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Trees on the move: using decision theory to compensate for climate change at the regional scale in forest social-ecological systems

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Abstract

The adaptation of social-ecological systems such as managed forests depends largely on decisions taken by forest managers who must choose among a wide range of possible futures to spread risks. We used robust decision theory to guide management decisions on the translocation of tree populations to compensate for climate change. We calibrated machine learning correlational models using tree height data collected from five common garden tests in France where *Abies alba* provenances from 11 European countries are planted. Resulting models were used to simulate tree height in the planting sites under current and 2050 climates (regional concentration pathway scenarios (RCPs) 2.6, 4.5, 6.0 and 8.5). Our results suggest an overall increase in tree height by 2050, but with large variation among the predictions depending on the provenance and the RCPs. We applied *maximin*, *maximax* and *minimax* decision rules to address outcomes under five uncertain states of the world represented by the four RCPs and the present climate (baseline). The *maximin rule* indicated that for 2050, the best translocation option for maximising tree height would be the use of provenances from Northwest France into all target zones. The *maximax and minimax regret rules* pointed out the same result for all target zones except for the 'Les Chauvets' trial, where the East provenance was selected. Our results show that decision theory can help management by reducing the number of options if most decision rules converge. Interestingly, the commonly suggested recommendation of using multiple provenances to mitigate long-term maladaptation risks or from 'pre-adapted' populations from the south was not supported by our approach.

Keywords Assisted migration · Decision theory · Forests · Phenotypic variation · Social-ecological systems · Uncertainty

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Introduction

In complex social-ecological systems (*SESs*), feedbacks from management decisions have impacts at different spatial and temporal scales (Walker et al. 2004). This lag between decisions and feedbacks is particularly critical for forest systems as decisions taken today can have long-lasting impacts (Fernández-Manjarrés and Tschanz 2010). Under a stable climate, managers within *SESs* can develop rules for using ecosystem services based on their accumulated experience. However, under changing climates, there is no guarantee that former rules of use will still work or if ecosystems are able to adjust by themselves. Managed forests, including those with planted trees and naturally regenerated populations, typically concern commercial trees for which seed source regions have been carefully designed based on the differences among locally adapted populations (Savolainen et al. 2007). In principle, if the requirements of local adaptation are well understood, seeds can progressively be planted in new areas to track the shifting optimum climate. But decisions regarding optimal

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seeds may be more complicated than just following shifting climates as the genetic adaptive variation is not distributed evenly across tree populations. Selecting local or exotic seed sources to compensate for climate change is a typical case of decision-making in *SES* that can have positive or negative impacts. In fact, without human intervention, the ability of some species to survive in changing climates is heavily reliant on their specific capacity to adapt locally to new climates (Aitken et al. 2008; Valladares et al. 2014), which remains largely unknown for long-lived species like trees. Under such rapid external perturbations, the integrity of forests systems clearly depends on the decisions taken by the social component of the *SES*.

Rules for translocating trees under stable climates have been developed based on precise knowledge of local adaptation of different populations. These levels of local adaptation to climate have been studied using spatial models that incorporate the variation of phenotypic traits measured in provenance tests (i.e. common gardens, defined as transplant experiments for testing the effect of environment and genetics on tree populations in the case of commercial tree species) established in different environments (Mátyás 1994; Savolainen et al. 2007). These models incorporate the effects of climatic transfer distances by reciprocally quantifying the performance of populations in the climate where the seeds were collected and where the trees were planted (Leites et al. 2012). Despite having different common drawbacks, such as the lack of common gardens outside the species ranges to test the ecophysiological limits of the species, this approach has empirically shown that some populations are already more suited than others to expected future climates, providing clear applications for guiding management decisions (Benito Garzón et al. 2011; Oney et al. 2013; Rehfeldt et al. 2014a; Valladares et al. 2014; O'Neill et al. 2014).

