

Supporting Information

Appendix S1. Modelling the spread of *Ambrosia artemisiifolia*

Methods

By pooling information about native and invaded ranges, SDMs provide better predictions (Broennimann & Guisan 2008). SDMs were calibrated using the *A. artemisiifolia* distribution in North America, Eurasia and Australia gathered in Petitpierre *et al.* (2012) consisting in 4470 cells at a 0.5° resolution (about 50 km) with information of presence of the species. These biogeographical realms characterized an extent where 20,000 pseudoabsences were selected to depict the background conditions. These occurrences were related to 8 climate variables known to be important for plants and used in similar studies (e.g. Thuiller *et al.* 2005; Broennimann *et al.* 2007; Petitpierre *et al.* 2012): annual mean temperature (T), temperature seasonality (Tvar), minimum temperature of the coldest annual quarter (Tmin), maximum temperature of the hottest annual quarter (Tmax), precipitation of the wettest annual quarter (P), annual precipitation seasonality (Pvar), annual moisture (M) and annual moisture seasonality (Mvar). Climate data were downloaded at a 0.5° resolution from the Climonde database (Kriticos *et al.* 2011), which also provides climatic scenarios. We used the A1b scenario, estimated with the CSIRO MK3 GCM for 2050 and 2100 (+ 2.48°C and + 4.8°C respectively of average increase in annual mean temperature) to project the potential distribution of *A. artemisiifolia* under possible future climate. Different modelling techniques were averaged to provide an ensemble model: Generalized Linear Models (GLMs, with second order polynomial coefficient and stepwise selection using the Bayesian Information Criteria, McCullagh & Nelder 1983), Generalized Boosted Regression Models (GBM, Friedman, Hastie & Tibshirani 2000) and Maxent (Phillips, Anderson & Shapire 2006). Modeling was achieved using the R packages BIOMOD for GLM and GBM (Thuiller *et al.* 2009) and dismo for Maxent (Hijmans 2010), keeping the default set of parameters. Models were calibrated on 70% of the data and evaluated with the 30% of the remaining data. Variables contributions were estimated by assessing the impact on predictions of variables randomizations (see the documentation of BIOMOD for further details; Thuiller *et al.* 2009).

SDMs were evaluated with the Area Under the Curve of a Receiver Operating Characteristics (AUC, Zweig & Campbell, 1993) and the Boyce index (B, Hirzel *et al.* 2006). AUC is very commonly used for SDM but may be biased with the use of pseudoabsences. Additionally, as biological invasions are recent and ongoing phenomena, absences may not

reflect true absences but possible dispersal limitation. This is why we also used B, a presence only evaluator, calculated as in Hirzel *et al.* (2006). AUC varies between 0 (meaning, complete counter predictions of the model) and 1 (perfect fit with the observed distribution), 0.5 being random predictions. B varies as a correlation coefficient between -1 and 1.

The modelling procedure was replicated 10 times and the final results consist in an average of the 10 replicates. To quantify the change of potential distribution of *A. artemisiifolia* through time, continuous predictions were binarized into presences/absences using a threshold maximizing both sensitivity and specificity. As predictions are not reliable in non-analog climates (i.e. climates that do not exist in the calibration dataset, Fitzpatrick & Hargrove 2009), such conditions were underlined using a MESS analysis (Elith, Kearney & Phillips 2010) and not included in the measure of potential distribution changes through time.

References

- Broennimann, O. & Guisan, A. (2008) Predicting current and future biological invasions: both native and invaded ranges matter. *Biology Letters*, **4**, 585–589.
- Broennimann, O., Treier, U.A., Müller-Schärer, H., Thuiller, W., Peterson, A.T. & Guisan, A. (2007) Evidence of climatic niche shift during biological invasion. *Ecology Letters*, **10**, 701–709.
- Elith, J., Kearney, M. & Phillips, A.S. (2010) The art of modelling range-shifting species. *Methods in Ecology and Evolution*, **1**, 330–342.
- Fitzpatrick, M.C. & Hargrove, W.W. (2009) The projection of species distribution models and the problem of non-analog climate. *Biodiversity and Conservation*, **18**, 2255–2261.
- Friedman, J.H., Hastie, T.J. & Tibshirani, R. (2000) Additive logistic regression: a statistical view of boosting. *Annals of Statistics*, **28**, 337–374.
- Hijmans, R.J., Phillips, S., Leathwick, J. & Elith, J. (2010) dismo: Species distribution modeling. pp. R package version 0.7-17. Available at: <http://CRAN.R-project.org/package=dismo>. Last accessed 8 August 2012.
- Hirzel, A.H., Le Lay, G., Helfer, V., Randin, C. & Guisan, A. (2006) Evaluating the ability of habitat suitability models to predict species presences. *Ecological Modelling*, **199**, 142–152.
- Kriticos, D.J., Webber, B.L., Leriche, A., Ota, N., Macadam, I., Bathols, J. & Scott, J.K. (2011) CliMond: global high-resolution historical and future scenario climate surfaces for bioclimatic modelling. *Methods in Ecology and Evolution*, **3**, 53–64.

