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Updating beliefs and combining evidence in adaptive forest management under climate change: A case study of Norway spruce (*Picea abies* L. Karst) in the Black Forest, Germany

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A B S T R A C T

We study climate uncertainty and how managers' beliefs about climate change develop and influence their decisions. We develop an approach for updating knowledge and beliefs based on the observation of forest and climate variables and illustrate its application for the adaptive management of an even-aged Norway spruce (*Picea abies* L. Karst) forest in the Black Forest, Germany. We simulated forest development under a range of climate change scenarios and forest management alternatives. Our analysis used Bayesian updating and Dempster's rule of combination to simulate how observations of climate and forest variables may influence a decision maker's beliefs about climate development and thereby management decisions. While forest managers may be inclined to rely on observed forest variables to infer climate change and impacts, we found that observation of climate state, e.g. temperature or precipitation is superior for updating beliefs and supporting decision-making. However, with little conflict among information sources, the strongest evidence would be offered by a combination of at least two informative variables, e.g., temperature and precipitation. The success of adaptive forest management depends on when managers switch to forward-looking management schemes. Thus, robust climate adaptation policies may depend crucially on a better understanding of what factors influence managers' belief in climate change.

1. Introduction

Climate change is projected to have significant impacts on forest resources (Kirilenko and Sedjo, 2007; Xu et al., 2009). However, uncertainty regarding the degree of climate change we are facing, and uncertainty regarding how forest ecosystems will respond to climate change (Millar et al., 2007; Xu et al., 2009) present severe challenges with respect to developing robust adaptive management strategies (Kirilenko and Sedjo, 2007; Yousefpour and Hanewinkel, 2009). While previous studies have addressed adaptive decision approaches in relation to climate change (e.g. Jacobsen and Thorsen, 2003; Armstrong et al., 2007; Prato, 2008; Heltberg et al., 2009; Probert et al., 2010; Williams, 2011), few have explicitly considered how uncertainty influences the adaptive decision making process (Williams, 2012), or how managers' beliefs regarding climate change will influence their management decisions.

Information about climate change is dynamic and as more reliable information becomes available, the uncertainty that the decision maker deals with is reduced over time (Prato, 2008; Heltberg et al., 2009; Probert et al., 2010; Bernetti et al., 2011; Williams, 2011). The aim of this study is to evaluate how managers may use a combination of information sources to update knowledge and beliefs relevant for adaptive decision making. Most studies of adaptive forest management implicitly assume managers to be rational and to have perfect knowledge of both the state of the system and its possible future trajectories or distributions, given available information (Pukkala and Miina, 1997; Jacobsen and Thorsen, 2003; Yousefpour and Hanewinkel, 2009). However, forest managers often base their decisions on multiple information

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sources that may be contradictory or be associated with varying uncertainty (Ducey, 2001; Ananda and Herath, 2005; Hoogstra, 2008). In response to this divergence decision-making models incorporating various levels of 'bounded rationality' have been developed to address variations in forest managers' use of information and formation of expectations regarding the future (Hoogstra, 2008; Jacobsen et al., 2010; Probert et al., 2010).

In a general adaptive management approach, each decision is based on observed trends and fluctuations of particular stochastic variables and the resulting beliefs about the future states of nature. Since we are not always able to describe and quantify uncertainty comprehensively, it is useful to include the formation of beliefs in the decision making model. A central aspect of such an approach is to decide what information and observations to include in belief formation and in which combinations. In the case of climate change and decision making for forest resources, one could argue that there are two obvious main sources of natural science information for assessing on-going and future climate change: climate and forest variables. Repeated, direct observations of climate variables have the advantage of providing reliable information on variations and changes of climate. Information on the development of forest variables is less direct measures of climate change, as they are influenced also by other factors, and subject to lagged effects of past conditions. However, they have the advantage that that there is a long tradition of observing forest resources in established monitoring frameworks. Furthermore, forest variables – in the long run – contain information on the response of forests to climate change. Therefore, we consider climate and forest variables and mixtures thereof as the basis for forming beliefs about on-going climate change and its impacts.

We used climate scenario simulations and climate sensitive forest ecosystem model to address three research questions: 1) What is the relative value of climatic and forest state data for updating beliefs regarding future climate trajectories? 2) Does combining multiple data sources lead to a quicker convergence of a manager's belief state about climate change? 3) How do information and updated beliefs affect adaptive decisions on forest resources under climate change impact?

We seek to answer these questions for a case study in the Black Forest area of Germany by investigating decision making patterns for a manager maximizing at each decision node the expected value of objective function, using available information to form beliefs about forthcoming climate changes, and deciding upon a set of alternative actions. In this process, decision-maker applies Dempster's rule (Dempster, 1967) for combining evidence from both climate state and forest state observations, and by using Bayesian theory (Bayes and Price, 1763) for updating beliefs. Thus, the modelling concept in this study is a combination of microeconomic and experience-based decision-making in the modelling context of coupled human-natural systems (An, 2012).

2. Material and methods

We consider a decision maker who aims to optimize management so as to maximise either long-term forest productivity (Total Biomass Production,[1] **TBP**) or minimize forest windthrow damages. These objective functions, ***OBJ***, are optimized by choosing at a given time step the best performing. We calculate the expected ***OBJ*** to determine the optimal decision, taking into account the process and value of learning about climate and forest variables. The ***OBJ*** measure represents the expected value of a particular management of the forest area that has been found as the best available conditional on the beliefs about the different climate change scenarios being true. In the following, we first describe a generic approach of how to apply the method for a given case, and then we specify how specific data are used for the case study.