Models based on provenance tests can help us in the design of adaptation programmes to climate change by translocating populations within and beyond their natural distribution (Isaac-Renton et al. 2014; Benito-Garzón and Fernandez-Manjarrés 2015; Prasad et al. 2016). However, the ecological knowledge generated by these models needs to be integrated in more formal decision frameworks to fully understand the risks of all the possible options related with climate change uncertainty (Polasky et al. 2011), as for example those related to maladaptation of a translocated population to an unexpected climate extreme (Pedlar et al. 2012; Benito-Garzón et al. 2013b). Currently, various examples of decision frameworks that incorporate the economic value associated with forests exist (Hildebrandt and Knoke 2011; Yousefpour et al. 2012), but translocation of tree populations has not yet been integrated into any decision framework. The multiple combinations resulting from different climate change models and different population sources make it very difficult to choose arbitrarily one solution over the other, so techniques to reduce the number of choices are urgently needed. One option is to use 'robust decision theory' that develops decision rules allowing to choose one action among all the possibilities under uncertainty (Regan et al. 2005). In decision-making, uncertainty is represented by the likely 'states of the world' (i.e. different scenarios of climate change including current climates), and the combinations of the actions that can be taken under these states of the world constitute the outcome or utility representing the net benefits of choosing one action from a set of alternative actions (Polasky et al. 2011).

For testing the utility of the robust decision approach, one would ideally need population samples from a species in which adaptive genetic variation is already known to be large and in which climate change effects are already apparent. In Europe, mortality and decline have increased during the last decades in populations of temperate tree species at the southernmost limit of their ranges (Allen et al. 2010; Carnicer et al. 2011; Benito-Garzón et al. 2013c). It is probable that rear-edge, southern European populations contain rare adaptive genetic combinations of local and range-wide interest for adaptation under climate change (Fady et al. 2016a). One species that embodies all of these characteristics is the European silver fir *Abies alba* (Mill.), a mountain conifer tree with ecological and economic importance in central and southern Europe (Roschanski et al. 2016). *A. alba* ranges from the Pyrenees at its south-westernmost location, where there is evidence of the existence of refugia during the Last Glacial Maximum (Liepelt et al. 2009), to Central Poland in scattered populations. The species presents high mortality in the Pyrenees linked to climate warming (Linares and Camarero 2011), and in Southern Alps due to the succession of droughts associated to bark beetle attacks (Cailleret et al. 2014; Durand-Gillmann et al. 2014), whereas in the core of its distribution in central Europe, there is an increase in its growth, which could also be explained by climate change bringing warmer and more humid summers in certain areas (Büntgen et al. 2014).

Here, we propose to incorporate robust decision theory to guide the translocation of populations under climate change as an example of decision-making in a SES. The ultimate goal is to generate weighted outcomes in an attempt to guide stakeholders and decision-makers to minimise the risk of moving populations within their species range. We present an example based on a network of 29 *Abies alba* provenances derived from across the species range in Europe and planted in five common gardens in France. Tree height was analysed as a function of climatic distance between the sources and the experimental sites obtained by the random forest algorithm (Breiman 2001) and projected onto current and future climate scenarios. The five experimental sites were selected as target zones for applying the decision framework. Tree height models were run for all of the representative concentration pathways described by the IPCC (AR5) for the year 2050 using the average of 10 global circulation models.

Material and methods

Climate scenarios

Current and future climate scenarios were downloaded from WorldClim at a resolution of 30 s (Hijmans et al. 2005), which is approximately 1 km, a good resolution for spatial prediction at the national level. Current climate data in this dataset was estimated by averaging climate data for the period 1960–2000. Future scenarios were built by averaging 10 global circulation models: IPCC AR5 (BCC-CSM1-1, CCSM4, GISS-E2-R, HadGEM2-AO, IPSL-CM5A-LR, MIROC5, MIROC-ESM-CHEM, MIROC-ESM, MRI-CGCM3 and NorESM1-M) for four representative concentration pathways (regional concentration pathway scenarios (RCPs) 2.6, 4.5, 6.0 and 8.5), which predict an average increase of global mean surface temperature between 0.1 and 2 °C in France by 2050 (IPCC 2014).

From the 21 climatic variables initially tested, only nine were used in the models because they retained the highest proportion of the variance explained in preliminary runs: mean annual temperature (MAT), maximum temperature of the warmest month (MTWM), minimum temperature of the coldest month (MTCM), annual precipitation (AP), temperature seasonality (TS) defined as the variation of the annual temperature in relation with the monthly temperature average, annual range of temperature (ART; MTWM−MTCM) and precipitation seasonality (PS) defined as the variation in monthly precipitation over the total annual precipitation (variation coefficient). Two long-term indices of climate extremes for maximum temperature (DTMAX) and minimum temperature (DTMIN) were calculated as the differences between the maximum and minimum temperatures, respectively, recorded between 1901 and 2005 by the Climatic Research Unit (http://www.cru.uea.ac.uk/data) and the mean temperature for the selected period (the present and the four RCPs for 2050). In addition, climate transfer distances (TD) were calculated for all of the climatic variables as the difference for the given climatic variable between the planting sites and the locations of provenance origin (seed sources) and added to the model as another source of climate variation.

