* 100 2008; Nock *et al.* 2011), none of them have quantified how asymmetric gene flow might 101 affect the inference of past demographic changes that can be drawn from molecular markers 102 in such ecosystems.

103 In this paper, we explored both theoretically and empirically the potential problem 104 posed by asymmetric gene flow to infer temporal changes in  $N_e$ . First, we analyzed genetic 105 data simulated under a stationary linear stepping-stone model to test if asymmetric gene flow 106 can generate false signals of demographic changes. This was done using three methods widely 107 used to infer demographic changes: those implemented in the programs BOTTLENECK 108 (Cornuet & Luikart 1996; Piry et al. 1999) and MSVAR 1.3 (Beaumont et al. 1999; Storz & 109 Beaumont 2002), and the M-ratio method (Garza & Williamson 2001). Second, we used the 110 same three methods to analyze empirical data involving four freshwater fish species (Squalius 111 cephalus, Leuciscus burdigalensis, Gobio gobio, Phoxinus phoxinus) sampled in two rivers, 112 which differ by their level of anthropogenic fragmentation and asymmetric gene flow.

113

### 114 Materials & methods

115 Simulated data

To explore the consequences of asymmetric gene flow on the inference of changes in  $N_{e}$ , we simulated genetic data under 27 different scenarios representing populations experiencing symmetric or asymmetric gene flow but no changes in  $N_{e}$ , and then used this data as input for three methods used to infer changes in  $N_{e}$ . 120

121 The population genetics model. We used the coalescent-based program ms along with the 122 microsat.exe program (Hudson 2002) to simulate genetic data under a strict Stepwise 123 Mutation Model (SMM). Specifically, we approximated a river, by considering a linear 124 stepping-stone population model composed of 10 demes (see Figure 1). All demes had the 125 same effective number of diploid individuals N, which remained constant across generations. 126 Each deme was characterized by three parameters: the scaled mutation rate  $\theta = 4N\mu$ , where  $\mu$ 127 represents the neutral mutation rate per locus, and two scaled migration rates (M) corresponding to the downstream- and upstream-directed gene flow:  $M_{Downstream} = 4Nm$  and 128  $M_{Upstream} = \frac{M_{Downstream}}{a}$ , where *m* is the migration rate and *a* is a parameter representing the 129 gene flow asymmetry (Figure 1). We used values of a > 1 to generate downstream-biased 130 131 gene flow. Deme 1 and deme 10 in Figure 1 can be considered as the most upstream and 132 downstream demes of the hypothetical river, respectively.

133 Parameter estimation and exploration. For all simulations, we assumed a unique neutral mutation rate of  $\mu = 5.56 \times 10^{-4}$ . This value corresponds to the average mutation rate calculated 134 135 for 49 microsatellite loci in the Cyprinid fish Cyprinus carpio L. (Yue et al. 2007). For 136 selecting values for all other model parameters (i.e., N, m and a, this combination of 137 parameters will hereafter be referred to  $\varphi$ ), we first estimated values that best characterizes 138 riverine fish populations by performing ABC-regression analyses (i.e., approximate Bayesian 139 computation, Beaumont et al. 2002) based on observed summary statistics compiled for 140 several populations through a literature survey (Table S1). Specifically, we first obtained or 141 computed for sixteen riverine fish populations from fourteen rivers (i) the mean allelic 142 richness *per* population (AR), and (ii) the Pearson's correlation coefficient (r) between the

143 mean AR per sampling location and the distance of each sampling location from the river 144 source. Significant positive correlations between AR and distance from the river source are 145 characteristic of river organisms that experience downstream-biased gene flow asymmetry 146 (Hänfling & Weetman 2006; Blanchet et al. 2010). In a second step, we generated a total of 147 1,328,784 different genetic datasets under the population genetics model described above, by 148 drawing values for  $\phi$  from grids, as in Weiss & von Haeseler (1998; see Figure S1). As noted 149 by Beaumont et al. (2002), grids of parameters can be seen as uniform priors. For each 150 genetic dataset, fifteen independent microsatellite loci were simulated, and a total of 22 151 diploid individuals were sampled for each deme. As for the literature survey populations, two 152 summary statistics (AR and r) were computed for each simulated dataset.

153 Next, we applied an ABC-regression algorithm (Beaumont et al. 2002) to each 154 surveyed population independently, by using the R package "abc" (Csillery *et al.* 2012). For 155 each ABC analysis, we retained 1% of the simulations whose summary statistics were the 156 closest from those calculated for the surveyed population. Imperfect matching between 157 observed and simulated data was corrected by using a local linear regression method 158 (Beaumont *et al.* 2002; Csillerv *et al.* 2012). We estimated the median values of  $\varphi$  from the 159 corrected posterior distributions of  $\varphi$  for each population (see Table S1) and, finally, we 160 averaged these median values over all surveyed populations to obtain a first set of  $\varphi$  values: 161 N=3147, m=0.053 and a=7.5 (Table S1). We assumed that this set of  $\varphi$  values approximately 162 characterizes riverine fish populations. Then, to explore and generalize the effects of varying 163 N, m and a on the inference of changes in  $N_e$ , we explored two additional values per 164 parameter (leading to exploring  $N = \{50, 500, 3147\}, m = \{0.01, 0.053, 0.1\}$  and  $a = \{1, 7.5, ..., n\}$ 165 50}), and crossed all parameter values in a full-factorial design so as to generate genetic data 166 under 27 different scenarios. An asymmetry of a=50 is probably unrealistic, but the goal here

167 was to explore the effect of asymmetry in extreme conditions so as to explore how it differs 168 from a more realistic scenario (i.e., a=7.5). These scenarios were used to generate input 169 genetic data for further demographic history analyses (see § *Demographic history inference*).