2.1. Generic model

2.1.1. Climate scenarios

We consider $\boldsymbol{I}$ scenarios of climate development (e.g. as Kirilenko and Sedjo, 2007 used realizations of in IPCC A1f) and calculate a time series of mean values (trajectories) for a given climate variable (e.g. temperature, precipitation). We add a stochastic component capturing the uncertainty and variation around any scenario development by including i.i.d. stochastic shocks according to a Wiener noise process with variance σ_i^2 across state and time. Thus, the observed state of the climate related variable $\hat{\theta}_t$ at time $\boldsymbol{t}$ for scenario $\boldsymbol{i}$ is given by:

$$\hat{\theta}_t(\text{scenario}_i, t) = x_{it}(\text{scenario}_i, t) + \varepsilon_{it} \quad \text{and} \quad \varepsilon_{it} \sim N(0, \sigma_i^2) \tag{1}$$

where $\boldsymbol{t} = 1,\ldots,\boldsymbol{T}$, $\boldsymbol{i} = 1,\ldots,\boldsymbol{I}$, $\boldsymbol{x_{it}}$ denotes the mean trajectory of scenario $\boldsymbol{i}$ at time $\boldsymbol{t}$, and ε_{it} is an error with normal distribution around mean $\mathbf{0}$ and scenario-specific variance, σ_i^2.

2.1.2. Decision maker's beliefs and information processing

We set up a decision framework where the decision maker holds a set of beliefs regarding the likelihood of each climate scenario being true. We also define how the decision maker may change his beliefs using Bayesian updating given new observations. Let $\boldsymbol{w_{it}}$ ($\boldsymbol{w_{it}} = \mathbf{Pr}(\mathbf{scenario}_{\boldsymbol{i}}, \boldsymbol{t})$) be the belief at a given point t that a particular climate scenario i is unfolding, such that beliefs are complete:

$$\sum_{i=1}^{m} w_{it} = 1, \quad w_{i,t} \geq 0 \tag{2}$$

As time passes and new information on the climate (either from forest or climate variables), as given by $\hat{\theta}_t$, is obtained, the plausibility of each climate change scenario is reassessed and the weights $\boldsymbol{w_{it}}$ are updated using Bayes' theorem (Bayes and Price, 1763):

$$w_{it+1}\left(\hat{\theta}_t\right) = \Pr\left(\text{scenario}_i|\hat{\theta}_t\right) = \frac{\Pr\left(\hat{\theta}_t|\text{scenario}_i\right)\Pr(\text{scenario}_i, t)}{\sum_{i=1}^{I}\Pr\left(\hat{\theta}_t|\text{scenario}_i\right)\Pr(\text{scenario}_i, t)} \tag{3}$$

The weights at time $\boldsymbol{t+1}$ depend on the belief in a climate change scenario and on the observed climate state at time $\boldsymbol{t}$. The observed $\hat{\theta}_t$ is a measure indicating the present climate state, and its values are simulated as described in Eq. (1). Based on the updated probability values ($\boldsymbol{w_{it+1}}$), we assign a belief mass to each scenario to be the actual development of the climate state.

2.1.3. Combination of evidence

We applied Dempster's rule (Dempster, 1967; Bernetti et al., 2011) for the combination of multiple updated beliefs (each based on a different observed variable) to produce a single combined

[1] The total biomass production (**TBP**) at a given time is defined as a flow consisting of the sum of harvested biomass (HB), biomass from mortality (BM: competition, fire, windthrow, dieback) and the decadal biomass increment (DBI: cumulated growth (not harvested) in the forest ($\text{biomass}_t - \text{biomass}_{t-1}$)).

belief in each climate change scenario. The combination of two beliefs $\boldsymbol{w_{it}(A)}$ and $\boldsymbol{w_{it}(B)}$ based on two sorts of evidence, $\boldsymbol{A}$ and $\boldsymbol{B}$, and supporting a climate change scenario (***scenario$_i$***) is calculated in the following manner:

$$\begin{aligned} & w_{it}(\text{scenario}_i) = \frac{\sum_{A\cap B=\text{scenario}_i} w_{it}(A)w_{it}(B)}{1-k} \\ & \text{when} \quad \text{scenario}_i \notin \emptyset \quad \wedge \quad w_{it}(\emptyset) = 0 \\ & \text{where} \quad k = \sum_{A\cap B=\emptyset} w_{it}(A)w_{it}(B) \end{aligned} \tag{4}$$

where $\boldsymbol{k}$ measures initial beliefs in conflict between different sorts of information and is determined by summing the products of the beliefs for all sets where the intersection is null, i.e. where one of the pieces of information does not support **scenario$_i$** at all. This rule is commutative, associative, but not idempotent or continuous (Dempster, 1967; Jøsang and Pope, 2011). The denominator in Dempster's rule, $\mathbf{1}-\boldsymbol{k}$, is essentially a normalization factor, which has the effect of leaving out conflict and attributing beliefs associated with conflict to the null set. Dempster's rule can easily be generalized for a combination of three (or more) different sources of information.

2.1.4. Choice of management actions

We determine the management action as a function of the objective, time, and current observed state of the system and the beliefs in the various climate change scenarios ($\boldsymbol{w_{it}}$). At each decision point, alternative decisions are evaluated for all possible combinations of scenario weights, $W_t = \{\boldsymbol{w_{1t}}; \boldsymbol{w_{2t}};\ldots; \boldsymbol{w_{It}}\}$. Therefore, the decisions depend on the forest managers belief-type probabilities for the transition from one state to another (Eq. (3)) and the value associated to that state.

We use $\boldsymbol{E(W_t, t; \theta_t, x_t)}$ to denote the expected value of a management strategy, $\boldsymbol{a_{tj}}$, from time $\boldsymbol{t}$ to the end of planning period $\boldsymbol{T}$, given the observed state of information and other relevant state variables x so that the optimal action $\boldsymbol{a_{tj}}$ satisfies

$$\max_{a_{tj}}/\min E(W_t, t; \theta_t, x_t) = \sum_{i=1}^{I} w_{it} OBJ_{it}(a_{tj}; \theta_t, x_t) \tag{5}$$

The value function $\boldsymbol{E(W_t, t; \theta_t, x_t)}$ is the weighted sum of the expected rewards at decision point $\boldsymbol{t}$ from action $\boldsymbol{j}$ given **scenario$_i$** (Eq. (5)). The scenario weights $\boldsymbol{w_{it}}$ are the updated beliefs as in Eqs. (3) and (4), and it is this updating and combination process that ensures that our management is adaptive by definition.

