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3 Title

- 4 Weather at the winter and stopover areas determines spring migration onset, progress, and
- 5 advancements in Afro-Palearctic migrant birds

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- 18 B.H., O.H., and F.B. conceptualized the study and contributed ideas. B.H. designed and
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22 Abstract

Climate change causes changes in the timing of life-cycle events across all trophic 23 24 groups. Spring phenology has mostly advanced, but large, unexplained, variations are 25 present between and within species. Each spring, migratory birds travel tens to tens of 26 thousands of kilometers from their wintering to their breeding grounds. For most 27 populations, large uncertainties remain on their exact locations outside the breeding 28 area, and the time spent there or during migration. Assessing climate (change) effects on 29 avian migration phenology has consequently been difficult due to spatial and temporal 30 uncertainties in the weather potentially affecting migration timing. Here, we show for six trans-Saharan long-distance migrants that weather at the wintering and stopover 31 32 grounds almost entirely (~80%) explains inter-annual variation in spring migration 33 phenology. Importantly, our spatiotemporal approach also allows for the systematic 34 exclusion of influences at other locations and times. While increased spring 35 temperatures did contribute strongly to the observed spring migration advancements 36 over the 55-year study period, improvements in wind conditions, especially in the 37 Maghreb and Mediterranean, have allowed even stronger advancements. Flexibility in 38 spring migration timing of long-distance migrants to exogenous factors has been 39 consistently underestimated due to mismatches in space, scale, time, and weather 40 variable type.

41 Significance Statement

42 Migratory birds show alarming declines across the globe, especially birds that migrate over 43 long-distances. A limited ability to adjust spring arrival to climate change at the breeding 44 grounds, especially compared to residents and shorter-distance migrants, is thought to be a 45 major cause. Our results show that breeding area arrival of cross-continental migrant birds is nevertheless, similarly to short-distance migrants, largely driven by weather conditions at the 46 47 wintering and stopover grounds. Additionally, our study indicates that not only temperature 48 rise but also more favorable wind conditions have allowed birds to arrive earlier. A better 49 understanding of climate change influences on the timing of biological phenomena is vital to 50 understanding and ultimately battling the consequences of climate change on population 51 demographics.

52 Introduction

53 Ample evidence now exists that climate change is already impacting a broad range of 54 organisms across all taxa, from plants to mammals, and across the globe (1-3). Migratory 55 species are likely to be particularly vulnerable to climate change, as they presumably evolved 56 to profit from spatiotemporally distinct, yet largely predictable, seasonal patterns of natural 57 resource productivity (4, 5). Populations of long-distance, e.g. trans-Saharan, migratory bird 58 species are currently declining considerably faster than those of resident or short-distance 59 migrants (6, 7). Climate change has been repeatedly suggested to be one of the major causes of these (differences in) population declines (4, 6, 8, 9), yet the specific mechanisms through 60 61 which this might be occurring are anything but clear (4, 6, 7, 10–12). A limited ability of 62 long-distance migrants to adjust spring arrival to climate change at the breeding grounds has 63 been suggested to be a major contributing factor (8, 13). If the distance between wintering and

breeding grounds is rather limited, spatiotemporal (auto-)correlations in the weather between the two areas render the conditions at the former to be a somewhat reliable cue to estimate appropriate arrival at the latter (14). For larger distances, these connections no longer hold, which, together with reduced seasonality in the tropics, has contributed to the hypothesis that

68 long-distance migrants must rely primarily on endogenous rhythms for spring migration

69 timing (15).