Provenance test design

One of the major limitations with existing provenance tests is that most of them have been designed to test for local adaptation *within* the range of the species. Because the levels of local adaptation are unknown, researchers look for as many populations as possible coming from as many different places from the natural species distribution. In practice, from all the provenances tested, only a subset may show enough phenotypic and genetic divergence useful for the management question in mind. In our case, as we focused on translocations under climate change scenarios, we needed to identify first those that stick out as having clear local adaptation to a given climate. For other purposes, not finding differences between populations is actually a good thing as different provenances can be easily exchanged for one another.

Hence, we first tested for differences among provenances from the complete network available that comprises tree height measured at five trial sites located across France (Supplementary Table S1), where 29 provenances from 11 European countries (France, Switzerland, Czech Republic, Denmark, Slovakia, Italy, Austria, Poland, Bulgaria, Bosnia Herzegovina and Germany) were tested (Supplementary Table S2). Non-parametric one-way Kruskal-Wallis analysis of the variance showed significant provenance effect on tree height in four out of the five planting sites (Supplementary Table S3). Post hoc Mann-Whitney-Wilcoxon tests indicated that differences among provenances within planting sites were due only to a few provenances (Supplementary Table S3). Among them, we selected those with French origin planted in at least two planting sites: 'Fanges', 'St. Evroult' and 'La Joux' for modelling purposes. We dubbed them regarding their geographical location as 'South', 'Northwest' and 'East' provenances, respectively. Conveniently, for a southern-northern simulation of translocations, these provenances represent the range limits of the species in Europe, at its southernmost and north-westernmost limits and in the core of the distribution of the species, namely, its eastern limit in France. We used trial locations as target zones for predicting tree height to avoid geographical extrapolation to far regions that have not been considered when training the model (Fig. 1).

Tree height measures

We used individual tree height data because it can be considered a surrogate for growth potential and overall fitness when provenance tests are planted in optimal climatic conditions (Rehfeldt et al. 2014b). To maximise the number of trees used in the analyses, we chose height measured at 9 years old (H9) as the trait of interest as it had been measured in all sites (tree height measures used in this analysis are available at Aalba.xls (Electronic Supplementary Material 5)). All of the analyses were performed with the standardised tree height ranging between 0 and 1 (with 1 representing the height of the tallest tree in the planting site). For simplicity, hereafter, the term 'tree height' is equivalent to standardised tree height.

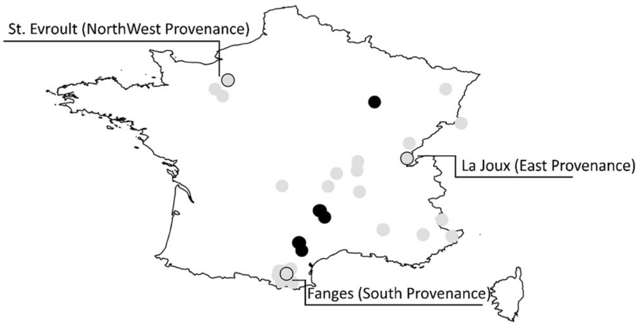

Fig. 1 Location of the planting sites (black circles) and the provenances tested (grey circles) for *Abies alba* in France. The three provenances outlined with black were used in the analysis to assess the effect of tree height as focal provenances for their region (South, Northwest and East regions of provenances). Planting sites (also used as target planting zones) are represented by black circles. At the scale of the map, two pairs of planting sites overlap even though they are physically separated

Modelling set-up

Only the three provenances showing significant differences among them in tree height were used for modelling. We ran tree height models for the present and 2050 climates for each of the three selected French provenances and predict into the trial sites. Finally, we included phenotypic variation in tree height (the difference between 2050 and the present by target region), in a decision framework that accounts for future climatic uncertainty defined by the RCP scenarios and the present climate as baseline. Next, we explain in detail each of the steps (Fig. 2).