2.2. Case study

2.2.1. Study area

The simulated landscape is a 570 ha block of even-aged Norway spruce forest located between 500 and 800 m a.s.l. at the westerly side of the Northern Black Forest mountain range (48°40′ N, 8°13′ E), Germany. The forest is comprised of 401 stands that range in size from <0.1 ha to 11.5 ha. Norway spruce dominates the forest because of afforestation and historic management. Under non-managed conditions, a mixed European beech (*Fagus sylvatica* L.) forest is expected, with oaks (*Quercus* spp.) increasing in proportion towards lower elevations, and Silver fir (*Abies alba* Mill.) and Norway spruce (*Picea abies* (L.) Karst) increasing at higher elevations (Müller et al., 1992; Ludemann, 2010).

2.2.2. Data for climate scenarios

In our analysis, climate data are used in two ways. First, they are one of the primary drivers of forest dynamics in the applied forest ecosystem model LandClim model and therefore influence forest state through time. Second, they influence the forest manager's belief about climate state ($\boldsymbol{w_{it}}$), and therefore the manager's propensity to adopt and implement alternative management actions.

We used three different climate scenarios (Table 1): A no-change scenario (**Historic**), a moderate (**SMHI**) and a high (**HCCPR**) climate change scenario (Collins et al., 2006; Kjellström et al., 2011; Temperli et al., 2012). The **Historic** climate scenario is based on observed monthly temperature and precipitation data from 1950 to 2000. The climate change scenarios cover a range of uncertainty about predicted mean figures of climate variables over time. The influence of climate uncertainty on managers' belief state was included by assuming that all forest and climate variables had a standard deviation of $\sigma_i = 0.3$ (in Eq. (1)) that follows Allen et al. (2000), Collins et al. (2006) and Kjellström et al., 2011, studying the forecasting uncertainty of climate change, and Xu et al. (2009), studying the uncertainty of forest landscape response to climate change.

2.2.3. Simulation of forest development and management

We simulated forest development and forest management actions in the case study region using the forest landscape model LandClim (Schumacher, 2004, 2006; Elkin et al., 2012; Temperli et al., 2012). The model simulates forest development (regeneration, growth and mortality of 32 tree species represented as age cohorts) within 25 × 25 m grid cells on a yearly time step, while landscape disturbances (fire, wind) and forest management are updated every decade (Schumacher, 2004; Schumacher and Bugmann, 2006). Fire disturbances are climate dependent and reflect the influence that climate change has on fire occurrence and spread, whereas the frequency and size of windthrow disturbances is a user defined variable. The three climate scenarios that we tested did not include any projected shifts in wind disturbances, and we therefore use the same wind disturbance settings in each. Climate change driven shifts in forest composition and structure will alter windthrow risk depending on tree species and tree size, but these long term indirect changes are not projected to impact windthrow occurrence until the later part of the 21st century. Nevertheless, risk of extreme events and observation of consequent damages is very important for the behavioural study of forest managers' perceptions and beliefs about climate change and consequent decisions (Spence et al., 2011). For a more detailed description of the application of the model to the case study region, see Temperli et al. (2012) with similar simulation basis. However, we include different timings when the management actions are implemented (2010 vs. 2050) and in the forest stand level than the entire landscape. Moreover, the set of simulations in this study involves shifts in management regimes (i.e. from mixed forest to Douglas fir in 2050), which do not occur in Temperli et al. (2012).

Table 1
Climate change scenarios i.e. regional circulation model realizations for the IPPC AR4 A1b emission scenario at 828 m a.s.l. in the Black Forest case study area.

Climate scenario	Temperature [°C]			Precipitation [mm]		
	Annual	Summer[a]	Winter[b]	Annual	Summer[a]	Winter[b]
Historic (1950–2000)	7.1	12.4	1.8	1086	573	513
SMHI (2081–2100)	9.3	14.6	4.0	1041	491	550
HCCPR (2081–2100)	11.7	17.3	6.1	1042	473	569

SMHI: Model (RCA30/CCSM3) realization by the Swedish Meteorological and Hydrological Institute (Kjellström et al., 2011), **HCCPR**: Model (HadRM3Q0/HadCM3Q0) realization by the Hadley Center for Climate Prediction and Research (Collins et al., 2006).
[a] April–September.
[b] October–March.

We simulated four alternative management regimes (a_{tj}) by varying species- and age class-specific thinning intensities and assuming that future management will vary along a gradient of timber production vs. biodiversity provision oriented management goals. The first represents a business-as-usual scenario that continues even-aged Norway spruce management. The other three regimes represent potentially adaptive alternatives that aim to convert the current monocultures of even-aged spruce to uneven-aged forests, and to promote a transition to more regionally adapted deciduous species. These alternatives were developed using descriptions of the management regimes that are currently applied or recommended for the study area (MLR, 1999; Spiecker et al., 2004; Duncker et al., 2007; cf. Temperli et al., 2012 for details). The management alternatives are described in order of decreasing management intensity and timber production focus.

M1: Under the past (business-as-usual) even-aged Norway spruce regime, highest possible timber production is achieved by clear-cutting stands when dominant trees reach a target diameter (DBH) of 45 cm. Following clear-cutting, the stands are replanted with Norway spruce and thinned to foster growth and maintain the monoculture.

M2: The first adaptive strategy converts stands to uneven-aged mixed Douglas-fir/silver fir using target diameter harvesting. Windthrow resistance is believed to be improved and the species mixture is better adapted to a warming climate while valuable coniferous timber is still produced (Schütz et al., 2006).

M3: The second adaptive strategy is an uneven-aged mixed forest management regime, combining timber production with promotion of biodiversity; a structurally rich Norway spruce-dominated forest with continuous cover was promoted, allowing naturally regeneration of deciduous trees, Douglas-fir and silver fir comprising 20–40% of the species mixture.