70 For a long time, it was indeed, and perhaps continues to be, thought that spring migration of long-distance migrants, especially the onset, relies primarily, or at the very least much more 71 72 than for short-distance migrants, on endogenous rhythms (11, 15–18). Initially, this led to the 73 suggestion that neither conditions at the wintering nor stopover areas en route to the breeding 74 grounds have much influence on arrival at the breeding grounds (4, 13). Notwithstanding, 75 strong advancements in spring migration timing of long-distance migratory birds have been repeatedly reported over the past two decades (11, 19–22). This has led to an ongoing debate 76 77 with two somewhat opposing, albeit not necessarily mutually exclusive hypotheses. Some 78 argue that given spring departure is under strong endogenous control and long-distance 79 migrants have a limited ability to phenotypically adjust their advancement along the migration 80 route, the advancement in arrival at the breeding ground is thus most likely to be caused by an evolutionary response in spring departure timing at the wintering grounds (19, 20, 23). 81 82 Meanwhile, however, many studies have also been reporting on correlations between spring 83 arrival (or passage) advancement of long-distance migrants and climate (change) at 84 (approximate) wintering areas, but especially (potential) stopover areas along the migration 85 route (11, 20, 21, 24). As a result, some suggest that phenotypic responses to weather along the migration route is the main mechanism of advancement for long-distance migrants, while 86 spring departure from the wintering grounds changes little because it is under strong 87 88 endogenous control (17, 18, 21). While mainly limited to a number of songbirds, the 89 experimental evidence on internal clocks and the relevance of photoperiod as a trigger of 90 migration are irrefutable (15, 25). Nonetheless, under laboratory conditions, endogenous 91 rhythms often stray away rather far from one-year lifecycles, sometimes up to several months 92 (15). Moreover, outside of experimental laboratory settings, environmental conditions 93 encountered by individuals at the departure and stopover areas at the same date are different 94 each year. Making the best decision, hence, inevitably entails some flexibility in the migratory 95 response (25).

96 A major hurdle in investigating potential climate change effects on spring migration 97 phenology, and consequently in further unraveling the exact mechanisms through which the 98 observed advancements take place, has been the large uncertainties about where and when 99 most individual migratory birds or populations exactly go to outside the breeding area, 100 including which routes they take there (14, 25). One approach to deal with the spatial uncertainty has been to use large-scale climate indices, e.g. El Niño indices or the North 101 102 Atlantic Oscillation index (21). Others have similarly used summary values of weather (or 103 vegetation) conditions by averaging over (very) large areas, such as the entire Sahel region 104 (20, 25) or the entire known wintering area of the species. The validity and biological 105 meaning of the reported effects of such large-scale indices has recently, however, been 106 strongly questioned (26). Many others resorted to using climatic conditions measured at the 107 area of passage or arrival, even though these are not necessarily related to those where the birds are coming from and hence are more likely reacting to (14, 25). Next to these potential 108 109 mismatches in space and scale, strong assumptions are generally also made on the timing, i.e. 110 start and duration, of the climatic influence. The vast majority of studies use variables defined 111 by months, e.g. monthly average temperature or monthly precipitation (14). Only sometimes, ad hoc periods are decided upon based on the species' ecology (21, 25), and although the 112 113 exact timing of influences is in most migrant species and populations perhaps just as uncertain 114 as the locations, only very rarely an explicit time window search has been applied to 115 determine the most likely time period of influence (14, 24).

Temperature has been repeatedly shown to be the most important exogenous factor impacting spring migration timing (11, 14, 25, 27), yet precipitation and wind effects have also been shown to have an effect (14, 28). For migratory herbivores, e.g. geese, primary productivity has been proposed to be a more likely cue or even better predictor of spring migration phenology. While it has been suggested that this green wave hypothesis could even be extended to insectivorous (or carnivorous) migrants (29, 30), it actually seems, even for herbivores, far from ubiquitously applicable (5).

123 In summary, the ongoing debate about the extent and mechanisms of climate change 124 influences on spring migration phenology of long-distance migrants, has proven challenging 125 due to the difficulties in identifying the appropriate location, time, scale, and type of possible weather influences. This resulted in most studies to resort to very rough spatial and temporal 126 127 approximations or guesses of possible climatic influences. The inherent spatiotemporal inter-128 and auto-correlation of weather variables, however, strongly increases false positive 129 probabilities for such approaches, further exacerbating the issue by resulting in many 130 'significant' yet biologically meaningless correlations (14). Not surprisingly then, reported 131 effects of weather on spring migration timing have been strongly heterogeneous, and the current evidence on the location, time and types of climate change effects on spring migration 132 133 phenology of long-distance migrants birds has remained largely anecdotal and often 134 contradictory.

