Assessing the potential distribution of insect pests: case studies on large pine weevil (*Hylobius abietis* L) and horse-chestnut leaf miner (*Cameraria ohridella*) under present and future climate conditions in European forests*

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Forest insect pests represent a serious threat to European forests and their negative effects could be exacerbated by climate change. This paper illustrates how species distribution modelling integrated with host tree species distribution data can be used to assess forest vulnerability to this threat. Two case studies are used: large pine weevil (*Hylobius abietis* L) and horse-chestnut leaf miner (*Cameraria ohridella* Deschka & Dimič) both at pan-European level. The proposed approach integrates information from different sources. Occurrence data of insect pests were collected from the Global Biodiversity Information Facility (GBIF), climatic variables for present climate and future scenarios were sourced, respectively, from WorldClim and from the Research Program on Climate Change, Agriculture and Food Security (CCAFS), and distributional data of host tree species were obtained from the European Forest Data Centre (EFDAC), within the Forest Information System for Europe (FISE). The potential habitat of the target pests was calculated using the machine learning algorithm of Maxent model. On the one hand, the results highlight the potential of species distribution modelling as a valuable tool for decision makers. On the other hand, they stress how this approach can be limited by poor pest data availability, emphasizing the need to establish a harmonised open European database of geo-referenced insect pest distribution data.

Introduction

Climate change can alter in several ways the distribution and relative abundance of pest species in forest ecosystems (Rouault *et al.*, 2006; Lindner *et al.*, 2010; Sturrock *et al.*, 2011; Marini *et al.*, 2012; Spathelf *et al.*, 2014). Additionally, insect pest population dynamics can be affected by a longer warm season, variations in precipitation patterns, modifications in food availability, and qualitative and quantitative changes in their predator and parasite populations (Netherer & Schopf, 2010; Settele *et al.*, 2014). Although it is not completely clear how, and to what extent, these mechanisms may affect forest insect pests, there is evidence that the spatial and temporal range of different insects is shifting due to climatic change (Bebber *et al.*, 2013). For example, mild winters in temperate forests facilitates the proliferation of pests formerly controlled by frost sensitivity (Settele *et al.*, 2014).

In Europe, higher temperatures are likely to promote range expansion towards northern latitudes and higher elevations for some defoliating insects and bark beetles. In the southern Mediterranean region and in some continental zones, increments in temperatures and in the frequency of drought events could affect heat sensitive insects, producing a northward shift of their geographic range. Other heat tolerant species such as the pine processionary (*Thaumetopoea pityocampa*) or oak processionary (*Thaumetopoea processionea*) moth will probably benefit from warmer conditions and hence expand their geographical range (Battisti *et al.*, 2005; Baker *et al.*, 2009; Netherer & Schopf, 2010).

In this paper the authors demonstrate how species distribution modelling represents a valuable tool for assessing forest vulnerability to insect pests at pan-European level in the context of climate change. In addition, how this approach, despite its great potential, is strongly limited by the lack of geo-referenced open-data about forest insect pest distribution at the European level is discussed.

To test the advantages and disadvantages of the species distribution modelling approach, this work focused on two forest insect pests, namely the large pine weevil (*Hylobius abietis* L) and the horse-chestnut leaf miner (*Cameraria ohridella* Deschka & Dimič). Being the most serious pest affecting young coniferous forest in Europe, *H. abietis* has a huge ecological and economic importance. Planted seedlings are frequently damaged or killed by adult weevils feeding on stem bark which can completely girdle stems

and cause plant death. Although adult weevils have a broad host range including a wide variety of conifer and broad-leaved trees they mainly feed on pine (Leather *et al.*, 1999). *C. ohridella* is a leaf-mining moth that can spread so rapidly that phytosanitary measures are ineffective. In 2001 it was therefore removed from the EPPO Alert List. This insect produces visible damage in hosts, by mining the tree leaves. Heavy infestations of *C. ohridella* and associated bacteria (Percival & Banks, 2014) lead to brown discoloration and death of the leaves, and eventually to tree defoliation (Grabenweger & Grill, 2000).

The following sections describe the data and methodology used for assessing forest vulnerability to insect pests. The results are then discussed in the context of available pest data in order to set the grounds for action to improve forest insect pest geo-referenced data collection and dissemination.

Methods and data

The methodology of this paper follows that used by Evangelista *et al.* (2011), which aimed to assess potential distribution of forest pests in the US. The departing point of the present study with respect to the previous one is that it integrates potential distribution of forest pests with host tree species probabilistic maps obtained from the European Forest Data Centre (EFDAC), within the Forest Information System for Europe (FISE). In doing this, a more comprehensive assessment of forest vulnerability is provided, by combining the presence likelihood of a pest, with that of its suitable hosts.