Non-parametric random forest regression of tree height in France

Non-parametric, machine learning correlational models of individual tree height for each of the three provenances selected were calibrated as a function of the transfer climatic distance estimated for the nine climatic variables previously selected. The models were calibrated under current climatic conditions and then projected into future scenarios (Fig. 2). The transfer climatic distance is defined as the difference of a given climatic variable between the planting sites and the origin of the provenance. It represents a space for time transformation for studying climate change effects on tree performance, because the climate at the seed source can differ from the climate at the planting site (Leites et al. 2012).

We built 15 (3 provenances × 5 states of the world) provenance models using the random forest algorithm (Breiman 2001; *R library random forests* (Liaw and Wiener 2002)) to predict the response of tree height to climate change per provenance. Each model was run

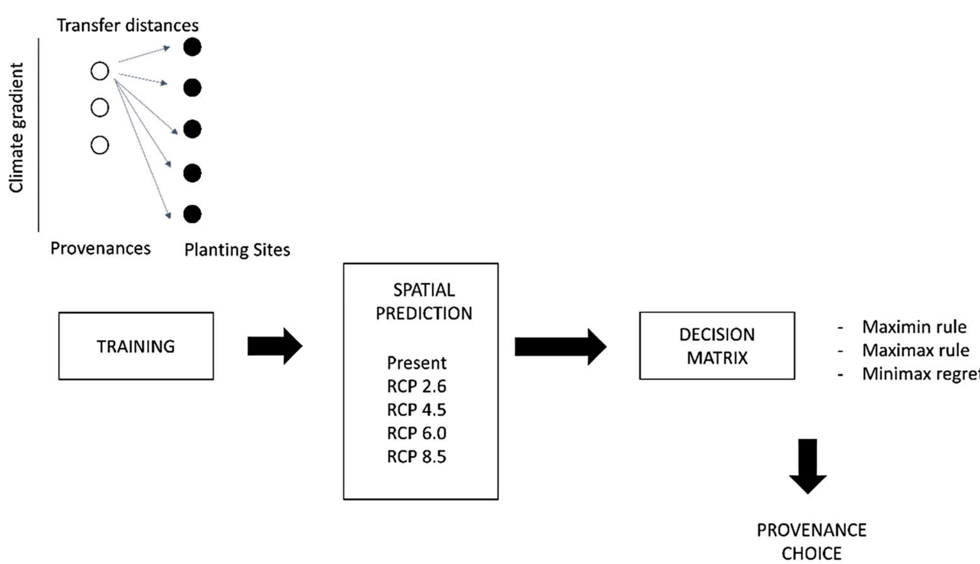

Fig. 2 Flow diagram depicting the main steps for decision-making under uncertainty for selecting the preferable translocation option. Climatic transfer distances between the origin of the provenances and the planting sites where the trees are growing are used to train a non-parametric model of tree height. Then, spatial predictions are performed for each of the target zones (in this case, the same locations where the planting sites were established). These predictions by target zones are compiled in a decision matrix that allows us to apply standard decision rules to select preferable options for translocation

100 times to increase the robustness of the model. An average of the prediction coming from the three models by provenances was used as a proxy of the performance of all provenances together.

The initial dataset was divided into calibration (2/3 of the total) and validation datasets (1/3) to allow the models to be independently evaluated. The random forest is a non-parametric technique that achieves regression by randomly building multiple individual regression trees (Breiman 2001). The algorithm contains three main steps. First, *n* groups of regression trees are included in the bootstrapping process using the original data (*n* was set to 500). Second, one regression tree is grown for each group, randomly selecting the number of variables at each node. The mean squared error 'out of the bag' (MSE_{OOB}) is calculated for each tree with the remaining data of each subgroup ($_{OOB}$):

$$MSE_{OOB} = n^{-1} \sum_{1}^{n} \left(\left(y_i - (y_i)^{OOB} \right)^2 \right.$$

where y_i^{OOB} is the mean of the $_{OOB}$ predictors. Finally, all of the trees are grown without 'pruning', and the final prediction results are produced by averaging all of the trees. The likelihood of the model is estimated using the proportion of the variance explained by the model and the capacity for generalisation using the R^2 coefficient calculated as the correlation between the test data and the values estimated using the formula derived in the training step. The percentage of the variance explained by the model was estimated using the following equation:

$$\%Variance\ explained = 1 - \frac{MSE}{Variance\ (response)}$$

where MSE is the mean squared error as calculated in the training of the algorithm and Variance (response) is the original observations.