170

171 Empirical data

*Biological models*. The four fish species considered here are all of the family Cyprinidae, belong to the same trophic level (i.e., they are essentially insectivorous) and differ principally in their maximum body length and dispersal abilities (Bolland *et al.* 2008; De Leeuw & Winter 2008). *Squalius cephalus* (the European chub) and *Leuciscus burdigalensis* (the rostrum dace) are two large-bodied fish (a maximum body length of 600 mm and 400 mm respectively), whereas *Gobio gobio* (the gudgeon) and *Phoxinus phoxinus* (the European minnow) are small-bodied fish (200 mm and 140 mm respectively).

179 Study area. Sampling was performed in two rivers that belong to the Adour-Garonne basin 180 drainage (South-western France): the Célé and the Viaur rivers (Figure S2). These rivers 181 present similar abiotic conditions but display differences concerning their level of 182 fragmentation. The Viaur River is highly fragmented with more than 50 small weirs (2-3 183 meters high, constructed within the last 800 years) and two recent hydroelectric dams (30 184 meters high, dating from 60 years ago, see Figure S2). We henceforth refer to this river as the 185 "highly fragmented river". In the Célé River, ten-fifteen small weirs are found along the river 186 gradient. These were established over the last century and most of them are equipped with 187 fish ladders. The Célé River will be referred to as the "weakly fragmented river". It is 188 noteworthy that asymmetric gene flow, effective population size and migration rate values 189 have been estimated for all these populations (i.e., a population here refers to a species within

190 a river system) through the ABC-regression algorithms presented above; these eight empirical 191 populations are characterized by a wide range of parameter values (see Table S1). 192 Sampling design. During summer 2006, a total of 10 and 11 sites were sampled on the Viaur 193 and Célé rivers respectively (Figure S2). We covered the entire upstream-downstream 194 gradient for both rivers to account for the entire genetic structure of the fish populations. At 195 each site, about 20 individuals per species were sampled by electric fishing. Small fragments 196 of pelvic fins were collected and preserved in 70% ethanol for later genetic analyses. L. 197 burdigalensis and S. cephalus were not found in all sampling sites, probably because the 198 habitat (notably temperature) is not favorable for these two species. 199 Genetic data. A salt-extraction protocol (Aljanabi & Martinez 1997) was performed to extract 200 genomic DNA from the pelvic fins of fishes. Phoxinus phoxinus and Gobio gobio were 201 genotyped at eight microsatellite loci, Squalius cephalus at ten loci and Leuciscus 202 burdigalensis at fifteen loci. Loci were amplified using multiplex PCRs and amplified 203 fragments were scored using the software GENEMAPPER® v.4.0 (Applied Biosystems, 204 Foster City, CA, USA). Neither departure from Hardy-Weinberg equilibrium nor null alleles 205 were detected for any of these loci (see Blanchet et al. 2010 for further details).

206

# 207 Demographic history inference

We used three approaches to infer past demographic changes through the analysis of genetic data. Two of them are moment-based methods that rely on summary statistics (i.e., the BOTTLENECK method, Cornuet & Luikart 1996; and the M-ratio method, Garza & Williamson 2001) and the third uses a full-likelihood Bayesian approach (i.e., the MSVAR method, Beaumont 1999; Storz & Beaumont 2002). For simulated data, analyses were

213 performed at two different spatial levels: (i) at the deme level, where each deme was analyzed 214 independently (i.e., 10 demes x 27 scenarios = 270 analyses, 22 individuals per analysis) and 215 (ii) at the population level, where all individuals from a same scenario were pooled together in 216 a single analysis (i.e., one analysis per scenario, 220 individuals per analysis). Pooling 217 individuals from multiple sampling locations counters potential biases induced by population 218 structure when looking for demographic changes and improves the characterization of 219 parameters associated to demographic changes at the population level (Chikhi et al. 2010). 220 Due to the computational burden inherent to MSVAR, population-level analyses were not 221 performed using this method. For empirical data, analyses were done (i) at the sampling site 222 level (i.e., 74 analyses, ~20-22 individuals per analysis) and (ii) at the population level (i.e., 8 223 analyses, between 140 and 220 individuals per analysis).