M4: The third adaptive strategy aims at biodiversity promotion by conversion to natural vegetation, e.g. beech. To this end, Norway spruce is thinned strongly. Otherwise, forest management is restricted to a minimum of infrastructure maintenance (e.g. hiking trails).

We simulated forest development between 2010 and 2100, and incorporated two decision points (2010 and 2050) when each of the four management alternatives could be implemented resulting in 16 different forest management pathways. All management pathways were simulated for each of the three climate scenarios that we used. To account for stochastic processes in LandClim (e.g., windthrow disturbance), we ran 15 independent forest simulation replicates. For this analysis we aggregated the results at the landscape level, and averaged the results over the 15 replicates.

2.2.4. Input for belief updating

Three forest variables, total biomass production, windthrow damage (expressed as annual biomass loss at the landscape level) and a biodiversity indicator (Shannon diversity, see Temperli et al., 2012), were selected as the observed forest variables. Three climate state variables were selected: two visible and known climate variables namely average minimum temperature and annual precipitation, and an annual drought index (ADI) as more complex and scientific understanding of climate condition. ADI was used to capture average dryness over the $m = 12$ months of the year. It measures amount of water transpired by the trees relative to their evaporative demand for soil water (see details in Schumacher 2004).

2.2.5. Implementation of the analysis for belief updating and decision-making

For each climate change scenario, we started the analysis with a simulation of the mean trajectories of climate variables (as described in Section 2.2.2) and the development of forest state under management actions (cf. Section 2.2.3). Monte Carlo sampling was carried out for the climate and forest variables (100,000 iterations for each period with replacement), from which sets of realizations were drawn, thereby providing information for the decision maker. Based on the simulated data, the belief in each climate change scenario was updated applying the Bayesian theorem (Eq. (3)). The process of acquiring climate data, implementing actions and updating beliefs was repeated at 10-year intervals. Simulations were run from current states of forest and climate (Temperli et al., 2012), thus establishing initial priors ($\boldsymbol{w_1}, \boldsymbol{w_2}, \ldots, \boldsymbol{w_I}$) to express the beliefs in the different climate scenarios. We analysed the sensitivity of the procedure to different sets of initial beliefs ($\boldsymbol{w_{it}} = \{0,0.2,0.4,0.6,0.8,1\}$ and subject to Eq. (2)) and applied Bayes' theorem (Eq. (3)) to update beliefs at each period (2010, 2020, …) and based on the observation of different climate and forest variables (Eq. (2)). At each decision point (i.e., 2010, and 2050), we combined the evidence using Dempster's rule (Eq. (4)) to calculate a unique updated belief about each climate change scenario ($\boldsymbol{w_{it}}$). We investigated different combinations of the examined evidence (e.g., temperature + precipitation, temperature + **TBP**, or **TBP** + windthrow) to evaluate how different combinations affected the speed towards certainty in belief in the actual scenario. Subsequently, we considered the performance of management actions as measured by $\boldsymbol{OBJ_{it}(a_{jt})}$ until the end of the planning horizon (2100) to identify the optimal adaptive action (Eq. (5)) incorporating the manager's current belief ($\boldsymbol{w_{it}}$). The entire exercise was undertaken for three different climate change scenarios being the underlying true scenario, allowing us to assess interactions between type of future and belief formation.

3. Results

3.1. Learning about the actual climate development

Fig. 1 shows the results of a sensitivity analysis for different underlying true scenarios (left-most column) and across the set of initial beliefs ($\boldsymbol{w_{it}} = [0,1]$). Different sets of initial beliefs result in different updatings, we show the mean and variance of the beliefs masses across initial beliefs. These are shown in Fig. 1, where the size of squares represents the mean degree of beliefs in the actual realization and the shade of squares illustrates the variance of updated beliefs across initial beliefs. The bigger the square, the stronger the belief and the darker the square, the larger variance between updated beliefs and the less sensitivity to initial beliefs and the less difference between initial and updated beliefs over time. The beliefs over the nine time, $\boldsymbol{w_{i1}}$–$\boldsymbol{w_{i9}}$ periods are shown until certainty is reached. Depending on the source of information, the average time needed for the decision maker to be certain of the actual climate change scenario varies considerably. For some sources of information (e.g. ADI), the signals are so weak that the decision maker remains unsure for the entire period ($\boldsymbol{w_{i9}} < 50\%$). This is particularly true for **SMHI** and **HCCPR**. However, if there are very large change in climate states, e.g. in the case of precipitation under **HCCPR**, typical changes over the next ten years will allow the decision maker to make up his mind already by 2020.

Climate variables like temperature and precipitation were evidently more reliable sources of information under some climates than forest variables. In contrast, the climatic and ecological index **ADI** performed poorly. Within the forest variables, the