The proposed approach integrates information from different sources. Insect pest distribution data (P^{obs} in Fig. 1) were collected from the Global Biodiversity Information Facility (GBIF, 2014). Bioclimatic gridded variables for present and future conditions (A1B scenario) were sourced, respectively, from WorldClim (Hijmans *et al.*, 2005) and from the Research Program on Climate Change, Agriculture and Food Security – CCAFS (2014). Maps of host tree species were provided by EFDAC (2014). The approach consists of two steps. First, maps of present and future potential pest distribution are produced using the Maxent model (Phillips *et al.*, 2006; Phillips & Dudík, 2008; Elith *et al.*, 2011), with insect pest occurrences and a set of 19 bioclimatic variables representing present and future climate conditions as input. Then, the distribution of the
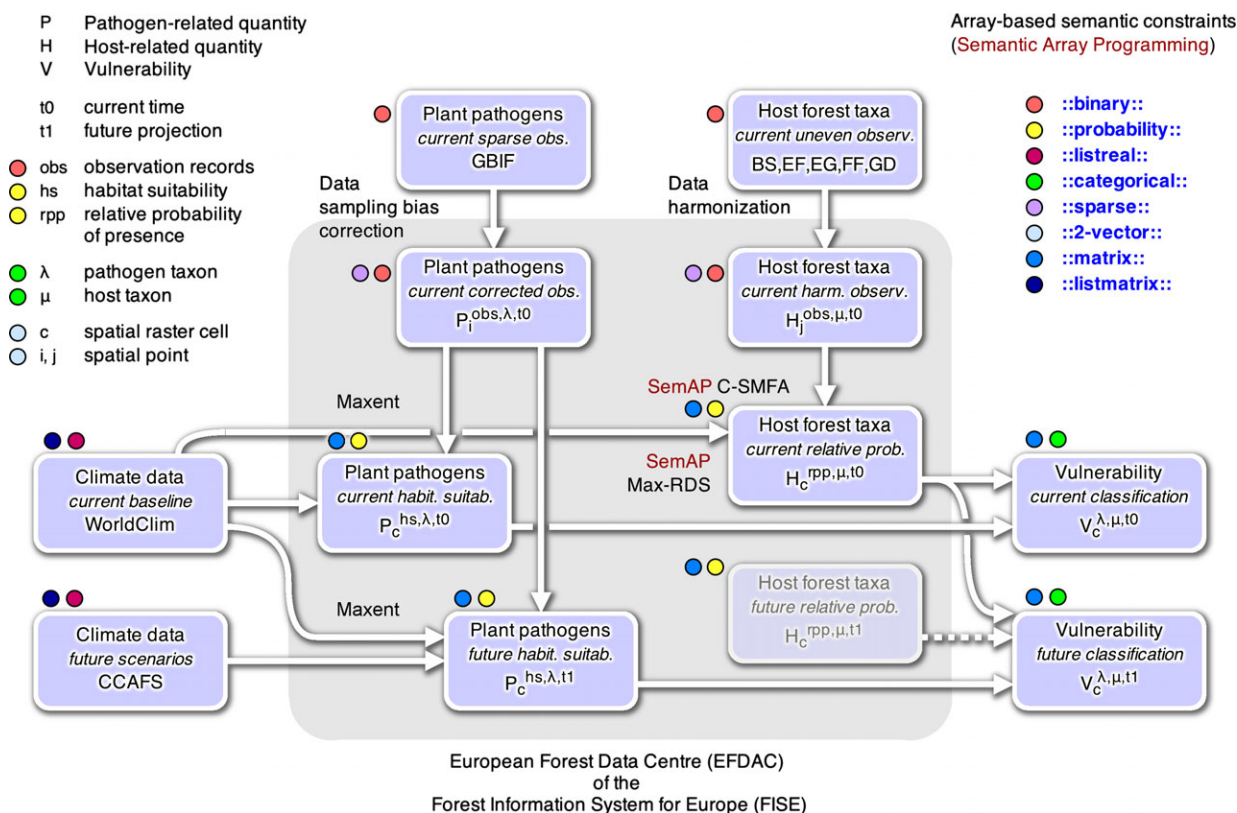
Fig. 1 Workflow of the modelling approach. The workflow shows the array of geospatial data, either initial input data or intermediate data, derived by each data-transformation module (D-TM). The Semantic Array Programming (de Rigo, 2012a,b; de Rigo *et al.*, 2013) notation is followed for highlighting the array-based semantics associated to each data layer (de Rigo, 2012a,b). For estimating the future vulnerability, a simplified proxy D-TM was exploited by integrating the predicted future habitat suitability $P^{hs,\lambda}$ of the insect pest λ with the current ($t0$) relative probability of presence (rpp) raster layer $H^{rpp,\mu}$ of the corresponding host tree species μ. The future rpp in $t1$ (currently unavailable) could be used for a more accurate prediction of the future vulnerability $V^{\lambda,\mu,t1}$.

corresponding host tree species for each pest is integrated with the pest potential distribution maps to estimate forest vulnerability.

WorldClim is a global observational database of climate monthly data representing the average of the period 1960–1990 (*t0* in Fig. 1). In this study data were used at a spatial resolution of 5 arc-min (~10 km). Two future climate simulations representing the A1B emissions scenario (Nakicenovic & Swart, 2000) were sourced from the CCAFS (2014). A1B is a moderate emission scenario with a balance across all sources of emissions, i.e. not relying too heavily on one particular energy source. The simulations represent the average climate in the 30-year period 2071–2100 (hereafter 2080s; *t1* in Fig. 1) disaggregated to 5 arc-min resolution and corrected for bias according to Osborn (2009, 2010) using the ClimGen approach and the change-factor disaggregation technique (Tabor & Williams, 2010). The original simulations were produced by two general circulation models (GCM), the Max Planck Institute (MPI) ECHAM5 model and the Canadian Centre for Climate Modelling and Analysis (CCCMA) CGCM3 model.

Nineteen bioclimatic layers were inputted to Maxent for both the present reference climate and future conditions (Table 1). The original un-projected (latitude and longitude in degrees) layers were projected to an equal area projection (ETRS 89 LAEA) to eliminate the effects of grid cell area size due to the curvature of the earth, an issue that may produce spurious effects in Maxent algorithm (Elith *et al.*, 2011). Maxent is a general purpose habitat modelling algorithm for estimating probability of distributions based on the principle of maximum entropy and applicable to presence-only species occurrence data (Phillips *et al.*, 2006; Phillips & Dudík, 2008; Elith *et al.*, 2011). The machine learning algorithm of Maxent is non-linear, nonparametric and not sensitive to multicollinearity of the input variables.