224 BOTTLENECK method. We applied the moment-based method of Cornuet & Luikart (1996) 225 as implemented in the BOTTLENECK software (Piry et al. 1999). This method compares the 226 expected heterozygosity computed from a sample  $(H_e)$  through observed allele frequencies 227 with the expected heterozygosity  $(H_{eq})$  based on the allele frequencies expected at the 228 mutation-drift equilibrium (given the observed number of alleles  $n_A$  of the sample). The 229 significance of deviations from mutation-drift equilibrium was tested through Wilcoxon's 230 signed rank tests. For simulated data, we performed analyses assuming the Stepwise Mutation 231 Model (SMM, Piry et al. 1999), as it is the mutation model used by ms to simulate the data 232 (Hudson 2002). Additionally, we calculated from the output of BOTTLENECK departures from mutation-drift equilibrium averaged over loci:  $\Delta H = H_e - H_{eq}$  (Broquet *et al.* 2010). For 233 234 empirical data, we performed analyses assuming a Two-Phase mutation Model (TPM), which 235 is more appropriate for empirical microsatellite data (Di Rienzo et al. 1994; Piry et al. 1999).

236 We parameterized the TPM with 90% single step mutations (Garza & Williamson 2001),

assuming a conservative variance among multiple steps of 10.

238 *M-ratio method*. To detect significant population declines in our datasets, we applied Garza & 239 Williamson's M-ratio test (Garza & Williamson 2001). It is noteworthy that this method 240 (contrary to the two other methods) does not allow the detection of demographic expansions. 241 In bottlenecked populations, the number of alleles on microsatellite loci  $(n_A)$  is expected to be reduced more quickly than the range in allele size ( $r_A$ ). As a result, the ratio  $M = n_A / r_A$  will 242 243 be smaller in bottlenecked populations than in stable populations (Garza & Williamson 2001). 244 Accordingly, we calculated M for both empirical and simulated datasets. Then, we compared 245 M values obtained from our data with 95% critical M values ( $M_c$ ), calculated from 10,000 246 simulations of stable populations with the Critical M program (Garza & Williamson 2001). 247 An M value that falls below the  $M_c$  value indicates that the population has experienced a 248 significant bottleneck. For simulated scenarios, we assessed  $M_c$  values assuming the SMM, 249 and using the  $\theta$  values previously used to simulate the data. For empirical data,  $\theta$  was calculated assuming  $\mu$ =5.56x10<sup>-4</sup> and using N<sub>e</sub> values reported in Blanchet *et al.* (2010). We 250 251 assumed a TPM model with a proportion of one-step mutations of 90% and an average size of 252 non-one-step mutations of 3.5 (Garza & Williamson 2001).

*MSVAR method.* To detect and quantify changes in  $N_e$ , we used a method relying on a hierarchical Bayesian model based on a coalescent framework (as implemented in MSVAR 1.3, Beaumont 1999; Storz & Beaumont 2002). This model assumes that a stable, closed population of ancestral size  $N_l$  increased or decreased exponentially to its current size  $N_0$  over a time interval *ta* (in years). Given lognormal prior distributions and microsatellite data (i.e., allelic distribution and relative allele sizes), the method infers the model parameters  $\Phi =$  $\{N_0, N_l, ta, \theta\}$ , where  $\theta = 4N_0\mu$  and  $\mu$  is the mutation rate. The posterior probability density of  $\Phi$ 

260 is established through Markov Chain Monte Carlo (MCMC) techniques. Loci are supposed to 261 be independent and to evolve under a strict SMM, but the method is also robust against 262 deviations from strict SMM (Storz & Beaumont 2002; Girod et al. 2011). For each MSVAR analysis, we performed four independent runs of  $5 \times 10^9$  steps, varying the starting values and 263 264 means for priors and hyperpriors (values in Table S2). Parameters were thinned with an interval of  $5 \times 10^4$  steps, resulting in output files with  $1 \times 10^5$  values. To avoid bias induced by 265 266 the starting values on parameter estimation, the first 10% of the chains was discarded (i.e., 267 burn-in). We checked the convergence of the chains visually and with the Gelman & Rubin 268 analysis (Gelman & Rubin 1992). We considered that chains converged well when values 269 smaller than 1.1 were obtained (Gelman & Hill 2007).

270 For each independent run of MSVAR, the magnitude of the demographic change was 271 estimated through the calculation of an effect size (i.e., Hedges'd, Hedges & Olkin 1985) and 272 its 95% confidence interval. Hedges'd is a mean standardized difference (i.e., independent of the original scale) between the log of the ancestral population size  $(log(N_l))$  and the log of the 273 274 current population size  $(log(N_0))$ . The standardization of the mean difference is obtained by 275 dividing the mean difference by a pooled standard deviation (formulas in Appendix S1). We 276 combined the four effect sizes of each independent run to calculate a mean effect size (MES) 277 per analysis, along with its 95% confidence interval (Rosenberg et al. 1997). A MES value 278 whose confidence interval includes zero means that the population did not experience a 279 significant demographic change. Significantly negative values correspond to significant 280 bottlenecks, while significantly positive values are significant population expansions. Pairs of 281 MES were considered as significantly different when their 95% confidence intervals did not 282 overlap. Information about these methods along with an illustrative example is provided in the 283 Appendix S1.