- McCullagh, P. & Nelder, J.A. (1983) *Generalized Linear Models: First Edition*. Chapman and Hall, London, New-York.
- Petitpierre, B., Kueffer, C., Broennimann, O., Randin, C., Daehler, C. & Guisan, A. (2012) Climatic niche shifts are rare among terrestrial plant invaders. *Science*, **335**, 1344–1348.
- Phillips, S.J., Anderson, R.P. & Schapire, R.E. (2006) Maximum entropy modeling of species geographic distributions. *Ecological Modelling*, **190**, 231–259.
- Thuiller, W., Lafourcade, B., Engler, R. & Araujo, M.B. (2009) BIOMOD - a platform for ensemble forecasting of species distributions. *Ecography*, **32**, 369–373.
- Thuiller, W., Richardson, D.M., Pysek, P., Midgley, G.F., Hughes, G.O. & Rouget, M. (2005) Niche-based modelling as a tool for predicting the risk of alien plant invasions at a global scale. *Global Change Biology*, **11**, 2234–2250.
- Zweig, M.H. & Campbell, G. (1993) Receiver-Operating Characteristic (Roc) Plots - a fundamental evaluation tool in clinical medicine. *Clinical Chemistry*, **39**, 561–577.



Fig. S1 Appearance of *Ambrosia artemisiifolia* populations in habitats that are most invaded in Europe: (a) road side (near Austrian-Hungarian Border); (b) railway station (near Vienna); (c) field (maize field, southern Styria); (d) ruderal habitat (disturbed grassland, near Vienna); (e) ruderal waste site (near Cottbus, Germany). © F. Essl (4x), D. Brandes (1x).

