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Abstract We analyse effects of uncertain climate change and technological development on cost-effective abatement of nitrogen and phosphorus for a eutrophied sea. A dynamic model is developed which accounts for differences in the sea's adjustment to the loads of the two nutrients, uncertainty in climate change effects with probabilistic constraints on nutrient pool targets, and uncertain technological development in a mean-variance framework. The analytical results show that introduction of uncertainty increases abatement costs but that the effect on marginal abatement cost differ for the two types of uncertainty. Marginal abatement cost is increased by technological uncertainty but decreased by the reduction in the risk discount of climate change uncertainties. It is also shown that abatement along the optimal time path is delayed by the introduction of technological uncertainty, but made earlier when considering climate change uncertainty. An application to the eutrophied Baltic Sea indicates that climate change and technological development can reduce total abatement cost by 1/3, but also increase it considerably when uncertainty is included.

Key words; cost-effectiveness, nutrients, climate change, technological development, uncertainty, Baltic Sea

JEL: D99; O13; Q52; Q53; Q54

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1. Introduction

Eutrophication of coastal marine waters is globally considered to be a serious environmental problem (e.g. Gilbert et al., 2007; Heisler et al. 2008). It is caused by unbalanced and excessive loads and pools of nutrients, which create damages from eutrophication, such as increased frequency of harmful algal blooms, sea bottom areas without biological life, cyanobacteria, and decreases in water transparency and populations of commercial fish species. These environmental damages were realized in mid 1970s and manifested by the implementation of different types of abatement measures directed mainly towards households' and the industry's discharges into the seas (see Elofsson et al. 2003 and Rabotyagov et al. 2014 for reviews). However, in spite of these measures and development of new abatement technologies such as construction of nutrient traps in drainage basins, damages have aggravated because of excessive nutrient loads mainly from agriculture. Further degradation is expected from climate change effects on nutrient pools and on biological activities which may require more stringent and expensive eutrophication policies. On the other hand, further technological development can make nutrient abatement less expensive. However, impacts of both climate change and technological development are uncertain, and the perceived abatement cost then depends also on society's attitudes towards these risks. The purpose of this study is to calculate cost effective management of a eutrophied sea under conditions of uncertain climate change effects and technological development. The study is applied to the Baltic Sea, which is regarded as the most damaged sea in the world (e.g. Elmgren and Larsson, 2001; Conley et al., 2009).

Climate change is likely to have direct effect on a sea and indirectly through alterations in nutrient loads from the drainage basins (e.g. Kabel et al., 2012). Direct effects occur through increases in pH in seawater, biological activities, and nutrient pools. Nutrient pools, in turn, are determined by several processes, denitrification, nitrogen fixation, and nutrient sedimentation and burial, which are affected by nutrient loads from the catchment. Changes in precipitation and temperature affect runoff of nutrients from the catchment to the sea, but also the nutrient retention in the catchment, which may counteract the effects of nutrient runoff alteration. These changes in nutrient loads and the sea's responses may need revisions of nutrient load targets, which can be made more or less stringent. The net effect on abatement costs of climate change then depends on these two climate change forces, i.e. on nutrient pools and targets, which can either counteract or reinforce each other.

In this study we consider climate change effects on both nutrient pools and target, and a safety-first decision framework is applied when including uncertainty in these effects. Targets are formulated as maximum future nutrient pools which are to be obtained at minimum cost and with a minimum probability. This, so-called chance-constraint programming, has an old tradition in economics and has been applied to, among others, food supply and water quality management (e.g. Shortle 1990; Kataria et al., 2010). There is also a large literature on the economics of technological development (see e.g. Carraro et al., 2010 for a review). We use the learning by doing approach, where costs decline over time as firms gain experience in using a technology. Learning by doing is most often described as a function of the production process where repetition of the process leads to efficiency gains, but can also occur through abatement activities, since cutting back on emissions usually means that new, cleaner technologies are adopted (Rosendahl, 2004). Uncertainty in technological development is treated in a mean-variance framework where the objective function includes mean and variance in total abatement costs.

Our study is mostly related to the empirical literature on economics of eutrophication. Starting in mid1990s there is by now a relatively large body of literature on cost effective or efficient nutrient load reductions to eutrophied sea. To the best of our knowledge, only two studies evaluate effects of climate change, Gren (2010) and Lindqvist et al. (2012), and one considers implications of technological development (Lindqvist and Gren, 2013). Most studies calculate cost effective or efficient allocation of abatement among the riparian countries in a deterministic setting (Gren et al., 1997, 2013; Elofsson, K., 2006, 2007; Ollikainen and Hokatukla 2001, Laukanen and Huhtala 2008; Laukanen et al. 2009; Ahlvik and Pavlova, 2013). The focus is often on optimal nutrient management in one drainage basin including only agriculture (Hart and Brady, 2002, Hart 2003) or this sector together with sewage treatment (Elofsson, 2006; Helinet al., 2008; Laukkanen and Huhtala, 2008; Laukkanen et al., 2009). However, none of the studies applied on eutrophication in a sea consider uncertain climate change effects and technological development. On the other hand, this combination of uncertainties has been applied to energy policy in a dynamic context (Held et al, 2009; Schmidt et al., 2011) who use a similar approach as in this study by assigning probabilistic constraints on emission targets. In our view, this paper extends the literature on dynamic management of eutrophied seas and lakes by adding uncertain climate change effects and technological development.