284 For empirical data, we further estimated the beginning of the exponential demographic 285 changes inferred with MSVAR by calculating Bayes' factors (BFs), which measure the 286 weight of evidence of alternative time intervals for ta (i.e., the time of the beginning of the 287 demographic change). BFs were first computed for time periods of 10 years in a sliding 288 window from 0 to 100 years, then for periods of 100 years from 200 to 10,000 years ago. BFs 289 greater than 4 are usually interpreted as positive evidence, while BFs greater than 7 are 290 considered as significant (Storz & Beaumont 2002; Sousa et al. 2008). For each species on the 291 highly fragmented river, we also calculated (through the posterior distribution of ta) the 292 probability that the detected demographic changes occurred (i) after dam construction (p<sub>(dam)</sub> 293 ta between 0-60 years ago), and (ii) after weir construction began ( $p_{(weir)}$ , ta between 0-800 294 years ago). We considered a generation time of three years for S. cephalus and L. 295 burdigalensis, and of two years for G. gobio and P. phoxinus (Poncin et al. 1987). For the 296 sake of clarity, we present only BFs computed for *ta* at the population level.

297 *Effects of N, m, a and distance from the source on demographic history inference.* In order to 298 synthesize results obtained from the simulated datasets, we ran Generalized Linear Models 299 (GLMs) to statistically test for each method independently the effects of N, m, a and distance 300 from the putative source (D) on inferences of changes in Ne. In these models, the dependent 301 variables were  $\Delta H$ , M and MES (calculated at the deme level) for the BOTTLENECK, M-302 ratio and MSVAR methods respectively. Explanatory variables were N, m, a and D. They 303 were all treated as fixed effects, and we further included all two-term and three-term 304 interactions so as to test the significance of interacting effects between explanatory variables. 305 We assumed Gaussian error terms for all dependent variables and the significance of each 306 fixed effect was assessed using F-ratio tests.

# 309 Simulated data

310 BOTTLENECK method. At the deme level and over all scenarios, 47 datasets (47/270=17.4%) 311 exhibited significant departures from mutation-drift equilibrium. Most of them (32/47=68%) 312 displayed significant heterozygosity deficiencies, which are generally interpreted as signals of demographic expansions. Only 15 demes displayed significant heterozygosity excesses, which 313 314 are generally interpreted as signals of bottlenecks. At the population level, and over all 315 scenarios, we detected 14 (14/27=51.9%) significant departures from mutation-drift 316 equilibrium, all in the form of heterozygosity deficiencies. Additionally, our GLM-based 317 analysis revealed a significant three-way interaction between N, m and a (Table 1). This 318 analysis indicates that the BOTTLENECK method detected false signals of expansion (i.e., 319 negative values of  $\Delta H$  under moderate (i.e., a=7.5) and strong (i.e., a=50) gene flow 320 asymmetries, although this pattern was altered by the effective population size at the deme 321 level (Figure 2A-C).

*M-ratio method.* At the deme level and over all scenarios, 36.3% of the demes (i.e., 98/270) displayed a significant signal of population decrease. However, at the population level, no significant signals of demographic decline were detected. The GLM-based analysis also highlighted a significant three-way interaction between *N*, *m* and *a* (Table 1). This analysis confirmed that the M-ratio method detected false signals of bottlenecks, but only for symmetric gene flow, and under some specific combinations of *N* and *m* (Figure 2D).

328 *MSVAR method*. 41.85% of deme-level datasets (i.e., 113/270) indicated significant signals of 329 demographic change. Among these significant signals, false signals of expansion were more 330 frequent than false signals of bottleneck (69% vs. 31% respectively). According to the GLM

331 analysis, we detected two significant two-term interactions, one implying N and m, and the 332 other implying m and a (Table 1). The first interaction indicated that, irrespective of a, false 333 signals of bottleneck were mainly detected for low values of N and m, whereas false signals of 334 expansion tended to be greater for intermediate values of m (0.053) and large values of N (> 335 500, Figure 3A). The second interaction indicates that, irrespective of N, strong signals of 336 false bottlenecks were mainly detected for situations of symmetric gene flow (i.e., a=1), but 337 only for low migration rate (m=0.01, Figure 3B). In contrast, strong signals of false 338 expansions were detected under several and contrasted combinations of *m* and *a* (Figure 3B). 339 Indeed, false signals of expansion were detected under symmetric gene flow and with high 340 migration rate (m=0.1), but also under asymmetric gene flow (a = 7.5 or 50) and low to 341 medium migration rates (m = 0.01 or 0.053, Figure 3B). We additionally found that, overall, 342 the magnitude of the false demographic expansion increased with the distance from the 343 putative source (Table 1).