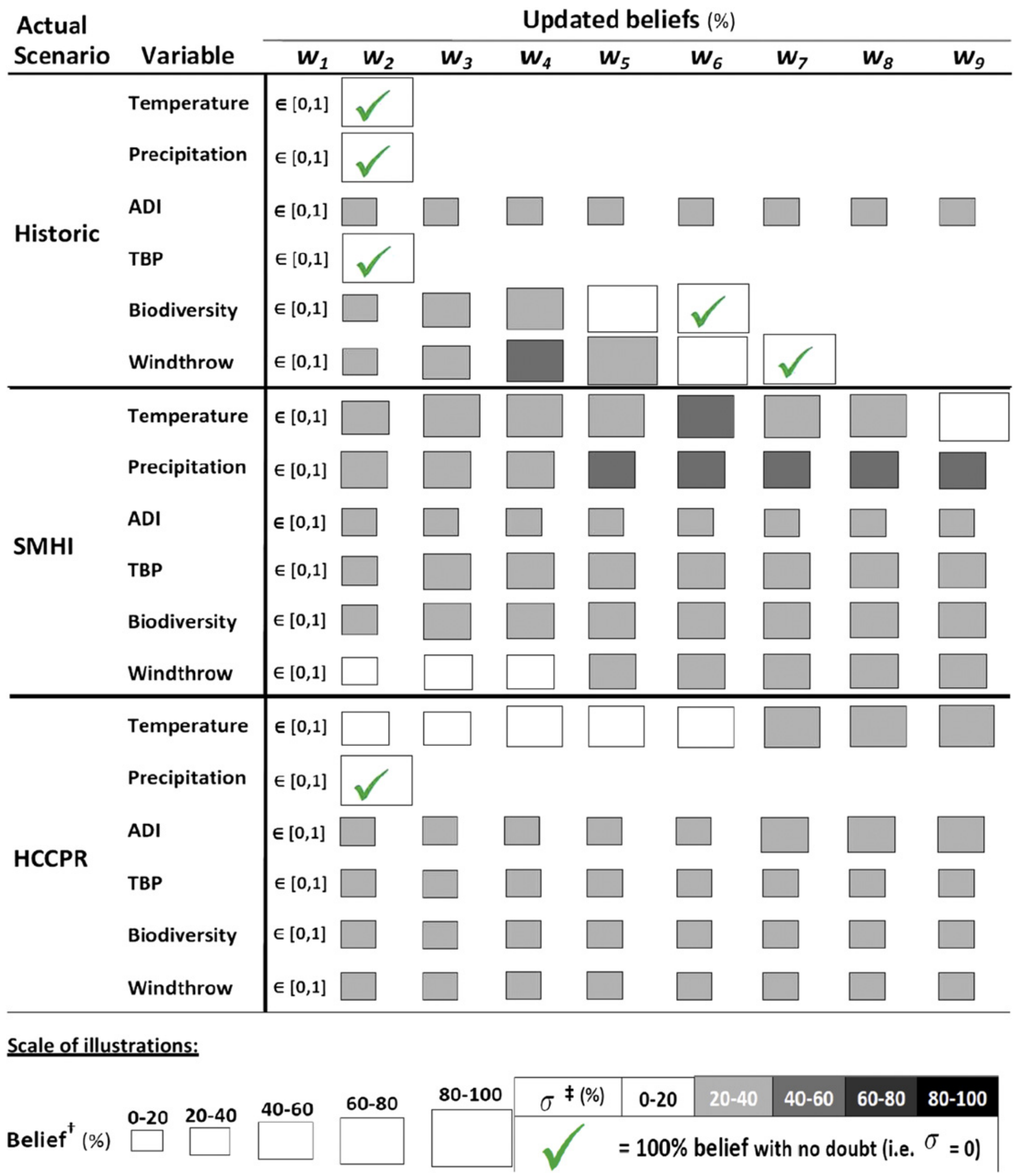

Fig. 1. Updating beliefs about actual climate change scenario, when Bayesian updating is based on the observation of different climate and forest variables drawn from 100,000 Monte Carlo samplings. Size of squares shows the mean degree of beliefs in the actual realization (the bigger the square, the stronger the belief) and the shade of squares illustrates the variance of updated beliefs across initial beliefs (the darker the square, the less sensitivity to initial beliefs). **Scenario** = Actual climate change scenario i.e. **Historic**, **SMHI** and **HCCPR** (see details in Table 1), **ADI** = Annual Drought Index & **TBP** = Total Biomass Production, †Average belief mass in the actual climate change scenario (the bigger the square, the stronger the belief), where averaging is across initial beliefs varied systematically in 20% intervals, w1i = {0, 0.2, 0.4, 0.6, 0.8, 1} and summing up to 100% (i.e. $\sum$wit = 1, e.g. w1(Historic) = 0.2, w1(SMHI) = 0.6 and w1(HCCPR) = 0.2), ‡Standard deviation in the measured belief mass in the actual climate change scenario (the darker the square, the larger variance between updated beliefs and the less difference between initial and updated beliefs over time), $\boldsymbol{w_1}$–$\boldsymbol{w_9}$ = Belief on the actual climate change scenario over time (2010–2090, e.g. $\boldsymbol{w_5}$ = belief at 2050), cf. † and ‡.

development of annual biomass production, **TBP** would be the best choice compared to the observations of windthrow damage or species diversity, which are much less sensitive in the short term. Note that forest properties are influenced by a range of other factors besides climate. In this model, climate may change the species composition which in turn changes the forest's windthrow susceptibility and consequently would affect windthrow damage and species diversity. In this case these indirect climatic effects were not strong enough and/or were masked by other factors influencing forests dynamics to serve as reliable sources of information about climatic developments.

3.2. Combining different sources of evidence

When several lines of climatic evidence are used in combination, the manager's belief state can converge on the actual climate scenario in a single 10 year time step (Fig. 2). This happens no matter what the actual scenario is. For forest variables, however, the time needed before complete confidence in the actual scenario is reached is somewhat longer (20 years). Combining two forest variables i.e. **TBP** and biodiversity (species richness) may yet delay the inference and add more uncertainty e.g. $\boldsymbol{w_2}$ = 76% (standard deviation around 42%), when the actual climate change scenario is