135 We use a recently developed spatiotemporally systematic method (14, 31) to overcome much 136 of the challenges and uncertainties in matching the right location, time, and type of weather 137 influences on spring migration phenology. The method consists of two main analyses parts. 138 First, a per grid cell analysis is performed for each species of all possible time windows of 139 any length between two given dates, for each weather variable and over a spatial grid 140 covering the area of interest to the studied process. In other words, as few as possible 141 assumptions are made on which weather variable influences spring migration in which 142 location or during which timeframe. Instead, we search for the best performing time window 143 for each grid cell and weather variable type (using the 'climwin' R package (32, 33)), by 144 comparing AICc model values with a base model that consists of the temporal trend for that 145 particular species. By applying the same procedure to a number of randomizations of the 146 weather data, we then estimate the probability of obtaining a similar performing 'best' time 147 window by chance only. Importantly, the method not only enables identifying the area, time, and type of the most likely weather influences for each species, but also excluding other areas, 148 149 times, and types of weather that are very unlikely to be of any influence. For each species, this 150 first step leads to a long-list of "weather variable – location – time window" combinations. 151 henceforth called candidate weather signals, that might possibly be influencing the migration 152 phenology at the location of observation. Due to spatiotemporal (auto-)correlation in the 153 weather data, however, the long-list still contains many spurious candidate weather signals 154 (14). In the second part of the analysis, the long-list of candidate weather signals for each 155 species is then analyzed using an ensemble of variable importance methods to obtain a final 156 list of the few most likely "weather variable - location - time window" influences on 157 migration phenology.

We applied the method to the mean spring passage dates of six long-distance migrant species at the island of Helgoland (Germany) over the period 1960-2014 (Table S1 and Table S3), searching a spatial grid that covers all somewhat possible wintering or spring stopover locations prior to passage at Helgoland (see the Methods - Weather data section). As such, we first simultaneously determined the space, time window, and type of the most likely weather influences on the inter-annual variability in spring migration phenology (Table S8 to Table S10). After determining the most influential weather influences for each of the six species, we then combined their effects on migration phenology with their change over time to assess the contribution of each climatic effect to the overall advancement in spring migration of the respective species (Table S12 and Table S13). A more detailed description of each step of the methodology is provided in the Materials and methods section. The code and data to replicate our results are available in a public repository (34).

170 **Results**

171 We found that a mixture of wind, temperature, and precipitation effects at the winter and 172 spring stopover grounds (Fig. 1), explains between 72% and 86% of the variance in spring migration phenology of long-distance migrants (Table 1). Predictive R² (calculated using 173 leave-one-year-out) were very similar to adjusted R^2 (35) values, confirming robustness of the 174 175 final identified weather signals. Repetitions of the analysis over 200 randomizations of each species' MSPD, furthermore, confirmed that such strong relationships (i.e. such high adjusted 176 and predictive R^2 values) are extremely unlikely (0%) to be obtained due to chance alone 177 178 using our method (see Materials and Methods, Fig. S5 and Table S11). While we searched for 179 weather influences over an area spanning from northern Scandinavia to Cameroon, and from 180 Iceland and the Canary Islands to Poland, Greece, Libya, and Chad (see Materials and 181 methods, Table S2, and Fig. S1 to Fig. S4), we only found weather influences at locations that 182 are very likely winter or spring migration stopover locations (Fig. 1). The majority of the weather influences, especially in the case of winds, seem to typically be located just prior or 183 184 after crossing an ecological barrier, such as the Sahara desert or the Mediterranean Sea (Fig. 185 2a). Additionally, temperature in central Europe, especially Germany, just prior to passage at 186 Helgoland, seems to play an important role in fine-tuning migration progress over the last stretch of spring migration. An apparent lack of wind influences after crossing the 187 Mediterranean strongly fits with the fact that from thereon birds are migrating almost 188 189 exclusively over land. They can hence make a landing to rest or refuel at any time, rendering 190 favorable wind conditions less important. Temperature conditions this far north along the 191 route, however, are likely to indeed become much more informative and predictive about the 192 conditions further north at the breeding grounds, indicating similar cue responses at these 193 latitudes as observed in many short-distance distance migrants (14).

194 The time windows of the weather influences typically occurred from about one to two months 195 before the start of their migration passage at Helgoland (across the whole study period) up to 196 just prior or during the period of migration passage at Helgoland (Fig. 1). Most, if not all, of 197 the time windows occurred just prior or during periods that birds are likely to be present at 198 their winter and stopover locations, even though we allowed for time windows of any size 199 between 1 and 365 days or 1 and 182 days, and starting up to 365 or 182 days prior to July 1 200 for temperature and precipitation, and wind, respectively. For some of the time windows, 201 some uncertainty was present in the exact timing due to the inherent temporal autocorrelation 202 of weather variables (Table S10).