Table 1 Bioclimatic variables used for habitat modelling of *Hylobius abietis* and *Cameraria ohridella*

| BIO1	Annual Mean Temperature
BIO2	Mean Diurnal Range (Mean of monthly (max temp − min temp))
BIO3	Isothermality (BIO2/BIO7) (*100)
BIO4	Temperature Seasonality (standard deviation * 100)
BIO5	Maximum Temperature of Warmest Month
BIO6	Minimum Temperature of Coldest Month
BIO7	Temperature Annual Range (BIO5-BIO6)
BIO8	Mean Temperature of Wettest Quarter
BIO9	Mean Temperature of Driest Quarter
BIO10	Mean Temperature of Warmest Quarter
BIO11	Mean Temperature of Coldest Quarter
BIO12	Annual Precipitation
BIO13	Precipitation of Wettest Month
BIO14	Precipitation of Driest Month
BIO15	Precipitation Seasonality (Coefficient of Variation)
BIO16	Precipitation of Wettest Quarter
BIO17	Precipitation of Driest Quarter
BIO18	Precipitation of Warmest Quarter
BIO19	Precipitation of Coldest Quarter

Maxent is flexible, being able to handle continuous and discrete input variables, and has been used in many different applications, including assessments of insect habitat distribution (Elith *et al.*, 2011; Evangelista *et al.*, 2011).

The authors sourced 2868 occurrence records for *H. abietis* and 1188 occurrence records for *C. ohridella* from GBIF (2014). The records were searched for the entire European continent with no date restriction. These two species are among the insect pest species occurring in Europe which have the most data records available from GBIF. Among all available records, those having latitude and longitude coordinates with an accuracy of at least one tenth of decimal degree (DD) were selected. In addition, the dataset was corrected for sampling bias according to the spatial filtering technique developed by Kramer-Schadt *et al.* (2013) by (randomly) eliminating records at a distance of <10 km from the closest record and finally, by removing replicated records within the same grid cell of 10 × 10 km of the bioclimatic variables. This procedure reduced the dataset to 677 occurrence records for *H. abietis*, and 152 occurrences for *C. ohridella* (Fig. 2A,F).

Distribution raster layers of host tree species have been generated from the harmonised presence/absence observations (H[obs] in Fig. 1) hosted by EFDAC. These are based on National Forest Inventory (NFI) data complemented with four additional European-wide datasets. In particular, de Rigo *et al.* (2015) harmonised data from BioSoil database (Durrant *et al.*, 2011), European Information System on Forest Genetic Resources (EUFGIS, 2014), Forest Focus Monitoring (Hiederer *et al.*, 2007, 2008) and Geo-referenced Database of Genetic Diversity (GD Database, 2014). Host tree species distribution was implemented by means of the Constrained Spatial Multi-Frequency Analysis (C-SMFA) by de Rigo *et al.* (2012, 2015) to model the relative probability of presence (*rpp* in Fig. 1) of the host tree species at 1-km grid size resolution.

According to the IMPACT (2014) project, *H. abietis* has as hosts a wide range of conifers such as *Picea sitchensis*, *Pseudotsuga menziesii* and *Pinus sylvestris*. Moreover, it can be found less frequently on *Picea abies* and other pine species (*Pinus* spp.). Distribution maps of these host tree species (H[rpp] in Fig. 1) were obtained from EFDAC (2014). The widely used 10th percentile training presence threshold (10-TP) was used to convert tree species probability maps into discrete presence-absence maps (Ficetola *et al.*, 2009; Marske *et al.*, 2009; Morueta-Holme *et al.*, 2010). The 10-TP predicts as absent the 10% most extreme presence observations, thus in the grid cells having a probability of presence below the value of the 10-TP the species is predicted as absent. This percentage indicates the probability value at which 90% of the training presence points fall within the potential presence area.

Maxent model results were evaluated using the area under the receiving operating characteristic curve (AUC; Hosmer *et al.*, 2013). In addition, the authors used the jackknife test (Tukey, 1958) to assess the contribution of
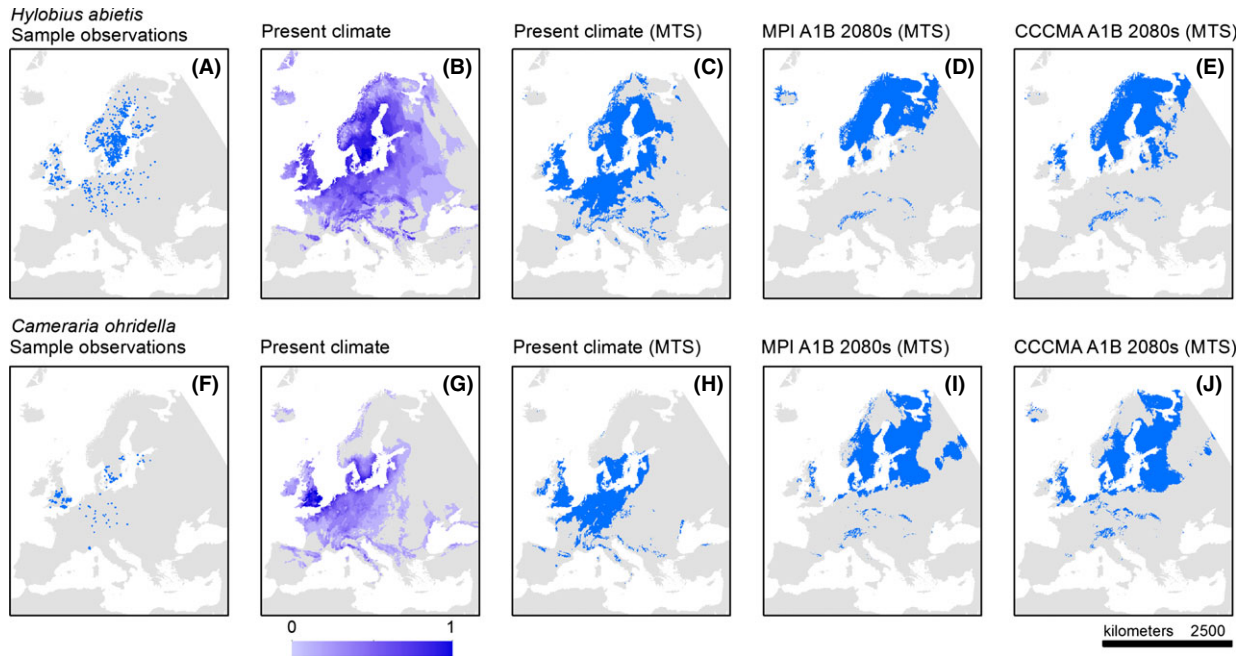
Fig. 2 Distribution data and habitat suitability maps of *Hylobius abietis* and *Cameraria ohridella*. (A,F) available data of observed insect pests sourced from GBIF after correction for sampling bias. (B,G) habitat suitability maps of present climate resulting from Maxent model. (C,H) habitat suitability maps of present climate recoded into suitable (blue) and not suitable areas according the maximum test sensitivity plus specificity (MTS) threshold. (D,I) projected (2080s) habitat suitability maps according to MPI ECHAM5 recoded into suitable (blue) and not suitable areas using the MTS threshold. (E,J) projected (2080s) habitat suitability maps according to CCCMA CGCM3 recoded into suitable (blue) and not suitable areas using the MTS threshold. All for *H. abietis* and *C. ohridella* respectively.