344

345 Empirical data

346 *BOTTLENECK method.* At the sampling site level, we detected a significant heterozygosity 347 excess in only one case (i.e., site V8 for *S. cephalus* in the river Viaur, Table S3). In contrast, 348 17 significant heterozygosity deficiencies were detected (Table S3). None of these deviations 349 were significant after Bonferroni corrections. In contrast, at the population level, significant 350 heterozygosity deficiencies were found for all species and in the two rivers (Table 2).

351

*M-ratio method*. At the sampling site level, the M-ratio test detected significant bottlenecks at all sites, irrespective of the species and the river (Table S3). At the population level, all

populations exhibited significant signals of bottleneck but one (i.e., *G. gobio* in the river Célé;
Table 2).

356

357 MSVAR method. At the sampling site level, most sampling sites displayed significant 358 bottlenecks (i.e., all MES values were significantly negative), a pattern that holds true for all 359 species and rivers (Figure 4). There were no clear spatial patterns along the upstream-360 downstream gradient (i.e., demographic changes did not tend to be larger either downstream 361 or upstream, Figure 4). However, there were striking site-to-site MES discrepancies. For 362 instance, for *P. phoxinus*, we found no significant demographic changes in downstream sites 363 for both the Célé and Viaur rivers (i.e., the MES 95% CI included 0), while other sites were 364 characterized by signals of bottlenecks of diverse magnitudes (Figure 4D).

Concerning population level analyses, we found significant bottlenecks for all species and rivers (Figure 5). These analyses indicated that the magnitude of the bottleneck tended to be stronger for the two largest species (*S. cephalus* and more particularly *L. burdigalensis*) than for the two smallest species (*G. gobio* and *P. phoxinus;* Figure 5). Furthermore, the magnitude of the bottleneck was significantly stronger in the highly fragmented river for *L. burdigalensis* and *G. gobio* (Figure 5).

Regarding the dating of the detected bottlenecks, we estimated that they most probably occurred more than 800 years ago (Figure 6) and thus before dam or weir construction. Accordingly, the probabilities that these bottlenecks occurred after dam or weir construction on the highly fragmented river were very low for all species ( $p_{(dam)} < 0.007$ ,  $p_{(weir)} < 0.052$ ). Only *P. phoxinus* showed a non negligible  $p_{(weir)}$  of 0.238. Over all species, the population declines tended to be more ancient in the highly fragmented river than in the weakly fragmented river,

except for *L. burdigalensis* (Figure 6). At the intra-river level, *ta* estimations were also
congruent for all species but *L. burdigalensis*. This species revealed the most ancient *ta* values
on the weakly fragmented river (Figure 6A) whereas it showed one of the most recent
bottlenecks on the highly fragmented river (Figure 6B).

381

# 382 **Discussion**

383 As expected, our simulated data showed that asymmetric gene flow can bias the 384 genetically-based inference of past demographic changes. We notably demonstrated that 385 asymmetric gene flow can -under certain conditions of migration rate and effective population 386 size- generate false signals of population expansion. Interestingly, this tendency was detected 387 in our empirical data, but only for one of the three inference methods we used. In contrast, the 388 other two methods revealed strong signals of bottleneck for the four fish species and across 389 the two rivers sampled, which are characterized by different levels of asymmetric gene flow 390 (see Table S1).

391

# 392 Effects of gene flow asymmetry on demographic history inferences

In most cases of significant –although spurious- demographic changes, our simulations showed that asymmetric gene flow generates false signals of demographic expansion. However, this pattern was sensitive to other population parameters, namely the migration rate and the effective population size. We indeed detected strong interactive effects of these population parameters on signals of false demographic changes. These interactive effects are yet difficult to biologically interpret, and make difficult to withdraw general predictions about the effect of asymmetric gene flow on estimates of historical demographic changes in natural

400 systems. Our results hence demonstrate the importance of simultaneously considering
401 multiple parameters such as the effective population size and the migration rate when testing
402 the robustness of analytical methods through simulations.

403 The effect of asymmetric gene flow on demographic change inferences was also 404 dependent on the method we used. Indeed, contrary to the MSVAR and the BOTTLENECK 405 methods, the M-ratio method was not affected by asymmetric gene flow, as we found no clear 406 evidence that downstream-biased asymmetric gene flow led to false signals of bottleneck. 407 However, under conditions of symmetric gene flow, the M-ratio method tended to detect false 408 signals of bottleneck, especially under low to moderate migration rates. As demonstrated 409 previously for the MSVAR method (Chikhi et al. 2010), this may be due to the confounding 410 effects of population structure, and of the sampling scheme on the representativeness of 411 genetic diversity.

412 We further observed correlations between distance from the upstream deme and the 413 magnitude of the demographic expansion (only for the MSVAR method). These differences 414 between upstream and downstream demes are probably the result of a source-sink like 415 dynamic, whereby downstream demes act as sinks and receive an excess of alleles through 416 downstream-directed migration (Kawecki & Holt 2002; Morrissev & de Kerckhove 2009). 417 Such source-sink dynamics generally lead to a gradual increase of allelic richness along the 418 upstream-downstream gradient in rivers (Hänfling & Weetman 2006; Blanchet et al. 2010), 419 and may therefore produce signals similar to those generated by demographic expansions. 420 This may be because the number and frequencies of alleles actually observed in downstream 421 sites are different than what expected under a demographically stable model. Finally, we 422 found that the symmetric gene flow scenario led to patterns of false bottlenecks (only for low

423 migration rate), as expected from previous simulations in n-island and two-dimensional
424 stepping-stone models (Städler *et al.* 2009; Chikhi *et al.* 2010).