203 Wind was the most influential weather type on inter-annual variability in spring migration phenology (44% of the overall weather type importance), but especially also in terms of 204 causing the spring migration advancement (52%; Fig. 2; Table S13). Temperature had a 205 206 similarly strong impact on inter-annual variability (41%), but this was somewhat reduced when assessing impacts on the temporal advancements in spring migration (36%). The role of 207 208 precipitation was comparatively rather minor (around 15% in both cases). These results on the 209 relative weather type importance strongly question whether the somewhat established 210 hypothesis that temperature is the most important exogenous factor impacting spring 211 migration phenology (14, 18, 25, 27), actually holds for long-distance migrant birds in 212 specific, or even in general.

213 For two of the six study species, rather strong linear temporal trends towards advancement still remained after accounting for the most influential weather signals (Garden Warbler: -0.09 214 215 \pm 0.02 days/year or 47% of the original linear trend, and Willow Warbler: -0.12 \pm 0.03 216 days/year or 41% of the original linear trend; Table S14). For two more species, moderate 217 trends towards advancement remained (Common Whitethroat: -0.07 ± 0.03 days/year or 39% of the original linear trend, and Spotted Flycatcher: -0.05 ± 0.02 days/year or 31% of the 218 219 original linear trend; Table S14). The adjustment of spring migration phenology to weather 220 conditions at the wintering and stopover grounds was, hence, only sufficient to fully explain the observed trends in spring migration phenology for two of the six species (i.e. 33%; 221

222 Common Redstart and European Pied Flycatcher).

223 **Discussion**

224 As we did not work on individual birds, we cannot make any definite claims on whether the 225 observed relationships between the weather variables and spring migration timing are due to 226 phenotypic plasticity alone, or micro-evolutionary responses are also involved (10, 36). For 227 each species, however, a high amount of the variation in migration phenology was explained 228 by the weather conditions at only four or five winter or spring stopover areas (Table 1). This 229 does seem to strongly suggest that phenotypic plasticity plays a key role in the recent 230 advancements in spring migration phenology of long-distance migrants, including to a similar 231 extent as for short-distance migrants (14). As such, while endogenous rhythms and 232 photoperiod do play an irrefutable role in regulating spring migration (onset) in long-distance 233 migrants (15), the rigidness in the real world, i.e. outside of laboratory settings, and relative 234 importance compared to exogenous influences, i.e. conditions at the winter and stopover 235 grounds, may have been consistently overestimated. Despite the high amount of explained 236 variance in spring migration phenology by weather at the winter and spring stopover grounds 237 across all six study species (Table 1), the observed advancements in spring migration were 238 explained fully in only two (Table S14). Even if we were to attribute all of the explained 239 variance in spring migration timing to phenotypic plasticity to weather at the wintering and 240 stopover grounds, it would not suffice to fully explain the observed advancements. As such, 241 again similar to observations in short-distance migrants (14), other adaptive processes such as 242 micro-evolutionary processes (37, 38) or (winter or breeding) range changes (39) are, hence, 243 likely also pushing towards advanced spring migration.

244 The locations (and relative effect sizes) of the weather influences, i.e. a combination of sub-245 Saharan likely wintering areas and Mediterranean and European spring stopover sites (Fig. 1 246 and Fig. 2), confirm that much, perhaps most, of the spring migration advancement in long-247 distance migrants occurs in response to weather along the migration route (17, 18, 21). 248 Flexible responses to conditions at the wintering grounds, however, might also be very 249 common: five out of the six species had at least one signal from a very likely wintering area. 250 Depending on the species, their influence on the overall spring advancement may also play a 251 substantial role, e.g. up to almost 50% for European Pied Flycatcher (Fig. 1; Table S10 and 252 Table S12).

In summary, our results strongly suggest that there have been mismatches in space, time, scale, and weather variable type between the variables of influence and the variables used in analyses. This has led to a consistent underestimation of the flexibility of long-distance migrant birds in spring migration onset from the wintering areas, as well as adjustment of progress along the migration route. As such, the suggested negative impacts of climate change 258 on long-distance migrants' demographics due to their assumed inabilities of advancing spring 259 departure from the wintering grounds (8, 13) has at least been based on false assumptions. 260 While it is beyond doubt that climate change has already impacted the timing of several lifecycle events of migratory birds (1, 3, 4, 19, 26), strong evidence about how climate change 261 is impacting migrant bird species demographics through changes in the timing of the 262 263 migratory cycle, has yet to emerge (10). In fact, our results indicate that not only do, at least 264 some, long-distance migrants strongly adjust their spring migration timing to prevailing weather conditions at the wintering and stopover locations, but also that favorable migratory 265 conditions are now occurring more frequently (e.g. less days with headwind and more days 266 267 with tailwinds, Fig. 1 and Table S12). Interestingly, a similar increase in favorable wind conditions has also been projected for future spring migration in North America over the 268 269 current century (40). While many other potential pathways of climate change influences on bird population sizes have been suggested (4), current evidence still predominantly points 270 271 towards (anthropogenic) land use change effects (6, 7).