each independent bioclimatic variable to the obtained probability models. The model was fitted using reference present climate data, running ten replications. In each replication 80% of all available pest occurrences were used to assess species potential distribution, and the remaining 20% to compute AUC. The 80% and 20% of occurrence records were replaced randomly in each of the ten runs. The model was tuned using the default regularisation parameter of 1.0 in both present reference climate and future scenario runs. The authors also performed additional tests by setting the regularisation parameter at 0.5, 0.75, 1.5, 2.0 and 2.5. The final model was computed from the average of the ten runs, an option that decreases the uncertainty associated with a single run and a single set of training points. This approach was implemented independently for *H. abietis* and *C. ohridella*.

To map the current and future potential distribution of both insects a threshold needs to be set in order to convert the probability values provided by Maxent into presence/absence information. For this, the *maximum test sensitivity plus specificity* (MTS) threshold was used (Liu *et al.*, 2005), which is based on the same principles of the AUC accuracy test that the authors used to validate the model. Finally, the modelled present and future potential distribution maps of *H. abietis* were integrated with the corresponding host tree species maps, in order to assess forest vulnerability. Thresholded maps were combined producing a new map having four potential categories of suitable/non-

suitable habitat and presence/non-presence of the host tree species. In this map vulnerability areas are those having concomitantly suitable habitat of the insect pest and predicted presence of a host tree species.

Results

The potential suitable habitat of *H. abietis* covered around 2.3 million km^2 under the present reference climate. Suitable areas were mostly located in Central and Northern Europe, including the British Isles, and in other areas at high elevations (Fig. 2C). The mean value of AUC for the ten runs was 0.93 (SD: 0.003) which suggests "excellent" (AUC > 0.90) discriminatory power of the model (Araújo *et al.*, 2005). The three bioclimatic variables showing highest relative contribution to the Maxent model were maximum temperature of the warmest month (Bio 5) with a contribution of 54%, mean temperature of the warmest quarter (Bio 10) 11%, and mean temperature of driest quarter (Bio 9) 10%.

Under scenario A1B both GCMs showed comparable results, indicating a decrease in the total suitable areas for *H. abietis* expected by the 2080s. In particular, MPI predicted a decrease of about 27%, while CCCMA predicted a decrease of about 23% (Table 2). Results of both models suggest a shift in the distribution of suitable habitat for *H. abietis* towards Northern regions and other regions at higher elevations (Fig. 2D,E). Almost a half of the current

habitat will remain suitable according to CCCMA (49%) and MPI (40%). New habitats will represent 27–33% of the present suitable area, and previous habitats will decrease by 51–60%.

Potential suitable habitat of *C. ohridella* covered 1.3 million km^2 under present reference climate. Suitable habitat is mostly located in Central Europe, British Isles and Sweden (Fig. 2H). The mean of AUC values in the ten runs was 0.97 (SD: 0.006) which suggests excellent discriminatory power of the model. The three bioclimatic variables exhibiting the highest relative contribution to the model were temperature annual range (BIO7) with a contribution of 23%, followed by mean diurnal range (BIO2) with 17%, and maximum temperature of warmest month (BIO5) with 15%. In all models, different settings of the regularisation parameter did not improve AUC.

Under scenario A1B both GCMs showed comparable results towards increase of the total potential suitable habitat of *C. ohridella* expected by the 2080s. In particular, MPI predicted an increase of 41%, while CCCMA predicted an increase of 43% (Table 2). Results of both models suggest a shift in the distribution of suitable habitats towards Northern regions (Fig. 2I,J). Approximately 29% and 37% of the current habitat will remain suitable according to MPI and CCCMA respectively. New habitats will represent 105–112% of the present extent, and previous habitats will decrease by 63% and 71% according to CCCMA and MPI respectively.

Figure 3 shows four categories of presence-absence of the host tree species and the suitable-non-suitable distribution map of *H. abietis*. The first row (A–E) of Fig. 3 shows the present distribution of suitable habitat and of host tree species, and the second row (F–J) the suitable habitat of *H. abietis* expected by 2080s using the MPI data integrated with the current distribution of host species. The vulnerable areas where both host and pest are expected to be present are shown in red (V^{t0} and V^{t1} in Fig. 1). In the present climate, there are several large areas where the potential distribution of *H. abietis* overlaps that of *Pinus sylvestris* (C). The same is true for *Picea abies* (E) and *Pinus* spp