Predictions of tree height per provenance for the current and future climatic conditions were then performed for the geographical location of the five trials where the trees have been planted.

Robust decision-making matrix design

We classified our results in a decision matrix that allows us to apply robust decision theory to our results to guide the selection of optimal decisions under uncertainty. In robust decision theory, uncertainty is characterized by multiple equally probable views of the future where no probabilistic distribution can be attributed (Regan et al. 2005), as in our case the RCPs. RCPs can be achieved through different combinations of economic, technological, demographic, policy and institutional futures, i.e. they are not associated with unique socioeconomic or emissions scenarios which make difficult the attribution of a probabilistic distribution to each of them (Moss et al. 2010; van Vuuren et al. 2011). The decision matrix combines the outcomes of tree height prediction per provenance and target zones defined as the trials where the trees are currently planted to avoid geographical and climatic extrapolation of the model predictions. We classify the outcomes of our modelling analyses in the three main parts of a decision matrix: the *states of the world*, the *action* to be taken under each state of the world and the *expected outcome* (*utility*) for each combination of state of the world and action (Table 1). Our states of the world are represented by the equally probable climate scenarios for the future (year 2050; RCPs 2.6, 4.5, 6.0 and 8.5) and a baseline climate scenario (current climates), and our actions are defined by each of the provenances proposed for planting purposes under climate change. The outcomes are represented by the tree height averaged for each provenance in each scenario as predicted by the models. The same structure of the decision matrix was repeated independently for each of the five target zones (TZs) corresponding to the current planting sites for which we wanted to estimate the best planting option.

The goal of placing the results in a decision matrix is to choose the *action* that maximises the expected *utility* under the different *states of the world*. This selection can be performed by establishing *decision rules*. For the sake of simplicity, we chose the most typical decision rules (Peterson 2009; Polasky et al. 2011) as an example of how decision-making can be implemented in decisions taken at the regional scale, like for forests: *maximin*, *maximax* and *minimax regret*. Based on Table 1, the decision rules are defined as follows:

***Maximin* decision rule** The best alternative action is the one that maximises the minimum outcome obtained for each action: $a_1 \geq a_2$ if and only if $\min(a_1) \geq \min(a_2)$.

Table 1 Simple decision matrix table representing two states of the world (s_1, s_2), and two possible actions to be taken (a_1, a_2) with the outcomes or utilities (a_1s_1, a_1s_2, a_2s_1, a_2s_2) that are a combination of the states of the world and the actions

	s_1	s_2
a_1	a_1s_1	a_1s_2
a_2	a_2s_1	a_2s_2

***Maximax* decision rule** The best alternative action is the one that maximises the maximum outcome obtained for each action: $a_1 \geq a_2$ if and only if $\max(a_1) \geq \max(a_2)$.

***Minimax regret* decision rule** The best alternative action is the one that minimises the maximum loss with alternative decisions: $a_1 > a_2$ if and only if $\max\ \{[(a_1,s_1) - \max(s_1)],[(a_1,s_2) - \max(s_2)]\} > \max\ \{[(a_2,s_1) - \max(s_1)],[(a_2,s_2) - \max(s_2)]\}$.

where a_i are the possible values representing the different actions to be taken (i.e. provenance choice for a given target zone—TZ), s_i describes the states of the world (RCP scenarios and baseline climate) and the combination of a_i,s_i is the utilities or outcomes (differences in tree height between 2050 and the present conditions estimated for each provenance model) in which the decision rules rely for taking decisions.

Results

Prediction of tree height

Tree height models per provenance show medium–high goodness of fit, with percentage of the variance explained between 18.38 and 36.05 without considering the block design of the provenance trials and between 28.02 and 64.23 when considering it (Table 2). Note, however, that spatial predictions are only based on climate data because the block design of the experimental layouts cannot be incorporated in the predictions. The model calibrated with the East provenance shows the highest proportion of the variance explained (36.05%), and the model calibrated with the South provenance the lowest (18.38%).