272 Materials and methods

273 Spring migration passage data

The trapping garden on the island of Helgoland, Germany (54° 11' N, 07° 53' E; sometimes also spelled as Heligoland) is a constant-effort bird ringing site. Since 1960, comparable efforts and standardized methods are used with daily catches in the trapping garden throughout the whole year. Barely any landbirds breed on Helgoland, especially not longdistance migrants (21, 41, 42). Consequently, the birds used in this study to estimate spring migration phenology, are all birds in transit.

280 We analyzed data from six trans-Saharan, i.e. long-distance, migrants. We used yearly mean spring passage date (MSPD) over the period 1960–2014 as a measure of migration phenology 281 (Table S1). To minimize potential bias due to the use of the Gregorian calendar, we converted 282 283 trapping dates to Winter Solstice-based dates (WSD) instead of day-of-the-year (43), but 284 report dates throughout the paper as the approximate Gregorian calendar date. Yearly MSPD 285 was calculated as the mean of the winter solstice-based trapping date (WSD) of all birds between WSD 51 and 166, i.e. February 20 to June 14 approximately. To allow comparison 286 287 between species that are potentially subject to similar weather conditions prior to or during 288 their migration, the species in all the (supplementary) tables and figures in the paper are 289 ordered by mean spring passage date.

290 Birds of a certain species that migrate through Helgoland stem from different breeding 291 populations (44). As such, the measured MSPD at Helgoland will be influenced by changes in the spring phenology of each of these populations, which could potentially obscure the 292 293 relation between the measured MSPD and the influencing weather conditions for each 294 specific population. If the phenology of these different populations is, however, (a) related to 295 changes in weather in their wintering or stopover areas, (b) the different populations show a 296 relatively high winter and stopover-site fidelity, and (c) each population is represented by a 297 sufficient amount of birds in the trappings, the fact that the observed MSPD is influenced by 298 each of these populations should enable to link the observed MSPD to each of the different 299 wintering or stopover sites (25). Birds from different wintering areas may also be influenced 300 *en route* by the same weather conditions at a certain time and place, e.g. shared stopover areas 301 or prior to crossing an ecological barrier. The wintering or stopover areas of a species also 302 might have changed over the total analyzed time period (39, 45). Yet if these areas are 303 maintained for a long enough subset of the total analyzed time period, or the shifts are not 304 over large distances compared to the spatial resolution of the weather grids, it should be

- 305 possible to link the observed MSPD to all of the different wintering or stopover locations. As
- 306 such, using migration passage data has both advantages and disadvantages compared to
- 307 breeding area arrival data.

308 Weather data

309 We used spatiotemporal data of air temperature, precipitation, and wind from the NCEP Reanalysis I database (46, 47), which we acquired using the R package RNCEP (34, 48). The 310 spatial grid covered an area from roughly 2° to 74° N and 19° W to 24° E, ranging from 311 312 northern Scandinavia in the North to Cameroon in the South, and from Iceland and the Canary Islands in the West to Poland, Greece, Libya, and Chad in the East. The spatial resolution of a 313 314 grid cell ranged from 1.875° to 3.75°, depending on the weather variable (Table S2). Ocean 315 grid cells were masked from the analysis. For each day and land grid cell, we derived three variables from the NCEP database: mean daily air temperature, daily precipitation sum, and 316 317 wind direction at midnight (UTC). We analyzed midnight winds only, and not winds during 318 the day, as all species in our study are known to mainly migrate during the night. In the time 319 window analyses, the wind direction data were used to calculate the number of nights for both 320 winds originating from and in the direction of Helgoland within any given time window, by 321 counting every day with a wind direction that fell between -45 and $+45^{\circ}$ of the angle between 322 Helgoland and the center of the grid cell under analysis. Depending on the location of the grid 323 cell relative to Helgoland, we then interpreted these to be head- or tailwinds. We chose to test 324 both measures for wind effects on migration as both hypotheses, i.e. headwinds delay 325 migration and tailwinds advance migration, represent different processes.