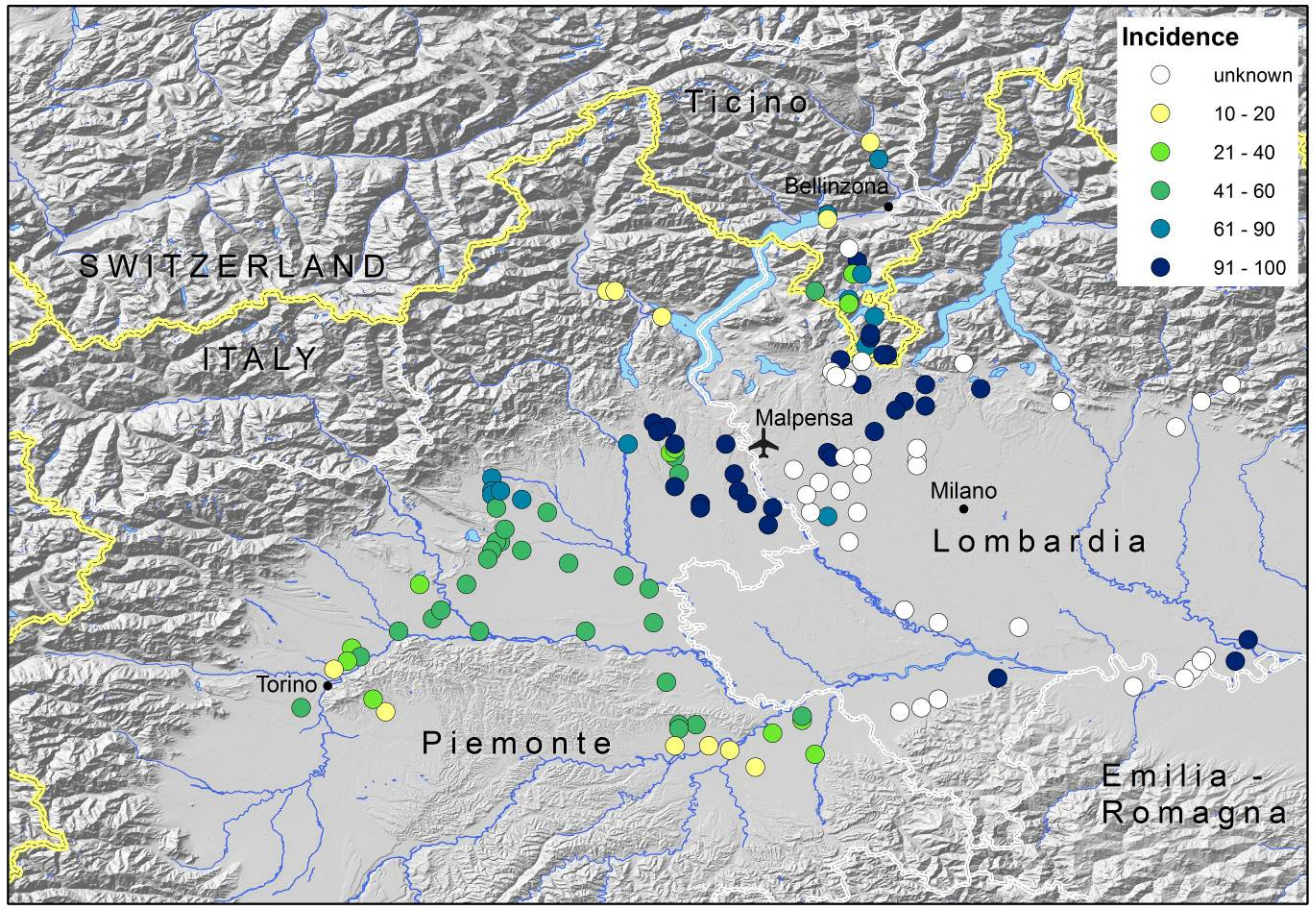


Fig. S2. Occurrence of *Ophraella communa* in Europe in 2013. Dots indicate sites where *O. communa* was found on *Ambrosia artemisiifolia*; colours represent the incidence of attack (% of plants attacked) at the time of observation (from Müller-Schärer *et al.* 2014).

