Appendix 1

Non-linearity and temporal variability are overlooked components of global 2

- **population dynamics** 3
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SM1: Temporal, geographical, and taxonomic extent of the analyzed database 5 6

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In the main text, we analyzed a subset of the Living Planet Database. We omitted populations which had less than twenty time points of monitoring data. This resulted in a final database constituted of 6,437 population time series. However, among these, only 6 were invertebrates population time series, relative to only one species in the same geographical region. Thus, for all analyses relative to taxonomic patterns, we omitted these populations. 8 9 10 11 12 13

In this appendice, we present the temporal (Fig. S1.1), biogeographical and taxonomic extent (Fig. S1.2, S1.3) of the analyzed database. First, this reveals that very few population time series were monitored more than 45 years (Fig. S1.1). Second, this highlights the fact that the database is highly biased geographically (73.2% of the population time series are monitored in North America and Europe, Fig. S1.2C, S1.3). Similarly, the taxonomic coverage is not satisfactory (Birds represent 67.3% of the analyzed time series, Fig. S1.2B). 14 15 16 17 18 19 20

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Figure S1.1: Distribution of the number of monitoring years among the population 23

time series. The dashed line represents the minimum number of years we selected (20 years) and the straight line represents the average number of monitoring years among the 24 25

6,437 population time series. 26

Figure S1.2: Distribution of time series across biogeographic and taxonomic groups. (A) Habitat types, (B) Taxonomic groups, (C) Regions, (D) IUCN Red List Categories and (E) Realms. The exact number of populations within each category are written in black. 28 29 30 31

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Table S1.1: Cross-distribution of population time series across habitat types and regions in the analyzed dataset. 34 35

- **Figure S1.3: Geographical distribution of population time series, colored according to different biogeographic and** 38
- **taxonomic patterns.** (A) Habitat types, (B) Taxonomic groups, (C) Regions, (D) Realms, (E) IUCN Red List Categories and (F) Linear or Non-linear trajectory. 39 40

SM2: Impact of the duration, number of years sampled, and starting 41

year of the time series on the proportion of non-linearity 42

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The population time series we studied range from 1950 to 2020, with both duration of monitoring and the frequency of surveys varying across time series. Eventhough we selected time series with twenty time points of monitoring data, previous studies demonstrated that capturing directional trends in population abundance depends on the length of the time series (Wauchope et al., 2019). Additionnally, recent studies highlighted the fact that trends should be interpreted in the light of the temporal window covered by the analyzed time series (Daskalova et al., 2020; Duchenne et al., 2022). We thus examined how the temporal baseline and the duration of the time series we analyzed influenced the proportion of non-linearity. To do so, we simply looked at how the proportion of non-linearity varied according to the strating year (Fig. S2A) and the number of points (Fig. S2B) of the time series we analyzed. This revealed that longer time-series capture more non-linearity that shorter time series (Fig. S2B). As longer time series (e.g. those having 65-70 years of data) necessarily start sooner (around 1955 on average) (Fig. S2C), the proportion of non-linearity decreases with the starting year of the time series (Fig. S2A). This suggests that in future research, the proportion of non-linearity should be examined relatively to specific periods of monitoring. Still, this reinforces the importance of non-linear modeling for long-term monitoring data. 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60 61

Figure S2: Impact of the starting year and number of years sampled on the

proportion of non-linearity. Proportion of non-linearity depending on (A) the starting year of the time series and (B) the number of points within the time series. Figure (C) shows the distribution of the starting years among time series for several

groups of duration.

SM3: Detailed analysis of non-linearity among biogeographic and taxonomic patterns 69 70

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Table S3.1: Model outputs for all Z-test analyses. Each row corresponds to the following test: $H_0: \hat{p} = \overline{p}$; $H_1: \hat{p} \neq \overline{p}$; \hat{p} being the estimate of the proportion of nonlinearity observed within the tested category (e.g. marine habitats for the first row), and \bar{p} being the mean proportion of non-linearity among all populations (0.448). We 72 73 74 75

used *α*=5%. Significant tests are highlighted in bold. 76

Figure S3.1: Representation of the proportion of linear or non-linear increases, 82

decreases or no trends among (A) habitat types, (B) Regions. "N" represents the number of populations within each category. Information relative to the linear trajectories are written in black whereas information relative to the non linear trajectories are written in white. 83 84 85 86

- **Figure S3.2: Representation of the proportion of linear or non-linear increases,** 87
- **decreases or no trends among (A) taxonomic groups, (B) IUCN Red List** 88

Categories. "N" represents the number of populations within each category. 89

Information relative to the linear trajectories are written in black whereas information 90

relative to the non linear trajectories are written in white. 91

SM4: Detailed analysis of populations' temporal variability 92

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1. Investigating temporal variability according to biogeographic and taxonomic patterns 94 95

To test if population temporal variability varied according to biogeographic and taxonomic patterns, we used a generalized linear mixed-effect framework. The models were structured as followed: 96 97 98

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- $R_{i,j,k} = \beta_0 + \beta_k E_{i,j,k} + \mu_{0,j} + \varepsilon_{i,j,k}$
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Where $R_{i,j,k}$ is the response variability metric (either D, CV or MSE) for the i^{th} population time series from the j^{th} species from the k^{th} category of the explanatory variable, $E_{i,j,k}$ is the category of the explanatory variable of the i^{th} time series from the j^{th} species, β_0 the global intercept, β_k the global slope estimates for the k^{th} category of the explanatory variable (fixed effect), $\mu_{0,i}$ is the species-level departure from 0 (random effect), and $\varepsilon_{i,i,k}$ the random error (unreliable measurements, random fluctuations). All mixed-effect models were fitted using maximum likelihood as implemented in the R package "lme4" (Bates et al., 2015). When differences were detected, we performed post-hoc tests using the *ghlt* function from the "multcomp" package (Hothorn et al., 2008). 102 103 104 105 106 107 108 109 110 111

