Appendix S1

Supplementary methods

Geographical and temporal variation in seed fall

A logistic function could not be fitted for a few years at some stands in Scotland with late seed fall. Given that seed fall in Scotland usually peaks in May (Summers & Proctor 2005) and that the interval between seed collection was longer in Scotland than elsewhere, we also included data for August for those years and stands to fit the logistic function. Variation in the estimated days including or excluding this month is minimal (e.g., usually a difference of 1–2 days for D50). Years with low seed fall at a given stand (16 of 64 stand-years) were excluded from analyses (Summers & Proctor, 2005).

Modelling observed crossbill distributions

Data in the Atlas of European Breeding Birds were collected during surveys in spring and early summer and thus do not represent fully the breeding distribution of crossbills, which also breed in winter and opportunistically at other times of the year (Newton, 1972, Summers et al., 2010). However, the Atlas surveys correspond to the period of greatest seed scarcity, so many of the crossbill occurrences during this time period should reflect where the last of the previous year's seed crop still remained in cones. Therefore, the distribution of each crossbill species in the Atlas is appropriate for modelling the presence of each species in relation to conifer species and climate variables that predict the proportion of the seeds remaining in the cones (i.e., available to crossbills) during late spring and early summer. For each species, grid squares reporting neither presence nor absence are distinguished from those reporting absence (i.e., grid squares where the species was sought, but not found). We used only those squares reporting presence or absence.

Boosted regression trees (BRTs) were fitted using several combinations of tree complexity (i.e., number of nodes in a tree), learning rate (0.01 or lower), and a bag fraction of 0.5. Optimal settings were identified by cross-validation for models with at least 1000 trees. The importance of the individual predictor variables was assessed based on the estimation of the relative influence (or contribution scaled so that the sum adds to 100) of each variable in reducing the loss function during the fitting process (Elith et al., 2008).

Modelling future shifts in crossbill distributions

Growing degree-days (GDD) was calculated from monthly maximum and minimum temperatures using a 5ºC base temperature (Synes & Osborne, 2011; Nieto-Lugilde et al., 2015). Absolute minimum temperature (AMT) was calculated following Prentice et al. (1992). Water balance was computed as the yearly sum of the monthly differences between precipitation and potential evapotranspiration following Skov & Svenning (2004). These three environmental variables represent heat requirements, cold tolerance, and moisture requirements, respectively (Skov & Svenning, 2004), and are important factors for European tree distributions (Svenning et al., 2008). The 1 × 1 km resolution conifer species maps were resampled using bilinear interpolation to match the 5’ grid of climate variables. Parameter settings for the BRT models of conifer cover were: tree complexity (1–3), learning rate (0.1 or lower), and a bag fraction of 0.7.

The fitted-BRT models for conifer cover across Europe performed well. Scots pine cover (number of trees fitted: 3200; % deviance explained: 52.1; Pearson correlation coefficient–COR: 0.70) was best explained by AMT (relative influence: 70.6%) and water balance (29.0%). Spruce cover (number of trees: 2600; % deviance explained: 51.9; COR: 0.64) was mainly explained by water balance (56.7%) and AMT (42.0%). Pine cover (number of trees: 3900; % deviance explained: 51.0; COR: 0.52) was explained most by water balance (53.8%), followed by GDD (27.9%), and AMT (18.4%).

The three Global Circulation Models used to forecast the future distributions of each crossbill species were: CNRM-CM5 (developed by Centre National de Recherches Météorologiques), HadGEM2-ES (Met Office Hadley Centre with contributions by Instituto Nacional de Pesquisas Espaciais), and MPI-ESM-LR (Max Planck Institute for Meteorology).

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