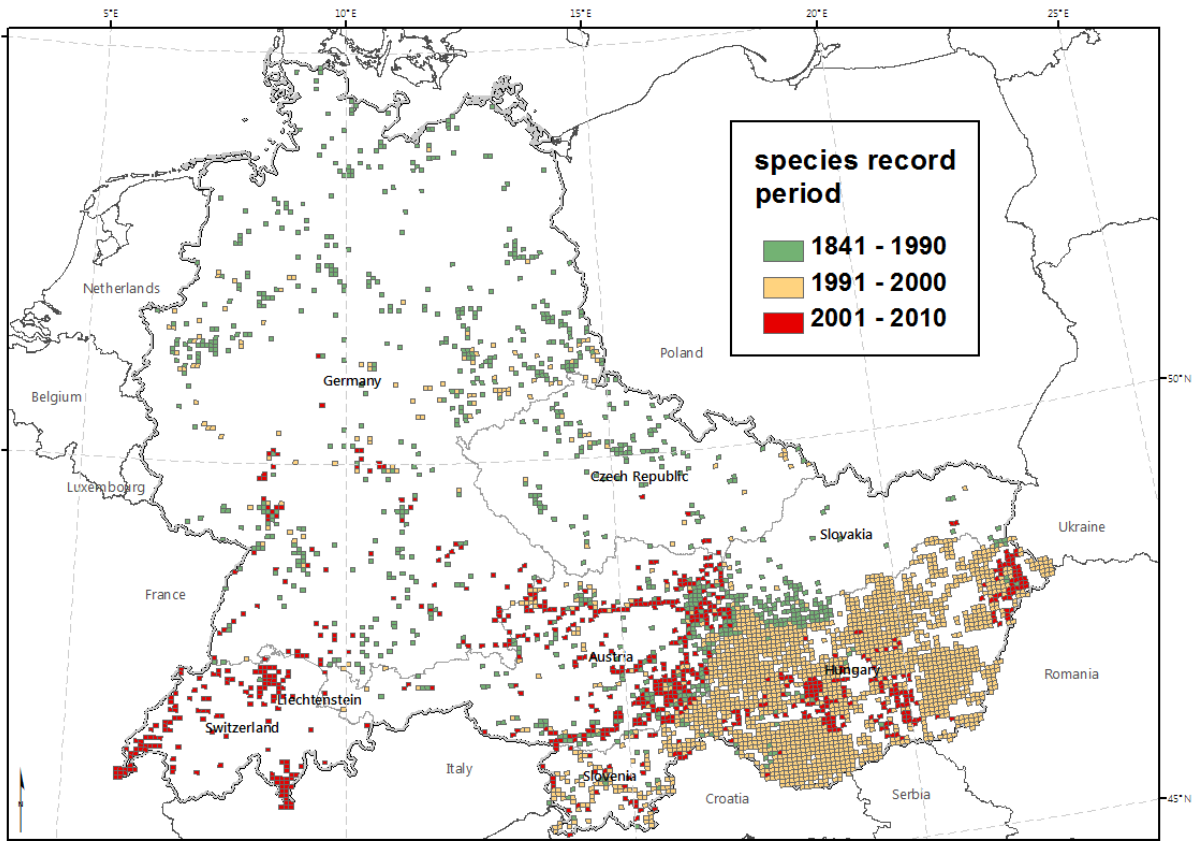


Fig. S3. The spread of *Ambrosia artemisiifolia* in Central and Eastern Europe (T. Mang unpublished data). The distribution is shown for grid cells of the Floristic Mapping Project of Central Europe (cell size: 5 x 3 geographic minutes, c. 35 km²) and for three different time periods. Note that historical data on common ragweed invasion for Hungary are incomplete.

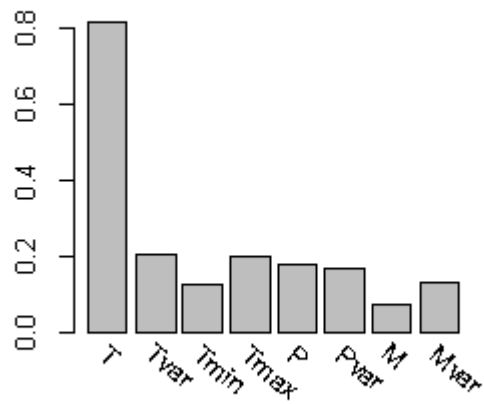


Fig. S4. The relative importance of variables used as predictors in SDMs. Abbreviations: T = annual mean temperature; Tvar = annual temperature seasonality; Tmin = minimum temperature of the coldest annual quarter; Tmax = maximum temperature of the hottest annual quarter; P = precipitation of the wettest annual quarter; Pvar = annual precipitation seasonality; M = annual moisture; Mvar = annual moisture seasonality.

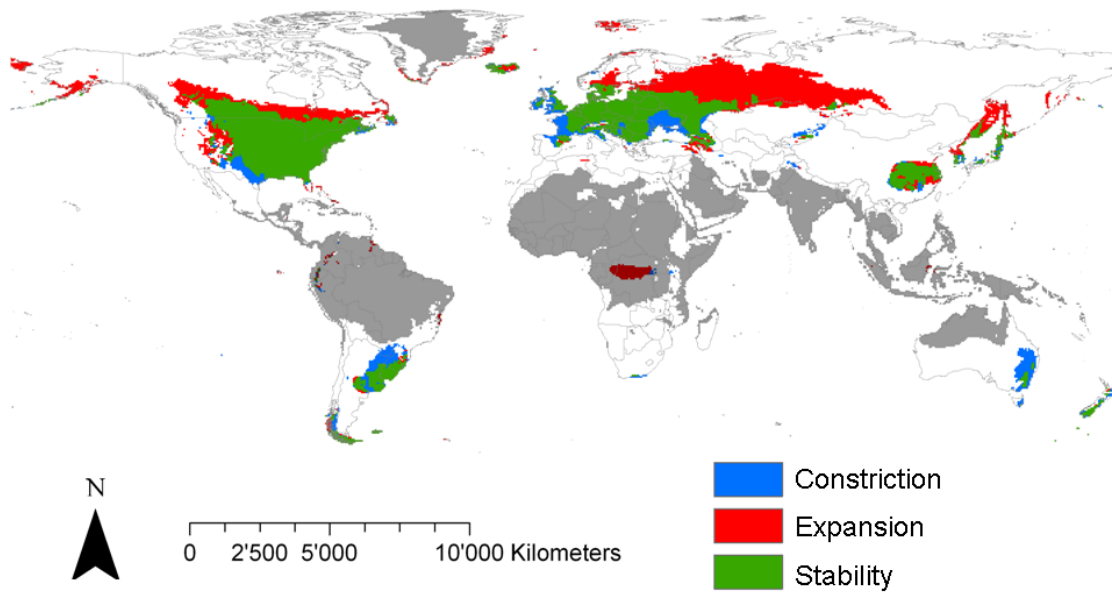


Fig. S5. The potential binarized distribution of *A. artemisiifolia* under current and future (A1b in 2100) climate as predicted by SDMs. Blue, red and green areas represent potential range constriction, expansion and stability. Shaded areas represent non-analog climate conditions compared to the range used for calibration of SDMs.