425

# 426 Effect of asymmetric gene flow on fish population demographic histories

427 We detected significant population bottlenecks for all species in the two rivers when 428 we analyzed the empirical data. Because two out of the three methods (MSVAR and M-ratio 429 methods) were concordant in highlighting significant bottlenecks, we could reasonably 430 assume that these populations had actually experienced demographic declines. However, 431 significant signals of expansions were identified for all species and rivers at the population 432 level using the BOTTLENECK method. This result is consistent with that obtained for the 433 simulated data (see above), suggesting that, in wild populations, this method may be subjected 434 to the type of bias induced by asymmetric gene flow. Overall, this would suggest that, despite 435 asymmetric gene flow may theoretically affect the inference of demographic changes (our 436 simulations), some inference methods may be powerful enough to bypass this type of bias 437 when a population has actually experienced a bottleneck.

438 We tested such a hypothesis by running an additional analysis in which we simulated a 439 scenario where the population was subjected to (i) a bottleneck of magnitude and timing 440 similar to that estimated for the empirical data, and (ii) post-bottleneck  $\varphi$  values equal to the 441 mean values estimated from the literature survey (i.e., N=3147, a=7.5, m=0.053). We found 442 that MSVAR detected a significant bottleneck (results not shown), which suggests that at least 443 under some conditions, MSVAR can bypass the bias induced by asymmetry. It is noteworthy 444 that we also detected a significant bottleneck using the M-ratio test, whereas BOTTLENECK 445 detected a significant heterozygosity deficiency (i.e., a population expansion signal).

Regarding our empirical data, we note however that some sampling sites did not display significant demographic changes. For instance, the absence of significant bottlenecks for *P*. *phoxinus* in downstream sites suggests that asymmetric gene flow was probably strong enough in these sites to counterbalance the effect of ancient bottlenecks. This means that more simulations varying both asymmetric gene flow and the characteristics (i.e., magnitude, date and type) of demographic changes are required to refine the conditions under which MSVAR adequately detects population size changes.

453 To summarize, our study suggests that the BOTTLENECK method may be less suited 454 than the MSVAR and M-ratio methods to infer demographic changes in wild populations 455 experiencing asymmetric gene flow. This conclusion is apparently solid, since our empirical 456 dataset includes fish populations covering a wide range of values regarding their levels of 457 asymmetric gene flow (i.e., 1.893 < a < 9.135), migration rate (i.e., 0.042 < m < 0.078) and 458 effective population size (i.e., 546.488 < N < 8,088.188; see Table S1). But, given the fact we 459 do not know the actual demographic history of these populations, we should remain cautious. 460 An important lesson from this is perhaps that each methods looks at the genetic data from a 461 slightly different angle, and uses different aspects of genetic diversity measures, which may in 462 the end mean that the methods could be used jointly once we better understand their joint 463 properties.

From a biological point of view, we surprisingly found that the dating of the bottlenecks experienced by these populations was similar for three of the four species. For all species, we found that the corresponding demographic declines were ancient and pre-dated the construction of the weirs and dams. For the highly fragmented river, the most likely inferred dates for the beginning of the bottlenecks range from 2,000 to 8,000 years ago, which contrasts with the first known mill weirs in this river (~800 years ago). Such dating suggests

470 that these bottlenecks occurred after the last glacial period (i.e., Würm glacial period, ta < t471 10,000 years), more precisely between the Atlantic and the middle Subatlantic chronozones of 472 the Holocene (Mangerud et al. 1974). These important bottlenecks might have been generated 473 by different events, such as post-glacial colonization (Hänfling et al. 2002; Swatdipong et al. 474 2010), environmental stochastic events or random catastrophes (Hedrick & Miller 1992; 475 Lande 1993). The dating obtained with the MSVAR method might only be loosely related to 476 any particular event. Improving our knowledge in the paleoenvironmental history of the 477 studied region would certainly help in understanding the potential causes of such strong 478 population declines. Moreover, in the case of a series of expansions and contractions (which 479 are likely to have happened in many natural systems), it is unclear which event would be 480 "identified" by MSVAR (Quéméré et al. 2012; Salmona et al. 2012). Simulation of multiple 481 events may thus be necessary for improving our interpretation of MSVAR outputs.