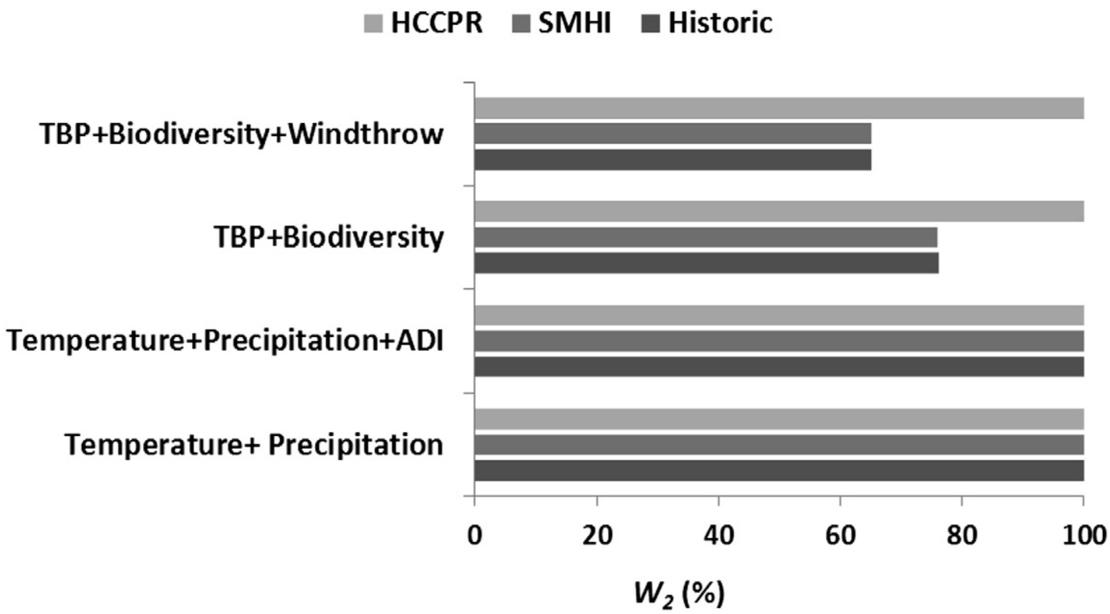

Fig. 2. Combining evidence about the actual climate change scenario and based on the observation of different climate and forest variables at 2020 (w_2). **Historic**, **SMHI** and **HCCPR** = Climate change scenario (see details in Table 1) , **ADI** = Annual Drought Index & **TBP** = Total Biomass Production, w_2 = belief about the actual climate change scenario at 2020 (after ten years of observations).

SMHI or **HCCPR** compared to climate variables (temperature and precipitation). This is less (w_2 = 65%) when we combine all three evidence from forest variables **TBP**, species richness and windthrow damage (standard deviation = 42%).

Under the climate change scenarios **SMHI** and **HCCPR**, combining a forest variable (i.e. **TBP**) with a climate variable (i.e. temperature) was not as efficient as combining two climate variables. When forest and climate variables were combined, 100% confidence in the actual climate was not achieved for twenty years. In this case, a confident belief in the actual climate change scenario could be reached after two decades of observations (i.e. after twenty years at 2030).

3.3. Management decisions over time

With the adaptive management concept of this paper it turns out that in the Black Forest area, at the initial decision point (2010), the optimal decision for **TBP** maximization throughout the entire planning horizon (2010–2100) would be **M2** (Uneven-aged mixed forest), irrespective of the initial beliefs. In this case, **M2** is therefore dominant. Note that this result also depends on the initial state of our case study in the Black Forest area (Temperli et al., 2012) and the values for maximum **TBP** varies between 7.2 and 9.5 m^3/ha/year. However, although **M2** is the optimal choice at the first decision point (2010), it loses dominance at the next decision point in the middle of the planning horizon (2050), where a change in management scheme may be considered. Thus we focus the presentation of results under **TBP** objective on the 2050 decision point, cf. Table 2. As shown in Fig. 1, the decision maker will know the true underlying climate with some certainty by 2050. At this point, if climate change is taking place and the objective is to maximise biomass production, **TBP**, adaptation will result in a switch from **M2** to **M4** (i.e. natural vegetation, see detail in Section 2.2.3). Table 2 shows details of the changes in management regimes for the decision point in 2050.

To maximize **TBP**, the adaptive decision under **SMHI** or **HCCPR** is to switch to **M4**, whereas continuing with **M2** is only best option if there is no change in climate state (Historic scenario). Perfect decisions (grey areas – and perfect in the sense of having beliefs in accordance with the true scenario) may not be different from decisions under doubt (w_{i5} < 100%), but they support decision-makers with correct expectations about the performance of management actions e.g. for the maximization of **TBP**. For example, the perfect decision on **TBP** maximization under the actual scenario **SMHI** will be **M4** with **TBP** = 8 m^3/ha/year, where the same decision **M4** will be made under a high uncertainty (w_5 = 34%, evidence = **ADI**) with a misleadingly high estimate of **TBP** = 10 m^3/ha/year (+25% comparing to the factual case).

To minimize windthrow damages, optimizing management decisions is more complicated even if changes in windthrow activity were not included in the scenarios. As we show in Table 3, the initial decisions (in 2010), are slightly more sensitive to the initial beliefs regarding the future climate development. Depending on the set of initial beliefs, any of the management regimes, except **M1** (Even-aged Norway spruce, the business as usual management regime), may come into consideration. However, **M4** (relying on natural vegetation) is dominant under strong **HCCPR** beliefs and, in most cases, the dominant choice under the **SMHI** and **Historic** scenarios. **M2** (Uneven-aged mixed forest) and **M3** (Uneven-aged Douglas/silver fir) would be optimal decisions if the initial belief in the **Historic** scenario is strong (>60%) under the **Historic** and **SMHI** climate scenarios, respectively. **M4** is the optimal adaptive decision if the simulated realised scenario is **SMHI** and results in a minimum of 0.19 m^3/ha/year biomass loss for the planning horizon (2010–2090). The decision is changed to decision **M3** if the initial belief is imperfect (w_{21} = 0–40%) based on a misleadingly high expected biomass loss of 0.23–0.27 m^3/ha/year (+2–4% compared to the simulated realised case in grey area).

However, in spite of this initial variation, once the decision maker reaches the next decision point (2050), there is a general preference for switching to **M3** (see Table 2) in order to minimize the windthrow damage for the rest of the planning horizon (2050–2090). This adaptation is not needed if **SMHI** is the realised climate change scenario and **M3** was already chosen as the optimal solution in 2010. Similar to **TBP** maximization, decisions for the minimization of windthrow disturbances under the condition of imperfect knowledge about the actual climate change scenario (w_{i5} < 100%) are the same as when beliefs coincide with perfect knowledge (grey

Table 2
Optimal decisions for adaptation to climate change at the foreseen decision point (2050) depending on updated beliefs and using different climate or forest variables.