(D). Vulnerable areas of *Pinus sylvestris* are seen in Scandinavia and Finland, the Baltic region, scattered areas of Central Europe, and in a few clusters in the Pyrenees, the Alps, South of France and a few Mediterranean regions. Vulnerable areas of *Pseudotsuga menziensii* (B) are evident in England, Scotland and South-east Ireland, in some areas of France, and in a large area including Germany, Belgium, the Netherlands and Denmark. Finally, vulnerable areas of *Picea sitchensis* (A) are evident in the British Islands, Ireland and Denmark. Note that the maps in Fig. 3 have a smaller spatial domain than the maps of Fig. 2. This is due to the fact that tree species maps in EFDAC contain data mostly for EU countries while the climatic datasets used for the maps in Fig. 2 cover the global domain.
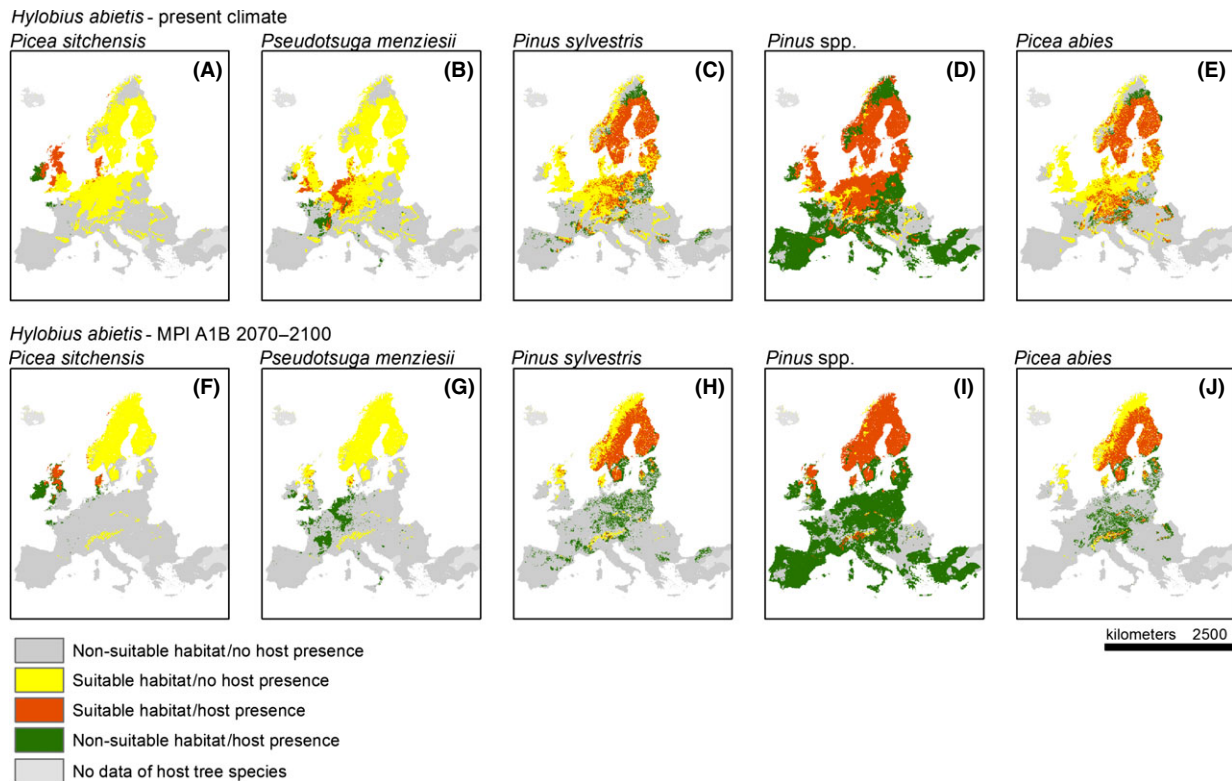
Range shifts of suitable habitat of *H. abietis* under A1B scenario indicate changes in the distribution of vulnerable areas of host tree species (Fig. 3F–J). Under future A1B (MPI) scenario *Pinus sylvestris* (H), *Picea abies* (J) and the *Pinus* spp. (I) are projected to have large areas of vulnerability towards *H. abietis*. The case of *Pseudosuga menziensii* (G) shows well the range shifts of suitable habitat of *H. abietis*. Future scenarios indicate a likely marked reduction of vulnerable areas for this species in respect to those identified according to present climate. Towards the end of the century only a few grid cells of concomitant suitable habitat and species presence, in the British Islands and Denmark, are expected. This is in contrast with that suggested by current climate, which identifies a much larger extent of vulnerable areas. A similar situation is evident for *Picea sitchensis* (F), and for the other species, even if their reduction of vulnerable areas is less marked.

Discussion and conclusions

This study presented an approach to assess forest vulnerability to insect pests. The results illustrate potential effects of a changing climate in the distribution of two forest insect pests in Europe. Furthermore, they show how climate change can influence forest pests in different ways, for instance by expanding or contracting the habitat range of

Table 2 Area change of potential suitable habitat of *Hylobius abietis* and *Cameraria ohridella* under present reference climate and A1B future scenario according to MPI and CCCMA GCMs (1000s km^2). Percent changes in brackets

	Total area	Current suitable areas that will remain suitable	New suitable areas	Areas which are currently suitable that will no longer be suitable
H. abietis	**Thousand km^2 (percent changes)**			
Present climate	2337	–	–	–
Projected A1B MPI – 2080s	1702 (−27%)	935 (+40%)	768 (+33%)	1402 (+60%)
Projected A1B CCCMA – 2080s	1792 (−23%)	1150 (+49%)	642 (+27%)	1187 (+51%)
C. ohridella	**Thousand km^2 (percent changes)**			
Present climate	1254	–	–	–
Projected A1B MPI – 2080s	1774 (+41%)	367 (+29%)	1407 (+112%)	887 (+71%)
Projected A1B CCCMA – 2080s	1788 (+43%)	467 (+37%)	1321 (+105%)	787 (+63%)

Hylobius abietis - present climate

Picea sitchensis (A) | *Pseudotsuga menziesii* (B) | *Pinus sylvestris* (C) | *Pinus* spp. (D) | *Picea abies* (E)