Making decisions under uncertainty

The decision matrix summarises the modelling results of tree height prediction per provenance for the baseline climate scenario and in the four RCPs for 2050 (Table 3 and Supplementary Table S4 for the estimation of the maximum regret) for the three actions and five target zones.

We applied the decision rules developed in the framework of the decision theory under uncertainty (Table 1) to the outputs of our predictive models of mean tree height for the present and future conditions (Table 3). The decision rules are considered independently for each target zone. For example, the *maximin decision rule* for the 'Les Chauvets' target zone suggests that the preferable action will be the one that has the maximum minimum value, which in this case is to translocate seed sources from the 'Northwest' provenance (minimum values of 0.672 relative tree height for all RCPs). In contrast, the *maximax rule* always suggested the option of translocation from the East provenance whatever target zone was selected.

The *minimax regret rule* involves choosing the action that minimises the highest regret. The regret is calculated as the missed opportunity through having made the wrong decision in each of the states of the world (Supplementary Table S4). In our example, this rule indicates that it would be best for the 'Northwest' provenance to be translocated into all the tested target zones.

Discussion

The main objective of formal decision rules is to reduce the number of options upon which an informed decision can be made. Here, we found that robust decision theory provided a consensus solution and that there was convergence among the three decision rules applied. The most preferable decision pointed out that in a limited geographical space, northern provenances can provide a good option to increase tree height in the coming years. Our scenarios do not show the expected outcomes for the future where tree population is showing lower heights than under current conditions. On the contrary, we showed here that for certain cases, climate change would likely increase tree height. In those cases, robust decision theory can be used to take advantage of climate change for increasing productivity for a shorter horizon where climate change is still considered to be moderate (2050 vs. 2100 for all RCPs).

Our approach can be applied to any tree species for which phenotypic data measured on several common gardens from several provenance tests exist. However, one of the main limitations is the lack of climatic analogues in the future, which would bias the height predictions for future climates and hence influence the decision matrix. We recommend therefore to keep this approach only for predictions at the short term (2050), where the climate is likely to be more similar to the current one than in the long-term predictions (2100).

Making decisions under uncertainty

The goal of decision-making under uncertainty is to select the action that maximises the utility using decision rules that do not depend on probabilities, because one state of the world is no more likely than any other. This is the case with the future IPCC scenarios, in which no probability can be assigned to any given scenario, and thus all of them should be considered equally likely (Moss et al. 2010; van Vuuren et al. 2011). The choice of a decision rule necessarily determines the final decision, and this choice is highly dependent on the trust that stakeholders have in

Table 2 Likelihood (percentage of the variance explained, PVE) and generalisation power (R^2 coefficient, R) of the models calibrated by provenances with the random forest algorithm including the block effect per site of the provenance trials (block structure + climate) and including only climate (climate). Results are shown as the mean and standard deviation after 100 runs. The results of calibrating the models with a combination of all three provenances are also shown (all 3 prov.)

Origin of the provenance	Block structure + climate				Climate			
	PVE		R		PVE		R	
	Mean	sd	Mean	sd	Mean	sd	Mean	sd
South	38.02	0.03	0.65	0.04	18.38	0.03	0.41	0.07
Northwest	40.27	0.03	0.66	0.04	19.19	0.04	0.40	0.07
East	64.23	0.02	0.81	0.02	36.05	0.03	0.58	0.04
All	51.55	0.01	0.75	0.02	26.58	0.02	0.51	0.03

their data and in their ability to deal with wrong decisions. In our case, we selected three straightforward criteria based on tree height to illustrate the possibilities of population translocations under climate change to maximise tree productivity, which can be easily discussed between researchers and forest managers as they represent extremes of optimistic versus pessimistic scenarios.