482

#### 483 Conclusion

484 Recent years have shown that several factors can play significant roles in producing 485 non-equilibrium patterns, such as isolation by distance (Leblois et al. 2006), population 486 structure (Städler et al. 2009; Chikhi et al. 2010, Peter et al. 2010), rapid decreases of gene 487 flow (i.e., fragmentation, Broquet et al. 2010), spatial expansions (Edmonds et al. 2002), or 488 departures from the assumed mutation model (Chikhi et al. 2010). However, the 489 consequences of asymmetrical gene flow have been neglected. Our simulations confirm our 490 expectation that asymmetric gene flow may generate biases when inferring demographic 491 changes from genetic data. However, the direction and magnitude of such biases depended 492 upon other population characteristics such as migration rate and effective population size.

This study demonstrates the complexity of inferring demographic changes from genetic data
in wild populations, and the importance of integrating multiple parameters in simulations
aiming at testing the robustness of inference methods in population genetics (e.g., Heller *et al. in press*).

497 In spite of these potential biases, our multi-specific empirical data suggests that, if 498 used with care and conjointly, most inference methods appear suitable to infer demographic 499 changes in populations experiencing asymmetric gene flow. Indeed, our empirical data 500 suggest that asymmetric gene flow was unlikely to have caused the bottlenecks observed in 501 the eight wild fish populations. We also found that if a major bottleneck was responsible of 502 the patterns observed, it was unlikely to have been caused by recent anthropogenic 503 fragmentation. However, we cannot claim that we have identified unambiguously the factors 504 generating the strong bottlenecks observed in all fish species, even if they dated around the 505 same period.

506 The last twenty years have seen major improvements in population genetics inference, 507 in particular with the development of full-likelihood methods. Our results and those from 508 previous studies clearly demonstrate that population structure and dispersal patterns have to 509 be considered for properly inferring the demographic history of wild populations (Chikhi et 510 al. 2010; Girod et al. 2011). An important step for future studies will be to quantify the ability 511 of emerging methods (such as those based on approximate Bayesian computations) to 512 efficiently disentangle signals of demographic changes from false signals arising from 513 population structure (see Peter et al. 2010 for instance).

514

## 515 Acknowledgements

516 We thank Éric Petit, Thomas Broquet, Vincent Dubut, Jérôme Chave, Camille Pagès, 517 Guillaume Evanno, Raphael Leblois and three anonymous reviewers for their constructive 518 and stimulating comments. Olivier Rev, Gaël Grenouillet, Loïc Tudesque, Muriel Gevrev, 519 Laetitia Buisson, Sébastien Brosse, Leslie Faggiano and Fabien Leprieur are thanked for their 520 help in the field. We also thank the CALMIP group, in particular Boris Dintrans and Nicolas 521 Renon. This work was performed using HPC (High Performance Computing) resources from 522 CALMIP (allocation 2010-P1003). We are grateful to Radika Michniewicz for correcting and 523 editing the English. The authors also thank the "Agence de l'Eau Adour-Garonne" for 524 financial support and the "Génopole Toulouse" for help with genotyping. IP is financially 525 supported by a MESR ("Ministère de l'Enseignement Supérieur et de la Recherche") PhD 526 scholarship. This work has been done in two research units (EDB & EcoEx CNRS Moulis) 527 that are part of the "Laboratoire d'Excellence (LABEX) entitled TULIP (ANR -10-LABX-(Q\_2\_\_\_\_\_) 528 41).

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658	
659	Data accessibility

- 660 R scripts for analyzing MSVAR outputs and for simulate genetic data with ms, empirical
- 661 microsatellite datasets and simulated microsatellite datasets are available at Dryad Digital
- 662 Repository doi:10.5061/dryad.5sc31.

#### Authors' contributions 663

- 664 IP, SB, GL, EQ and LC wrote the paper. SB, IP and GL designed the study and
- and . 665 managed the project. IP, SB, EQ and LC implemented the methods and analyzed the results.
- 666 All authors read and approved this version of the manuscript.
- 667

668	TABLE 1: Results for the Generalized Linear Models used to synthesize results					
669	obtained from the analyses of simulated datasets with (i) BOTTLENECK (associated					
670	dependent variable = $\Delta H$ ), (ii) the M-ratio method (i.e., $M$ ), and (iii) MSVAR (i.e., MES).					
671	"NS" indicates p-values > 0.05; * indicates p-values < 0.05; ** indicates p-values < 0.01;					
672	*** indicates p-values < 0.001. Significant effects indicates that explanatory variable					
673	significantly affect one of the three dependent variables, each being related to one of the					
674	three methods used to infer demographic changes. Significant single terms are not					
675	interpreted when they are involved in significant interaction terms.					
676						
	Explanatory variables Dependent variables					

676

Explanatory variables		Dependent variables		
	$\Delta H$	М	MES	
Distance from the source (D)	NS	NS	***	
Effective population size $(N)$	***	***	***	
Migration rate ( <i>m</i> )	***	***	NS	
Asymmetry coefficient ( <i>a</i> )	***	***	*	
D*N	NS	**	NS	
D* <i>m</i>	NS	NS	NS	
D*a	NS	NS	NS	
$N^*m$	***	***	**	
$m^*a$	**	**	***	
$N^*a$	***	***	NS	
D* <i>N</i> * <i>m</i>	NS	NS	NS	
D* <i>m</i> * <i>a</i>	NS	NS	NS	
D* <i>N</i> *a	NS	NS	NS	
N*m*a	**	***	NS	