326 Avoiding spurious correlations due to shared trends and temporal autocorrelation

327 If two time series both show a temporal trend, correlating the two series without taking into 328 account these shared trends will very often yield high, yet spurious, correlations (26, 49). 329 Even after temporal trends are accounted for, any remaining autocorrelation in the time series 330 may similarly produce spurious correlations (50). As such, we first determined whether a 331 linear, quadratic, or cubic temporal trend was most appropriate for the MSPD time series of 332 each species, by comparing the second-order Akaike Information Criterion (AICc) values (51) 333 for linear, quadratic, and cubic trend models. If a quadratic or cubic temporal trend model had 334 an AICc value that was more than two units lower than a linear trend model, we judged the 335 higher-order model to be a better approximation of the trend over time. The identified trend 336 model for each species was used as the base model (for comparison of reduction in AICc 337 values by adding a weather variable) in the subsequent time window analyses.

338 All species showed advancements in MSPD over the study period. Four of the six species had 339 a linear trend, while for Willow Warbler and Common Whitethroat a quadratic and cubic 340 trend, respectively, was most appropriate to account for trend (Table S3). We applied 341 Augmented Dickey-Fuller tests (using the urca R package (52)) to verify that the chosen 342 trends models had successfully reduced the MSPD time series to stationarity (Table S4). We 343 checked and found no remaining autocorrelation in the residuals of the trend models with a 344 Durbin-Watson test up to lag two (using the the car R package (53); Table S5). The observed 345 non-linearity of spring migration phenology in two of the six species could be occurring 346 through various mechanisms, e.g. non-linear trends of influencing weather variables, or 347 varying influences (in space and time) working in different proportions on different 348 populations of the birds migrating through Helgoland. Future meta-analyses across many 349 species, populations and time could provide insights into such potential underlying 350 mechanisms.

Finding the "weather variable – location – time window" combinations that influence spring migration phenology

353 To identify the most likely weather effects on the MSPD at Helgoland of each of the six study 354 species, we applied a recently developed spatiotemporal methodology (14, 31), which 355 involves a sequence of two main chunks of analysis. The first step consists of performing a 356 time window analysis on each grid cell for each of the weather variables of interest (i.e. 357 temperature, precipitation, number of days with tail- or headwind, Table S2) to find the best 358 performing time window. We searched all time windows of any size larger than 14 days and 359 up to 365 (temperature and precipitation) or 183 days (wind variables) in the past from the 360 reference date 1 July (Table S6 and S7). We did this using the 'climwin' R package (32, 33) by calculating AICc model values for all time windows, and comparing them to the AICc of 361 362 the predefined temporal trend model for that species (Table S3). The time window showing 363 the biggest AICc reduction was identified as the best-performing time window. To 364 subsequently estimate the probability of obtaining a similar performing best time window due 365 to chance alone, we then repeat the time window analysis for a number of randomizations of 366 the weather data. Ideally, one would do this for a large number of randomizations, e.g. a thousand or more, to accurately approximate the actual Δ AICc distribution obtained by 367 chance alone. Repeating such a high number of randomizations for multiple weather variables 368 369 and over a large number of grid cells, however, quickly becomes an extremely resourceintensive task. As such, we used the alternative probability statistic Pc of the 'climwin' R 370 371 package which was developed specifically for such situations (32, 33). Using as little as five 372 randomizations, the P_c statistic already provides a reliable estimation of whether a similar 373 performing best time window is likely to be obtained by chance. Pc ranges from 0 to 1, with 374 values closer to 0 expressing a higher probability that such a strong relation is unlikely 375 obtained by chance. Using simulated datasets with a sample size of 47, and a cut-off value of 376 $P_c < 0.5$ to decide on whether a signal is real, the false-positive and false-negative rate were 377 both between 0.05 and 0.08 (32). To even further lower the amount of false positives, we 378 lowered the P_c threshold to 0.3. Furthermore, our larger sample size (55 years compared to the 379 47 in the simulated datasets) also further decreased both false-positive and false-negative 380 rates. In summary, in the first step the correlation of the identified best time window of a grid 381 cell's weather with MSPD was considered to be unlikely due to chance when its P_c statistic was lower than 0.3. The time window analyses were performed on a per-species, per-weather-382 383 variable, and per-grid-cell basis. For ease of reference, we summarized all of the settings and 384 decision rules we used for the analyses in Table S6 and Table S7. Due to spatiotemporal 385 autocorrelation, neighboring cells often had similar best-performing time windows with, 386 sometimes only slightly, different Δ AICc values. This often resulted in spatial gradients in the 387 Δ AICc maps we obtained for each weather variable. We chose to select as the candidate 388 signals, the cells with the regional Δ AICc maxima as the most representative of the potential 389 relation between the weather variable for that area and the MSPD. This first step of the 390 analysis resulted in an initial long-list of 310 candidate weather signals across all six species 391 (38 to 67 candidates depending on the species; Table S8 and Fig. S1 to S4).