The *maximin* rule constrains the choice of actions by focusing on the minimum risk that can be afforded. In the case of translocation of populations, it provides a minimum threshold that a given population needs to reach to be translocated. Therefore, this rule avoids selecting the smallest growing provenance, without limiting for the maximum growth potential. In our example, the *maximin* rule prioritises the plantation

Table 3 Decision matrix used to address the choice of seed sources under uncertainty. The states of world are represented by the current climate (business-as-usual scenario) and the four representative concentration pathways from the IPCC. Results of mean tree height predictions were calibrated by provenance region (Provenance) and show average prediction for each target zone (planting sites). Emerging decisions derived from the three decision rules: *maximin*, *maximax* and *minimax regret*

Target zone (planting site)	Provenance	Present conditions Mean ± sd	2050 RCP 2.6 Mean ± sd	2050 RCP 4.5 Mean ± sd	2050 RCP 6.0 Mean ± sd	2050 RCP 8.5 Mean ± sd	*Maximin*	*Maximax*	*Minimax regret*[1]
Les Chauvets	South	0.614	0.601	0.601	0.575	0.601			
	Northwest	0.715	0.672	0.672	0.672	0.672	X		
	East	0.729	0.665	0.664	0.667	0.664		X	X
	All	0.686	0.646	0.645	0.638	0.645			
FD Du Bois Génard	South	0.542	0.601	0.601	0.575	0.601			
	Northwest	0.658	0.672	0.672	0.672	0.672	X	X	X
	East	0.611	0.664	0.664	0.666	0.664			
	All	0.603	0.645	0.645	0.638	0.645			
Les Boulaines La Brugère	South	0.614	0.601	0.601	0.575	0.601			
	Northwest	0.715	0.672	0.672	0.672	0.672	X	X	X
	East	0.644	0.665	0.664	0.667	0.664			
	All	0.658	0.646	0.645	0.638	0.645			
Somail Chinchidou	South	0.429	0.565	0.601	0.575	0.601			
	Northwest	0.567	0.672	0.672	0.672	0.672	X	X	X
	East	0.523	0.665	0.665	0.667	0.665			
	All	0.506	0.634	0.646	0.638	0.646			
Somail Sagassols	South	0.429	0.565	0.601	0.575	0.601			
	Northwest	0.567	0.672	0.672	0.672	0.672	X	X	X
	East	0.523	0.655	0.665	0.667	0.665			
	All	0.506	0.634	0.646	0.638	0.646			

[1] The intermediate regret table for calculating the *minimax regret* is shown in Supplementary Material (Supplementary Table S4)

of trees from the Northwest provenance whatever trial was selected as target zone.

On the other hand, the *maximax rule* has been criticised for being too optimistic because the outcome of one action is accepted only based on the maximum utility that it can generate (Peterson 2009). It has thus been considered a high-risk strategy, which would only be adopted by a decision-maker who is overly optimistic. In the example shown in this study, the *maximax rule* indicates that planting trees from the Northwest provenance is the preferable option to increase tree height in 2050 for the five studied cases except for the 'Les Chauvets' trial. This particular case is not a risky strategy because it was confirmed by the *minimax* and *minimax regret* rules as the preferable option. From the perspective of decision theory, the *maximax rule* does not provide a good option for making decisions because the risks of the worst case scenario are not taken into account for selecting the best action and using admixtures of provenances could be a good compromise to avoid an overly optimistic approach that might result in unwanted surprises.

The *minimax regret rule* chooses the action that minimises the maximum loss likely to occur (= regret) within the alternative actions. It is a good compromise between the *maximin* and *maximax rules*, and it was used in one of the few studies applying decision theory in the field of conservation biology to identify which species should be protected (Prato 2005). In our example, this rule indicates always the same output for each target zone: the preferable option would be to plant trees coming from the Northwest target zone, a result that was also obtained with the *maximax* rule and for the *maximin* rule for all the target zones except one ('Les Chauvets').

The intuitive solution of mixing as many populations as possible to increase the range of diversity available was not an outstanding option under any of the decision rules. However, we would expect that adding more provenances across the species ranges could change this result. Planting an admixture of trees from several provenances for the future has already been discussed in the framework of assisted gene flow to increase the genetic variability and therefore the range of possibilities to promote the future adaptation of trees (Sgrò et al. 2011; Havens et al. 2015) keeping in mind that more than one generation is needed to see a fitness increase in the populations.