- 678 TABLE 2: Results for the Wilcoxon's sign rank tests computed by BOTTLENECK for
- 679 the empirical data and for the M-ratio test. For the two methods, analyses were
- 680 conducted at the population level assuming a TPM mutation model.
- 681

Species	River	Status	Wilcoxon excess	Wilcoxon deficiency	<i>M</i> (sd)
S. cephalus	Viaur	highly fragmented	0.997 <sup>NS</sup>	0.005**	0.571 (0.217)*
L. burdigalensis	Viaur	highly fragmented	0.999 <sup>NS</sup>	0.002**	0.563 (0.197)*
G. gobio	Viaur	highly fragmented	0.996 <sup>NS</sup>	0.006**	0.6931 (0.233)*
P. phoxinus	Viaur	highly fragmented	0.980 <sup>NS</sup>	0.027*	0.748 (0.165)*
S. cephalus	Célé	weakly fragmented	0.999 <sup>NS</sup>	0.001**	0.5839 (0.146)*
L. burdigalensis	Célé	weakly fragmented	0.999 <sup>NS</sup>	<0.001**	0.664 (0.203)*
G. gobio	Célé	weakly fragmented	0.980 <sup>NS</sup>	0.027*	0.788 (0.201)
P. phoxinus	Célé	weakly fragmented	1.000 <sup>NS</sup>	0.008*	0.739 (0.171)*

For the BOTTLENECK analyses: \* indicates a significant deviation from mutation-drift equilibrium (p-value  $\leq$  0.05); \*\* indicates a significant deviation from mutation-drift equilibrium after sequential Bonferroni corrections for all populations, and <sup>NS</sup> means that there is not a significant deviation from mutation-drift equilibrium (p-value  $\geq$  0.05). Significant *He* excesses are evidences of recent population decreases. Significant *He* deficiencies can be interpreted as evidences of recent demographic expansion. For the M-ratio test: \* indicates a significant *M* value (i.e.,  $M \leq M_c$ ), which is interpreted as a significant signal of population decrease, and <sup>NS</sup> means that the test is not significant (i.e.,  $M \geq M_c$ ).

# 690 **Figure legends**

FIGURE 1. Diagram representing the linear stepping-stone model with asymmetric gene flow. Black circles are demes. M<sub>Downstream</sub> characterizes downstream-directed gene flow, while M<sub>Upstream</sub> indicates upstream-directed gene flow. Here, deme one is considered as the most upstream deme of a hypothetical river.

**FIGURE 2.** Barplots representing values of  $\Delta H$  (A, B and C) and M (D, E and F) in

696 function of three interacting parameters (as revealed by the GLM-approach: N, m

and *a*). Vertical lines correspond to the standard error. \* means that the population

- has experienced a significant bottleneck (i.e.,  $M < M_c$ ).
- FIGURE 3. Barplots representing values of mean effect sizes (MES) in function of
  two different two-term interactions (as revealed by the GLM-approach): (A)
  interaction between the parameters N and m, and (B) interaction between m and a.
  Vertical lines correspond to the standard error.

703 FIGURE 4. Sampling site level mean effect sizes (MES) calculated for all species 704 and rivers. Black squares characterize the weakly fragmented river (Célé) sites, 705 while white squares represent highly fragmented river's sites (Viaur). Dashed lines 706 represent the non-significant relationships between MES values and the distance 707 from the source at each site determined by GLMs. Grey vertical lines represent 708 MES' 95% confidence intervals (CIs). MES whose CIs include zero means that no 709 significant demographic changes have been detected. Negative values correspond to 710 significant bottlenecks. Intra-river and intra-specific MES can be easily compared 711 by seeing if their respective CIs overlap. Two MES are considered significantly 712 different when their CIs did not overlap.

713 FIGURE 5. Mean effect sizes (MES) for all species and rivers calculated at the 714 population level. Grey vertical lines represent MES' 95% confidence intervals 715 (CIs). Two MES are considered significantly different if their CIs did not overlap. 716 Here, we symbolized only the significance of intra-specific comparisons (i.e., 717 comparison between MES of the highly fragmented vs. the weakly fragmented river 718 for a single species). NS indicates no significant intra-specific difference between weakly fragmented vs. highly fragmented river and \*\*\* means significant 719 720 difference.

FIGURE 6. Bayes' factors (BFs) for the time of the beginning of the demographic changes (*ta*) calculated for the four species for the weakly fragmented river (A) and the highly fragmented river (B). Results correspond to the population level analyses. BFs greater than 4 are considered as "positive evidences", while BFs greater than 7 are considered as significant. Dashed vertical lines correspond to the construction of dams (*ta* = 60 years) and to the beginning of weir construction (*ta* = 800 years).



# 729 **FIGURE 1**







# 736 **FIGURE 3**



739 **FIGURE 4** 



741 **FIGURE 5** 



745 FIGURE 6