Actual scenario	Variable	w_5 (%, belief at 2050)			Decision on management scheme			
		Historic	SMHI	HCCPR	TBP↑	OBJ	Windthrow↓	OBJ
Historic	Temperature	100	0	0	Continue with M2	14	Switch to M3	0.21
	Precipitation	100	0	0	Continue with M2	14	Switch to M3	0.16
	ADI	35	33	32	Continue with M2/Switch to M4	10	Switch to M3	0.27
	TBP	100	0	0	Continue with M2	14	Switch to M3	0.16
	Biodiversity	100	0	0	Continue with M2	14	Switch to M3	0.16
	Windthrow	84	6	10	Continue with M2	13	Switch to M3	0.19
SMHI	Temperature	0	65	35	Switch to M4	8	Continue with/Switch to M3	0.32
	Precipitation	0	100	0	Switch to M4	8	Continue with/Switch to M3	0.32
	ADI	32	34	34	Switch to M4	10	Continue with/Switch to M3	0.29
	TBP	0	100	0	Switch to M4	8	Continue with/Switch to M3	0.32
	Biodiversity	0	90	10	Switch to M4	8	Continue with/Switch to M3	0.32
	Windthrow	7	91	2	Switch to M4	9	Continue with/Switch to M3	0.31
HCCPR	Temperature	0	35	65	Switch to M4	8	Switch to M3	0.32
	Precipitation	0	0	100	Switch to M4	8	Switch to M3	0.32
	ADI	32	34	34	Switch to M4	10	Switch to M3	0.29
	TBP	0	0	100	Switch to M4	8	Switch to M3	0.32
	Biodiversity	0	10	90	Switch to M4	8	Switch to M3	0.32
	Windthrow	11	3	87	Switch to M4	9	Switch to M3	0.31

Historic, **SMHI** and **HCCPR** = climate change scenario (see Table 1), **ADI** = Annual Drought Index, **TBP** = Total Biomass Production, **M1–M4** = Management schemes implying different set of silvicultural interventions in planning horizon (see details in Section 2.2.3), ↑ = Objective is to maximize a service, ↓ = Objective is to minimize a damage. OBJ = Value of the adaptive decision in biomass (m^3/ha/year), Grey area = The realised adaptive decision including perfect knowledge i.e. $\boldsymbol{w_{i5}}$ = 100% about the actual climate change scenario.

area) and the decision (continue with or switch to **M3**) is constant, but the expected outcomes can be different and misleading.

4. Discussion

4.1. Belief updates based on different sources of information

When uncertainty cannot be described by a simple known stochastic process or probability density function, but is instead reassessed in the form of beliefs, the adaptive decision behaviour depends strongly on what sources of information that beliefs rely on, and how these are linked to the underlying stochastic process of interest (Yousefpour et al., 2012). The implementation of effective adaptive management in response to climate change requires that managers have access to accurate information regarding the direction and magnitude of climate change, and an accurate assessment of how the system will respond to the climate drivers. Climate variables may be direct evidence of climate change, but are not necessarily easily available or straightforward to interpret. In contrast, forest data are well known to forest decision-makers, but may be influenced by factors other than climate, and there may be significant time lags before the forest ecosystem responds to the climate signal. However, monitoring forest state to adapt the management actions to the new conditions e.g. simulating forest growth under climate change is currently the most applied and recommended procedure in forest management (Jacobsen and Thorsen, 2003; Millar et al., 2007; Bernetti et al., 2011). We found that climate variables were the most efficient sources of information for rapidly revealing the simulated climate change scenario to a manager. Simulations suggested that an aggregate climate variable, such as a drought index, and forest response variables were less efficient. Moreover, if there is no change in climate conditions, most climate sensitive variables will be able to reveal this fact with certainty sooner ($\boldsymbol{w_2}$ = 100%) or later ($\boldsymbol{w_6}$ = 100%) depending on the variable under observation (Fig. 1). The reason for this in our model is the considerable difference between climate variables across climate scenarios as defined in Table 1.

Evidently, the results of the present study are subject to a set of assumptions especially about the trends and variability of forest and climate variables and the set of climate change realizations. Assuming a higher standard deviation than $\sigma_i = 0.3$ would delay the recognition of the actual climate change realization e.g. to several decades and a lower standard deviation would accelerate the recognition unrealistically e.g. to less than a decade. Considering different set of potential climate change realizations in the study will affect the results. The more divergent climate change realizations, the faster recognition of the actual realization. The important qualitative contribution of our study; that the type and combination of information matter for expectation formation and

Table 3
Optimal decisions at t = 2010 depending on initial beliefs, when the objective is to minimize windthrow damage.

w_1, (%, initial belief)			Decision on management scheme					
			Actual scenario					
Historic	SMHI	HCCPR	Historic	OBJ	SMHI	OBJ	HCCPR	OBJ
0	0	100	M4	0.19	M4	0.19	M4	0.19
0	20	80	M4	0.19	M4	0.19	M4	0.19
0	40	60	M4	0.19	M4	0.19	M4	0.19
0	60	40	M4	0.19	M4	0.19	M4	0.19
0	80	20	M4	0.19	M4	0.19	M4	0.19
0	100	0	M4	0.19	M4	0.19	M4	0.19
20	0	80	M4	0.29	M4	0.22	M4	0.17
20	20	60	M4	0.29	M4	0.22	M4	0.17
20	40	40	M4	0.29	M4	0.22	M4	0.17
20	60	20	M4	0.29	M4	0.22	M4	0.17
20	80	0	M4	0.29	M4	0.22	M4	0.17
40	0	60	M4	0.40	M4	0.25	M4	0.15
40	20	40	M4	0.40	M4	0.25	M4	0.15
40	40	20	M4	0.40	M4	0.25	M4	0.15
40	60	0	M4	0.40	M4	0.25	M4	0.15
60	0	40	M2	0.45	M3	0.27	M4	0.13
60	20	20	M2	0.45	M3	0.27	M4	0.13
60	40	0	M2	0.45	M3	0.27	M4	0.13
80	0	20	M2	0.46	M3	0.25	M4	0.12
80	20	0	M2	0.46	M3	0.25	M4	0.12
100	0	0	M2	0.47	M3	0.23	M4	0.10

Historic, **SMHI** and **HCCPR** = Climate change scenario (details in Table 1), OBJ = Minimum windthrow damage (m^3/ha/year) expected in average over the planning horizon (2010–2100), **M1–M4** = Management schemes implying different set of silvicultural interventions in planning horizon (see details in Section 2.2.3), Grey area = The realised adaptive decision including perfect knowledge i.e. $\boldsymbol{w_{i1}}$ = 100% about the actual climate change scenario.

adaptive behaviour, remain valid in spite of the model determinism.