Surprisingly, none of the decision rules proposed the intuitive solution of translocating from the south to northern locations in any of the target zones. This can be explained by the fact that southern populations present generally lower height potential than northern ones (our example is supporting this hypothesis, showing that the Northwest provenance was almost always the preferable option) and it is in line with the potential downsides of planting trees from southern provenances because of the risks of extreme frost events in these southern populations as have already occurred for some translocations (Benito-Garzón et al. 2013a; Benito-Garzón et al. 2013b; Martín-Alcón et al. 2016; Bucharova et al. 2016; Montwé et al. 2016). For instance, populations from the south of the range of *Pinus contorta* in North America and four perennial plants in Germany did not perform better than the local populations under extreme heat events (Bucharova et al. 2016; Montwé et al. 2016). Likewise, *Pinus pinaster* populations from southern Europe planted in northern locations suffered from high mortality after a frost event, whereas the mortality was lower for the local provenances (Benito-Garzón et al. 2013a). Other Mediterranean trees such as *Quercus coccifera*, *Q. ilex*, *Q. faginea* and *Q. pubescens* showed similar sensitivity to extreme cold events in recent translocations (Martín-Alcón et al. 2016). These examples show that moving populations from the south to the north is more complex than what is intuitively thought and it was not detected as a good choice by our decision framework based on the decision rules, probably because climate change brings non-analog climates that are probably too differentiated in north-south gradients and less differentiated between colder and warmer areas at similar latitudes (Benito-Garzón et al. 2014). There is a need for more experimental tests into warmer and dryer conditions as well as translocating not only up the mountains and up north for testing frost and cold resistance but from similar latitudes (i.e. a horizontal translocation) if populations exist.

Decision-making and socio-ecosystem trajectories

Our analysis shows that decisions within social-ecosystem (e.g. managed forest systems) can vary markedly even if rational rules of decision-making are incorporated into the decision-making process. First of all, for this case and with the available data, translocating trees from the South to the North does not appear to be a robust solution, at least for the early life stages of forest trees that we analysed. The translocation of populations from northern locations was supported in almost all the cases suggesting that the northern populations present generally higher height potential than the southern ones. We cannot answer with our data if this paradoxical result stems from having samples of populations coming from the core and the rear edge of the distribution of *Abies alba* or from the current RCP climate change models that project very dissimilar climates.

The common recommendation of planting trees from an admixture of provenances to increase forest growth potential, and thus also social-ecological resilience, is not supported in the case of *Abies alba* in France. We do not know whether this would be the case for other combinations of species, provenances and target sites, but even if that were the case, sufficient land is required if spreading risks with several provenances increasing operational costs. Planting at higher density than usual also needs to be considered when genetic diversity is part of the decision-making (see Lefèvre et al. (2014) and Fady et al. (2016b)), or if there is very little knowledge about the system. Extreme experiments of mixing populations that can show results in few years' time may be complementary approach to formal decision-making that requires in-depth knowledge of the system.

Our approach shows a strong convergence among the options considered, suggesting that northern provenances, even if contra intuitively, would have higher tree potential than populations coming from southern origin. However, we did not consider the survival rates in our approach which could probably turn our results in other direction. Moreover, we could not test here one of the most difficult decisions for forest managers to make, to favour translocated populations over local ones if needed (Whittet et al. 2016). We acknowledge that mixing populations from different provenances but always maintaining the local provenance seems a sensitive and sound strategy for the climate expected for 2050, but this option was not detected by our approach probably because of the low number of provenances included in the analysis.

Social, cultural and psychological dimensions all make part of real-life decision-making, and it would be unlikely that local provenances would be discarded in afforestation programmes because in almost all countries, if not everywhere, local provenances are automatically considered to be the 'best' adapted to local conditions (Havens et al. 2015; Fady et al. 2016b). Even if the message of planting from Northwest provenances is clear from our decision table, it is very probable that different forest managers would read the decision table in a different way. Forest management adaptation to climate change includes 'no change management' in contrast with 'trend-adaptive management' (Fitzgerald and Lindner 2013). A manager reading our results with the first management option in mind would outweigh the business-as-usual results (keep local provenances) before considering any other option because in this case, forest managers would prefer to make decisions about things they know well. On the other hand, foresters following 'trend-adaptive management' would prefer to make decisions based on the best choices defined by a decision framework as the one we presented here, consisting of 'assisted gene flow' by planting provenances from the Northwest that show a higher tree growth potential, at least in the trials considered but we are pretty sure they would also consider to leave some plots with local provenances for the sake of having an alternative plan if models happen to be wrong.

In any case, we see that following the procedures outlined here, the number of options for making educated guess can be effectively reduced bearing in mind that there will always be the need to experiment to adapt adequately to changing conditions.

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