Hylobius abietis - MPI A1B 2070–2100

Picea sitchensis (F) | *Pseudotsuga menziesii* (G) | *Pinus sylvestris* (H) | *Pinus* spp. (I) | *Picea abies* (J)

kilometers   2500

Legend:
- Non-suitable habitat/no host presence
- Suitable habitat/no host presence
- Suitable habitat/host presence
- Non-suitable habitat/host presence
- No data of host tree species

Fig. 3 Suitable habitat of *Hylobius abietis* under present reference climate (A–E) and A1B emission scenario 2080s according to MPI ECHAM5 (F–J), and present distribution of host tree species according to EFDAC (de Rigo *et al.*, 2012).

insects, as suggested by the projected range increment of *C. ohridella*, and the projected range reduction of *H. abietis*. This demonstrates that some areas that are not vulnerable under the present climate may become vulnerable under the future climate and *vice versa*. This aspect is illustrated in the vulnerability assessment implemented for *H. abietis* where shifts in the distribution of its suitable habitat towards the end of the 21st century suggests marked changes in the distribution of vulnerable areas, assuming no redistribution of host tree species.

Temperature-related variables exhibited the highest relative contribution to the models for both insect species. Variables describing warmest limits and temperature ranges were the most important contributors to Maxent models. This result is not surprising if heat sensitivity of the target insects is considered (Denlinger & Yocum, 1998). The models computed for both insects using current climate have shown strong predictability of suitable habitat. Nevertheless, caution is needed in assessing impacts of future climate due the degree of uncertainty as discussed below.

The results of this paper are in line with a number of recent studies suggesting shifts in the distribution of insects as consequence of climate change. For example, Evangelista *et al.* (2011) observed similar patterns in the interior West of the US, while Bebber *et al.* (2013) studied the phenomenon at the global scale. Netherer & Schopf (2010) provide a review on the potential effects of climate change

on the distribution of forest insect pests in Europe, indicating that climate change has had impacts, and will continue to have a major influence on the spatio-temporal dynamics of insect herbivores in European forest.

The present study proposes a framework to assess forest vulnerability to insect herbivores. However, the results are subject to a number of constraints. Suitable habitat involves the probability of presence under a set of environmental conditions, therefore it should be considered as an estimate of potential distribution and not as a distribution *per se*. In addition, other factors, not considered in this study, may affect the presence of insects, such as increasing concentrations of CO_2, insect-plant interactions, levels of UVB, irradiation levels, and variations in nutrient availability. Other sources of uncertainty in the modelling approach derive from Maxent model fitting, from the limited number of climate simulations used, two GCMs in this case, the projection of only one scenario (A1B), and the many gaps of available geo-referenced insect pest data. This issue is evident in the sampling bias correction that reduced raw observation data to 24% and 13% for *H. abietis* and *C. ohridella* respectively. Actually, it was found that availability of geo-referenced data is a problem common to most European tree pests. It is noteworthy that for demonstrative purposes, the study focused on two of the species for which most occurrence data were available.

The surprising lack or limited geo-referenced insect pest data availability at pan-European level is a major issue requiring coordinated further efforts. In particular, the results highlight how lack of data can strongly limit vulnerability assessments, making it difficult to communicate current and future forest threats to decision makers. Alleviating these limits would require a coordinated action of European organisations and stakeholders with the scope of setting an open Internet database of geo-referenced data useful for forest vulnerability assessment. In the next paragraphs the authors list the main features that the database should contain:

- Scientific and common name of the observed insect pest;
- Scientific and common name of the host tree species on which the insect was observed;
- Systematic geo-referencing (Latitude, Longitude). A minimum spatial accuracy, 30 arc-s (~1 km), would be desirable for integrating this information with high resolution environmental data such as WorldClim that is disseminated at a spatial resolution of up to 30 arc-s;
- Geo-referencing using latitude and longitude coordinates is the preferable option for modelling purposes, however the database should be able to accommodate other options in case geographic coordinates are not available, i.e. when insect species are aggregated at grid, region, or administrative or analytical unit. In consequence the database should be able to host observations represented in several formats, such as points, grid cells at different scales or polygons of specifically defined areas;
- Another fundamental piece of information to be collected is the date of the observation. This will offer the possibility of selecting specific time ranges of occurrence facilitating multi-temporal assessments, and giving the possibility to model specific outbreaks defined both spatially and temporarily;
- The landscape where the observation is taken, in terms of different land cover categories such as natural forest, forest plantation, agroforestry, green urban areas, etc. This information is useful for delineating critical pest areas and assessment of potential spread on the basis of land cover categories;
- A few generic items could be also easily recorded, for example, country of observation and observation method: direct, systematic survey, remote sensing, etc.;
- Information on the organisation responsible for the observation;
- Finally, the implementation of the database should take into consideration interoperability aspects defined by the INSPIRE Data Specification on Species Distribution – Technical Guidelines report (European Commission, 2014). This will facilitate dissemination and accessibility of datasets in the forest pest data users' community.

Acknowledgments

Évaluation de la répartition potentielle des insectes nuisibles: études de cas sur le grand charançon du pin (*Hylobius abietis* L.) et sur la mineuse du marronnier (*Cameraria ohridella*) dans les conditions climatiques actuelles et futures dans les forêts européennes

Les insectes nuisibles des forêts représentent une menace sérieuse pour les forêts européennes et leurs effets négatifs pourraient être aggravés par le changement climatique. Cet article illustre l'utilisation de la modélisation de la répartition des espèces, intégrée aux données de répartition des arbres-hôtes, pour évaluer la vulnérabilité des forêts à cette menace. Deux études de cas sont utilisées, toutes deux au niveau paneuropéen, pour le grand charançon du pin (*Hylobius abietis* L.) et la mineuse du marronnier (*Cameraria ohridella* Deschka & Dimič). L'approche proposée utilise des informations de différentes sources. Les données sur la présence des insectes nuisibles proviennent du service mondial d'information sur la biodiversité ('Global Biodiversity Information Facility', GBIF), les variables climatiques pour le climat actuel et des scénarios futurs ont été obtenues, respectivement, à partir de WorldClim et du Programme de recherche sur le changement climatique, l'agriculture et la sécurité alimentaire (CCAFS), et les données sur la répartition des arbres-hôtes ont été obtenues auprès du Centre européen de données sur les forêts (EFDAC), qui fait partie du système d'information forestière pour l'Europe ('Forest Information System for Europe', FISE). L'habitat potentiel des ravageurs étudiés a été calculé en utilisant l'algorithme d'apprentissage automatique du modèle Maxent. D'une part, les résultats indiquent que la modélisation de la répartition des espèces peut devenir un outil précieux pour les décideurs. D'autre part, ils indiquent que cette approche peut être limitée par le manque de données sur les organismes nuisibles, renforçant ainsi la nécessité de créer une base de données européenne harmonisée et ouverte pour les données géo-référencées sur la répartition des insectes nuisibles.