Focussing on short-term climate changes may be a poor basis for long-term decisions in forest management (Bugmann, 2003). Long-term analysis of management strategies for multiple rotations has a long tradition in forestry (Pukkala and Miina, 1997; Jacobsen and Thorsen, 2003; Spiecker et al., 2004). Adaptation to climate change necessitates the implementation of actions in the short term (Kirilenko and Sedjo, 2007; Yousefpour and Hanewinkel, 2009; Williams, 2011) to prevent forests from being adversely affected in the long term (Millar et al., 2007; Xu et al., 2009). Analysing the impacts of climate change on the risks of forest disturbances (e.g. windthrow, fire) may improve decisions about the timing and the appropriate adaptive actions to mitigate the loss and severe damages (Millar et al., 2007; Bernetti et al., 2011). In our study, the risk of windthrow is not related to the climate state but to the forest state, which in turn is affected by climatic conditions. This is the reason why windthrow was a poor variable for the recognition of actual climate state (Fig. 1) and may have been more affected by management actions than climate change.

4.2. Combination of evidence and effects of adaptation on forest management

We applied Dempster's rule of combination (Senz, 2002; Raje and Mujumdar, 2010) for considering more than one source of information to simulate the process of forming a belief about climate change. The combination results show that direct climate observations outperform forest variables as short-term indicators of climate state. Furthermore, we combined climate and forest variables to examine the efficiency of such combinations and found that they were less efficient than a combination of two climate variables, but equally efficient as two forest variables. Nevertheless, combining a climate variable with supplementary evidence, either in the form of forest state or additional climate variables generally does speed up updating the beliefs towards the recognition of the true climate trajectory. We note, however, that the application of Dempster's rule should be investigated further for the case of climate change in order to apply a suitable type of Dempster's rule for data fusion (e.g. Jøsang and Pope, 2011).

Adaptive management has been suggested as the most promising avenue of research to deal with decision making under uncertainty (Williams, 2012) especially the uncertainty inherent in climate change (Heltberg et al., 2009; Probert et al., 2010; Williams, 2011; Yousefpour et al., 2012), whether this will in fact lead to a change in management or not. Moreover, Hahn and Knoke (2010) outline that adaptive management maintains or even increases future options depending on the adaptive capacity of a system. In our example of adaptive forest management in the Black Forest, we found that a decision maker who focuses on total biomass production will initially favour conversion to an uneven-aged mixed forest. If the objective is to minimize windthrow damage, there will be a need for diverse interventions and adaptation measures by switching the management scheme through planning horizon. After revealing the actual scenario at the middle of planning horizon (2050), all management schemes would be switched to the robust strategy of uneven-aged Douglas/silver fir to maintain a windthrow resistant uneven-aged stand structure by adapting species mixture to dryer climate for the rest of the period (2050–2100, Table 2).

4.3. Implications for future research

We have focused on Dempster's rule of combination, but we stress that there are alternative rules for the combination of information in evidence theory. Many of these are adapted versions of Dempster's rule (e.g. Senz, 2002; Raje and Mujumdar, 2010; Bernetti et al., 2011), whereas others are more general (Jøsang and Pope, 2011).

In the simulations undertaken in this study, we found swift convergence in the decision maker's beliefs towards the actual scenario. This is true for the updating based on a single variable (Fig. 1), and even more so for the case of combined evidence. The scenarios (**Historic**, **SMHI** and **HCCPR**) are quite different from each other. This, in combination with the limited variation we allow around the inherent trend of the scenarios, implies that the distributions over a few decades diverge enough for most of the information sources to result in full or almost full concentration of the belief mass. Future research should focus on relaxing this restriction of the current simulations, and analyse the effects of variation in climate state variables across a more comprehensive set of possible climate scenarios. Furthermore, due to the computationally heavy forest simulation model used here, our simulations had to be restricted to ten-year intervals and two decision points only. While this has no influence on the qualitative results of our study, it does not suffice to answer important "real-world" questions such as those referring to the optimal timing of management switches. The conceptual approach presented in this study may be combined with balancing economic and environmental optimization procedures to chive multiple goals and manage the decisions' risks.

5. Conclusions

Uncertainty regarding climate change and its impacts on forests identifies the need for more accurate regional climate projections and forest models, and highlights the fact that forest managers make decisions within an uncertain environment. Modelling and analytic approaches that explicitly take into account how managers may update their beliefs about actual climate developments have the potential to lead to more robust policies regarding adaptive management. Continuous observation of climate states by the decision maker, and comparisons with the predictions of various climate models should ensure advancements in knowledge and updated assessment of the likely degree of changes. In the application analysed in this paper we find that updating climate beliefs based on climate data is superior to forest data, because the latter may include feedback processes and lags whereas the former directly and more rapidly indicates the direction and the degree of changes in climate. Finally, it should be stressed that the observations are of course case specific i.e. there may be sites where the predicted climate changes, e.g. those related to precipitation, are very variable and hence has little signal and value for indicating the direction of change. This is important for forest management as the tradition of forest managers is to observe what is happening in the forest and climate data may not be so easily acceptable and understandable. We found that a combination of evidence increase the value of the information considerably, but still information reflecting more directly climate change variables are the most important sources. Our results stress the importance of getting a better understanding of how forest managers form beliefs about future climate change and its impacts. If substantial groups of forest managers are reactive or base their beliefs on past observations and experiences from forest management (Hoogstra, 2008; Jacobsen et al., 2010), our results shows that they may continue to rely on risky non-adapted forest management strategies for a considerable part of the next century.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jenvman.2013.03.004.

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