- In the present appendix, we present the models outputs for all analyses. In total, we performed three models (corresponding to the three variability metrics we tested) for each explanatory variable (habitat type, regions, taxonomic groups, IUCN Red List Categories, and trajectory types), resulting in 15 models in total. The outputs present the estimates, corresponding to the effect size for the intercept (first row of each model) and to the relative deviation from the intercept for the other rows. The estimates thus represent $(\beta_0+\mu_{0,j})$ from the equation above for the intercepts and (β_k + $\mu_{0,j}$) for the other rows. In the main text and the main figures, we presented the $\mathsf{effect~size,~thus~}(\beta_{0}+\beta_{k}+\mu_{0,j}).$ 112 113 114 115 116 117 118 119 120
- Post-hoc tests were performed for each model using the *ghlt* function from the ''multcomp'' package (Hothorn et al., 2008). In the present appendix, we only present the letters of these pairwise comparisons that were obtained using the *cld* function 121 122 123
- from the ''lsmeans'' package (Piepho, 2004). 124
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Table S4.1. Model outputs for habitat types analyses. 126

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Variability differed among habitat types, with marine populations being significantly 128

more variable than freshwater and terrestrial ones when using D or CV as a proxy of temporal variability (Table S4.1). This was not consistent when using the MSE, in 129 130

which case terrestrial populations were significantly less variable than populations 131

from the other habitat types (Table S4.1). 132

Table S4.2. Model outputs for regions analyses. 133

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Variability differed among regions, with populations from Oceania being significantly more variable than populations from other regions, no matter the metric used (Table S4.2). However, 87 % of populations monitored in Oceania are marine populations (Table S1.1). These results may reflect the marine variability more than a regionspecific variability. Populations from other regions were slighlty different in their variability level (Table S4.2). 135 136 137 138 139 140

Table S4.3. Model outputs for taxonomic groups analyses. 141

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Variability did not differ that much between the different taxonomic groups, no matter the metric used (Table S4.3), even when the lmer test was significant (which was the case for models with CV and D). However, as highlighted before, the taxonomic extent of our database is highly biased, which may not allow consistent comparisons 143 144 145 146

between groups. 147

Table S4.4. Model outputs for IUCN Red List Categories analyses. 148

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Variability differed among Red List Categories, but the pairwise comparisons revealed that only populations from « Least Concern » species were less variable than populations from « Near Threatened » species. This result was consitent no matter the metric of temporal variability that was used (Table S4.4). 150 151 152 153

2. Testing the complementarity bewteen non-linearity and temporal variability 154

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- To test wether variability differed among the different types of trajectories, we used 156
- the same model as presented above, with the explanatory variable being the type of 157
- trajectory. 158
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Table S4.5. Model outputs for trajectory types analyses. 160

Figure S4.1: Temporal variability in population change differs according to trajectory types. Either the MSE (A) or the CV (B) is used here as a proxy of temporal variability. Half violins represent the density distribution of temporal variability in populations for each trajectory type, points represent the raw values, boxplots are represented including the median, first and third quartiles. Letters indicate the significance of pairwise comparisons, calculated with post-hoc tests after running the linear mixed effect model. 162 163 164 165 166 167 168

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Variability differed among the different types of trajectories, populations classified as « no trend linear » being consistently significantly more variable than other types of trajectories, no matter the metric that was used. 170 171 172

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3. Exploring the role of the trajectory types among biogeographic patterns of temporal variability 175 176

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Our results revealed for instance that marine populations were the ones expressing the lowest proportion of non-linearity while being the ones expressing the highest variability. However, we also showed that ''no trend linear'' trajectories were the ones with the highest variability, followed by the other linear types of trajectories. As marine populations expressed a higher percentage of ''no trend linear'' trajectories, we wondered whether the variability observed emerged from the marine characteristic of those populations, or wether this was a consequence of the types of trajectories observed. 178 179 180 181 182 183 184 185

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To investigate this question, we plotted the raw values of D according to each habitat types and trajectory types (Fig. S4.1). This already suggested that globally, marine populations still seemed to express higher variability, even within the same types of trajectory. For instance, among all ''no trend linear'' trajectories, marine populations were the ones showing the highest variability. 187 188 189 190 191

Figure S4.1: Illustration of temporal variability among habitat types within each

type of trajectories. The consecutive disparity index (D) is used here as a proxy of temporal variability. Half violins represent the density distribution of temporal variability in populations for each trajectory type and system, points reprensent the raw values.

In order to test this prediction, we used an additionnal generalized linear mixed-effect model. We took the consecutive disparity index (D) as the response variable and the habitat types as the explanatory variable (fixed effect). Only in this analysis, we included both species and trajectory types as random effects, to account for the possible correlation between populations from the same species and trajectory type. 198 199 200 201 202

This analysis confirmed that populations from marine habitats were the ones experiencing the highest variability (Table S4.6). 203 204

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Table S4.6. Model outputs for GLMM with both species and type of trajectory 206

as random effects. Freshwater category was the intercept, thus estimates from marine and terrestrial represent the deviation from the intercept. The mean column respresent the effect sizes. 207 208 209

References 211

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