392 The second main part of the analysis consists of a combination of several feature filtering and 393 variable importance algorithms to narrow down the long-list of candidates to those that are 394 most likely to be the most influential on the MSPD of each species. In this part of the 395 analysis, we no longer included the temporal trend variables. Spurious correlations due to 396 trend only have already been checked for, and are hence no longer an issue at this stage. 397 Instead, we now actually want to assess how strong the relationships are with MSPD without 398 accounting for temporal trends. First, we checked whether the weather variable still showed a 399 strong correlation with MSPD when not accounting for temporal trends. This led to the 400 removal of 50 candidate signals because the model without accounting for trends had an AICc 401 compared to an intercept-only model that was less than two units lower. Next, we checked for 402 collinearity among the remaining candidate signals. We removed 35 signals that had a 403 Pearson correlation > 0.7 with another candidate that had a bigger Δ AICc with an intercept-404 only model. Subsequently, we removed 135 more signals using the boruta method (54) to 405 reduce the maximum number of candidate signals per species to 15. Based on an ensemble 406 variable importance analysis (51, 54–56) (Table S9), we ultimately extracted 26 signals across 407 the six species that are very likely to be related to MSPD at Helgoland (Table S10, Fig. 1, and 408 Fig. 2).

409 Even though we tailored our approach towards avoiding false positives, we cannot exclude 410 them entirely (31). Even when no relationship whatsoever exists between MSPD and weather at any location and time window, we still might identify some in the time window analysis 411 412 step (32). While the variable filtering in the second part of the analysis likely removes many, 413 if not most, of these false positives, some might still remain, and may ultimately be 414 designated as (relatively) important influences. This means that even in the absence of any 415 relationship whatsoever between a biological response variable (i.e. MSPD in our case) and 416 weather at any location and time, the approach might still end up with a number of false final 417 weather variables by chance only. To estimate the probability of obtaining such a final list of (false) weather influences that show a relationship with MSPD that, due to chance only, is 418 419 similarly strong as those we obtained for each species (Table 1), we repeated the full 420 spatiotemporal analysis on 200 randomized versions of each species' MSPD. For each of these randomizations, we calculated the adjusted and predictive R^2 values of both: (a) the 421 422 model consisting of up to four variables identified as the most important influences, and (b) 423 the best-performing model (in terms of AICc). Using the distributions of all of the resulting adjusted and predictive R² values across each species' randomizations (Table S11 and Fig. S5, 424 425 we then estimated the probability of obtaining similarly performing final weather variables by chance only (i.e. 1 - the percentile of the R^2 values of Table 1, in the R^2 distributions of the 426 427 randomizations).

428 Contributions of each weather variable to the temporal trend in spring migration 429 phenology of the species

The influence of a weather variable on inter-annual variability in spring migration phenology will only result in a push towards advancement (or delay) in the temporal trend of the migration phenology if the weather variable itself is also changing over time to a certain degree in a certain direction. To calculate the combined effect of (1) the change in MSPD in response to the weather variable and (2) the change in the weather variable over time, and, hence, the contribution of each of the final weather variables' influence to the temporal trend in MSPD, we used the chain rule (31, 57):

437
$$\begin{array}{c} climate \ contributions \\ to \ trend \ in \ MSPD \end{array} = \sum_{i=1}^{n} \Big(\frac{\partial MSPD}{\partial Climate_{i}} \times \frac{dClimate_{i}}{dTime} \Big), \end{array}$$

439 where n is the total number of influencing weather variables for a given species. We used the 440 regression coefficients of a multiple linear regression between MSPD and all of the identified 441 final weather variables for each of the species separately to estimate the various 442 $\partial MSPD / \partial Climate_i$, and a simple linear regression between the respective weather variable 443 and time, i.e. years, to estimate $dClimate_i/dTime$. Standard errors were calculated following 444 error propagation rules (58). This approach by definition ignores any other (e.g. non-climatic) 445 factors that might possibly affect changes in MSPD over time.