Оценка потенциального распространения вредных насекомых на примере большого соснового долгоносика (*Hylobius abietis* L) и листового минёра конского каштана (*Cameraria ohridella*) при существующих и будущих климатических условиях в европейских лесах

Лесные вредные насекомые представляют серьезную угрозу для европейских лесов, и, с изменением климата, их отрицательное воздействие может усилиться. Эта работа иллюстрирует то, каким образом моделирование распределения видов, в сочетании с данными о распределении деревьев-хозяев, может использоваться для оценки уязвимости леса в отношении этой угрозы. Используются два примера: большой сосновый долгоносик (*Hylobius abietis* L) и листовой минер конского каштана (*Cameraria ohridella* Deschka & Dimič), причем оба они находятся на общеевропейском уровне. Предложенный подход объединяет информацию из различных источников. Данные о присутствии вредных насекомых были собраны из Глобального информационного фонда биологического разнообразия (GBIF), климатические переменные для нынешнего климата и будущих сценариев были взяты, соответственно, из базы данных WorldClim и из Программы исследований по изменению климата, сельскому хозяйству и продовольственной безопасности (CCAFS), а данные о распределении видов деревьев-хозяев были получены из Европейского центра данных о лесах (EFDAC), в рамках Информационной системы лесов Европы (FISE). Потенциальная среда обитания целевых вредных организмов была вычислена при помощи обучающего алгоритма модели Maxent. С одной стороны, результаты выдвигают на первый план моделирование потенциала распределения видов в качестве ценного инструмента для лиц, принимающих решения. С другой стороны, они подчеркивают, что такой подход может быть ограничен слабой доступностью данных о вредном организме, подчеркивая необходимость установления согласованной открытой *общеевропейской базы данных* о распределении вредных организмов.

References

Araújo MB, Pearson RG, Thuiller W & Erhard M (2005) Validation of species–climate impact models under climate change. *Global Change Biology* **11**, 1504–1513.

Baker R, Caffier D, Choiseul JW, De Clercq P, Dormannsné-Simon E, Gerowitt B *et al.* (2009) Scientific Opinion of the Panel on Plant Heath on a pest risk analysis on *Thaumetopoea processionea* L., the oak processionary moth, prepared by the UK and extension of its scope to the EU territory. *EFSA Journal* **1195**, 1–64.

Battisti A, Stastny M, Netherer S, Robinet C, Schopf A, Roques A *et al.* (2005) Expansion of geographic range in the pine processionary moth caused by increased winter temperatures. *Ecological Applications* **15**, 2084–2096.

Bebber DP, Ramotowski MAT & Gurr SJ (2013) Crop pests and pathogens move polewards in a warming world. *Nature Climate Change* **3**, 985–988.

CCAFS (2014) Research Program on Climate Change, Agriculture and Food Security. http://www.ccafs-climate.org/ [accessed on 1 February 2015]

de Rigo D (2012a) Applying semantic constraints to array programming: the module "check_is" of the Mastrave modelling library. http://mastrave.org/doc/mtv_m/check_is [accessed on 3 January 2014]

de Rigo D (2012b) Semantic Array Programming with Mastrave – Introduction to Semantic Computational Modelling. http://mastrave.org/doc/MTV-1.012-1.htm [accessed on 3 January 2014]

de Rigo D, Caudullo G & San-Miguel-Ayanz J (2015) *European Tree Species Distribution with Constrained Spatial Multi-Frequency Analysis*. Publications Office of the European Union, Luxembourg (LU), (in press).

de Rigo D, Caudullo G, San-Miguel-Ayanz J & Stancanelli G (2012) Mapping European forest tree species distribution to support pest risk assessment. *Bioforsk FOKUS* **7**, 21.

de Rigo D, Corti P, Caudullo G, McInerney D, Di Leo M & San-Miguel-Ayanz J (2013) Toward open science at the European scale: Geospatial Semantic Array Programming for integrated environmental modelling. *Geophysical Research Abstracts* **15**, 13245–13249.

Denlinger DL & Yocum GD (1998) Physiology of heat sensitivity. In: *Temperature Sensitivity in Insects and Application in Integrated Pest Management*, pp. 7–53. Westview Press, Boulder (US); Oxford (GB).

Durrant T, San-Miguel-Ayanz J, Schulte E & Suarez Meyer A (2011) *Evaluation of BioSoil Demonstration Project: Forest Biodiversity – Analysis of Biodiversity Module*. European Commission – Joint Research Centre, Publications Office of the European Union, Luxembourg (LU).

EFDAC (2014) European Forest Data Centre (EFDAC). http://forest.jrc.ec.europa.eu/efdac/ [accessed on 1 March 2015]

Elith J, Phillips SJ, Hastie T, Dudík M, Chee YE & Yates CJ (2011) A statistical explanation of MaxEnt for ecologists. *Diversity and Distributions* **17**, 43–57.

EUFGIS (2014) European Information System on Forest Genetic Resources. http://www.eufgis.org/ [accessed on 5 January 2014]

European Commission (2014) *Inspire D2.8.III.19 Data Specification on Species Distribution – Technical Guidelines*. European Commission Joint Research Centre, Ispra (IT).