- 446 While weather variable effects on inter-annual variation in MSPD consist of a mix of positive
- 447 and negative relationships, their contributions to the temporal trend in MSPD has been
- 448 consistently towards advancements (Fig. 1 and Table S12). In other words, throughout the
- 449 course of the 55-year study period, weather conditions favorable for migration progress have
- 450 been occurring earlier (e.g. temperature) or more frequently (e.g. tailwinds), and conditions
- 451 unfavorable for migration progress have been occurring less frequently (e.g. precipitation and
- 452 headwinds).

453 Relative importance of the weather variable types in terms of effect and temporal trend 454 contributions

- We calculated the relative overall importance across all species of the three different weather variable types, i.e. temperature, precipitation, and wind, on the inter-annual fluctuations in MSPD at Helgoland by summing their respective mean relative variable importance values. We, furthermore, also calculated the importance of each climate variable in terms of relative contributions to the temporal trends in MSPD over the past decades by summing the absolute values of the trend contributions for each climate variable, divided by the total sum of the
- 461 trend contributions (Table S13).

462 Assessing remaining linear trends in MSPD after accounting for the identified weather 463 signals

- 464 After identifying the weather variables influencing and determining their effects on MSPD,
 465 we checked whether their combined effect completely explained the observed trends in
 466 MSPD. We did this by comparing the AICc of the model including all influencing weather
- 466 MSPD. We did this by comparing the AICc of the model including all influencing weather 467 variables for that species with the model that additionally included a linear temporal trend, i.e.
- 468 a 'year' variable.

469 **Data and code availability**

470 All R code and the phenology dataset, necessary to replicate the results of this study can be 471 accessed at: <u>https://doi.org/10.5281/zenodo.3629178</u>.

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614 Figures



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Fig. 1. Location, timing, and resulting change in spring phenology over the years 1960-616 617 2014 of the identified most important weather variables that are likely to influence mean spring passage at Helgoland for (a) European Pied Flycatcher, (b) Common Redstart, (c) 618 Willow Warbler, (d) Common Whitethroat, (e) Garden Warbler, and (f) Spotted Flycatcher. 619 620 Marked locations may represent smaller or larger areas of influence than what is marked in the map (see text). T: temperature; P: precipitation; HW: headwind; TW: tailwind. The grey 621 background triangles in the upper right timing figures, represent the 5th and 95th percentile of 622 all birds passing at Helgoland over the entire study period 1960-2014. The resulting change 623 numbers in the maps are the number of days migration changed over the whole study period 624 625 due to that weather influence, calculated using the chain rule (see Materials and Methods 626 section, and Table S12). Helgoland is marked with a star. (Bird) Illustrations reproduced by 627 permission of Lynx Edicions.



628

629 Fig. 2. Comparison of relative weather variable importance in terms of the effect on 630 inter-annual variation of spring migration phenology (a, b), and their contributions to the advancement in spring passage over the study period 1960-2014 (c, d). (a) Locations 631 632 and relative effect sizes, based on the standardized regression coefficient using model averaging (see Methods), of the weather variables influences on inter-annual variation in 633 634 mean spring passage dates; (b) Overall weather variable type importance across all species, in 635 terms of explaining inter-annual variability in spring migration phenology; (c) Overall weather variable type importance across all species, in terms of contributions to the long-636 637 term advancements in spring migration passage; (d) Locations and relative sizes of the trend 638 contributions of each weather variable to the advancement in spring migration passage. Point 639 sizes in (a) and (d) are on a relative scale stretching from the respective overall minimum to 640 the maximum across all species. The location of Helgoland is marked with a star.

641 Tables

642 Table 1 Explained variance in spring migration phenology and predictive performance using a

643 linear model with all of the final identified weather signals for each species (see Fig. 1), but not

644 the temporal trend variables (Table S3). Adjusted R^2 is defined as in (35). Predictive R^2 was

645 calculated leave-one-year-out.

Species	Adjusted R ²	Predictive R ²
European Pied Flycatcher	0.86	0.83
Common Redstart	0.76	0.71
Willow Warbler	0.80	0.78
Common Whitethroat	0.72	0.69
Garden Warbler	0.80	0.77
Spotted Flycatcher	0.76	0.73

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