Evangelista PH, Kumar S, Stohlgren TJ & Young NE (2011) Assessing forest vulnerability and the potential distribution of pine beetles under current and future climate scenarios in the Interior West of the US. *Forest Ecology and Management* **262**, 307–316.

Ficetola GF, Thuiller W & Padoa-Schioppa E (2009) From introduction to the establishment of alien species: bioclimatic differences between presence and reproduction localities in the slider turtle. *Diversity and Distributions* **15**, 108–116.

GBIF (2014) Global Biodiversity Information Facility. http://www.gbif.org/ [accessed on 1 March 2015]

GD Database (2014) Geo-referenced Database of Genetic Diversity. https://gd2.pierroton.inra.fr/gd2/ [accessed on 5 January 2014]

Grabenweger G & Grill R (2000) On the place of origin of *Cameraria ohridella* Deschka & Dimiè (Lepidoptera: Gracillariidae). *Beiträge zur Entomofaunistik* **1**, 9–17.

Hiederer R, Durrant T, Granke O, Lambotte M, Lorenz M & Mignon B (2008) *Forest Focus Monitoring Database System – Technical Report 2006 Level II Data*. European Commission – Joint Research

Centre, Publications Office of the European Union, Luxembourg (LU).

Hiederer R, Durrant T, Granke O, Lambotte M, Lorenz M, Mignon B et al. (2007) *Forest Focus Monitoring Database System – Validation Methodology*. European Commission – Joint Research Centre, Publications Office of the European Union, Luxembourg (LU).

Hijmans RJ, Cameron SE, Parra JL, Jones PG & Jarvis A (2005) Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology* **25**, 1965–1978.

Hosmer DW, Lemeshow S & Sturdivant RX (2013) *Applied Logistic Regression*, 3rd edn. Wiley, New York (US).

IMPACT (2014) IMPACT – Integrated management of forest pests addressing climate trends. http://www.impactproject.eu/ [accessed on 1 February 2015]

Kramer-Schadt S, Niedballa J, Pilgrim JD, Schröder B, Lindenborn J, Reinfelder V et al. (2013) The importance of correcting for sampling bias in MaxEnt species distribution models. *Diversity and Distributions* **19**, 1366–1379.

Leather SR, Day KR & Salisbury AN (1999) The biology and ecology of the large pine weevil, *Hylobius abietis* (Coleoptera: Curculionidae): a problem of dispersal? *Bulletin of Entomological Research* **89**, 3–16.

Lindner M, Maroschek M, Netherer S, Kremer A, Barbati A, Garcia-Gonzalo J et al. (2010) Climate change impacts, adaptive capacity, and vulnerability of European forest ecosystems. *Forest Ecology and Management* **259**, 698–709.

Liu C, Berry PM, Dawson TP & Pearson RG (2005) Selecting thresholds of occurrence in the prediction of species distributions. *Ecography* **28**, 385–393.

Marini L, Ayres M, Battisti A & Faccoli M (2012) Climate affects severity and altitudinal distribution of outbreaks in an eruptive bark beetle. *Climatic Change* **115**, 327–341.

Marske KA, Leschen RAB, Barker GM & Buckley TR (2009) Phylogeography and ecological niche modelling implicate coastal refugia and trans-alpine dispersal of a New Zealand fungus beetle. *Molecular Ecology* **18**, 5126–5142.

Morueta-Holme N, Fløjgaard C & Svenning J-C (2010) Climate change risks and conservation implications for a threatened small-range mammal species. *PLoS One* **5**, e10360.

Nakicenovic N & Swart R (2000) *Special Report on Emissions Scenarios*, pp. 612. Cambridge University Press, Cambridge (GB).

Netherer S & Schopf A (2010) Potential effects of climate change on insect herbivores in European forests—General aspects and the pine processionary moth as specific example. *Forest Ecology and Management* **259**, 831–838.

Osborn T (2009) *A User Guide for ClimGen: A Flexible Tool for Generating Monthly Climate Data Sets and Scenarios*. Climatic Research Unit, University of East Anglia, Norwich (GB).

Osborn T (2010) *The CLIMGEN Model*. Climatic Research Unit, University of East Anglia, Norwich (GB).

Percival GC & Banks JM (2014) Studies of the interaction between horse chestnut leaf miner (*Cameraria ohridella*) and bacterial bleeding canker (*Pseudomonas syringae* pv. *aesculi*). *Urban Forestry & Urban Greening* **13**, 403–409.

Phillips SJ, Anderson RP & Schapire RE (2006) Maximum entropy modeling of species geographic distributions. *Ecological Modelling* **190**, 231–259.

Phillips SJ & Dudík M (2008) Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. *Ecography* **31**, 161–175.

Rouault G, Candau J-N, Lieutier F, Nageleisen L-M, Martin J-C & Warzée N (2006) Effects of drought and heat on forest insect populations in relation to the 2003 drought in Western Europe. *Annals of Forest Science* **63**, 613–624.

Settele J, Scholes R, Betts R, Bunn SE, Leadley P, Nepstad D et al. (2014) Terrestrial and inland water systems. In: *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel of Climate Change*, pp. 271–359. Cambridge University Press, Cambridge (GB) and New York (US).

Spathelf P, van der Maaten E, van der Maaten-Theunissen M, Campioli M & Dobrowolska D (2014) Climate change impacts in European forests: the expert views of local observers. *Annals of Forest Science* **71**, 131–137.

Sturrock RN, Frankel SJ, Brown AV, Hennon PE, Kliejunas JT, Lewis KJ et al. (2011) Climate change and forest diseases. *Plant Pathology* **60**, 133–149.

Tabor K & Williams J (2010) Globally downscaled climate projections for assessing the conservation impacts of climate change. *Ecological Applications* **20**, 554–565.

Tukey JW (1958) Bias and confidence in not quite large samples. *The Annals of Mathematical Statistics* **29**, 614.