The study is organised as follows. First, the model is presented, which is followed by an analysis of the properties of cost effective solutions. The model is applied to the Baltic Sea in Section 4, and the paper ends with a concluding section.

2. A simple dynamic model for dynamic cost effectiveness

The numerical dynamic model builds on Gren et al. (2013), but adds climate change and endogenous technical change under conditions of uncertainty. Total load of a nutrient to a sea, L_t^E with $E=N,P$ where N is nitrogen and P is phosphorus, is the sum of discharges from all countries $i=1,..,n$ is written as business-as-usual (BAU) loads, $I_t^{i,E}$, minus abatement, $A_t^{i,E}$, according to

$$L_t^E = \sum_i L_t^{i,E} \qquad (1)$$

where $L_t^{i,E} = I_t^{i,E} - A_t^{i,E}$.

The response mechanisms and time required for the sea's adjustments to the loads described by eq. (1) differ between nutrients. Phosphorus is cycling in the sea due to biotic activity, but is also sequestered in the sediment pool in normal oxygen conditions. Under conditions of oxygen deficit, part of this sequestered phosphorus can be released into the water body and returned into the cycle. In addition to similar biotic cycling, nitrogen is denitrified into harmless nitrogen gas and, thus, removed from the cycling, but can also be supplied to the Baltic Sea by the nitrogen-fixing cyanobacteria, under appropriate conditions. These adjustment mechanisms may result in a non-linear system with associated difficulties of identifying optimal abatement paths (e.g. Mäler et al. 2003). Furthermore, the responses of nitrogen and phosphorus cycles are connected. For example, reductions in phosphorus pools may decrease the nitrogen fixation by cyanobacteria (e.g. Savchuk and Wulff 2009). However, these connections are poorly understood in quantitative terms, and we therefore assign simple linear relations between stock of nutrient *E* in period *t+1*, S_{t+1}^{E}, and prior period *t* and nutrient load, which is written as:

$$S_{t+1}^{E} = (1-\alpha^{E})S_{t}^{E} + L_{t}^{E} \tag{2}$$
$$S_{0}^{E} = \overline{S}^{E}$$

Following Gren et al. (2013) targets are set on maximum nutrient pools in a certain period, K_{T}^{E}, which are expected to bring about desired improvements in water transparency, algal blooms, and populations of commercial fish. in turn. Climate change is then assumed to affect both nutrient stocks in each period of time, S_{t}^{E}, and the target, K_{T}^{E}. We assign simple representations of these effects by assuming multiplicative impact of climate change on S_{t}^{E}, $\phi^{E} > 0$, and on K_{T}^{E}, $\gamma^{E} > 0$. When $\phi^{E} = 1$ and $\gamma^{E} = 1$ there is no climate change impact. For parameter values below(above) unity climate change implies a decline(increase) in nutrient pools and a reduction(increase) in the acceptable nutrient pools in the target year. The net effect is then either a reduction or an increase in total abatement cost for achieving the target.

Both climate change parameters are assumed to be normally distributed with an average of $\mu^{\phi,E}$ and variance $\sigma^{\phi,E}$ for ϕ^{E}, and $\mu^{\gamma,E}$ and $\sigma^{\gamma,E}$ for γ^{E}. When decision makers hold relatively strong aversion against deviations from a target or threshold safety-first decision rules can be particularly useful. The safety first criteria can, in turn, be formulated in different ways, which in general give rise to different outcomes (e.g. Pyle and Turnovsky, 1970). This paper makes use of the safety –first criterion originally suggested by Tesler (1955) which allows for the adoption of relatively easy and accepted decision rules, minimization of costs under emission constraints, where the emission constraint is formulated in probabilistic terms. It is then required that the predetermined nutrient pool targets, K_T^E, must be achieved with a minimum level of a chosen probability $\beta^E \in (0,1)$, which is written as

$$\phi^E S_T^E \leq \gamma^E K_T^E \text{, and } prob(\phi^E S_T^E \leq \gamma^E K_T^E) \geq \beta^E \tag{3}$$

Similar probabilistic target formulations have been made in several studies in environmental economics; water quality management (Shortle, 1990; Byström et al. 2000; Elofsson, 2003; Kataria et al. 2010), biodiversity protection (Gren et al., 2013), and climate change (Held et al., 2009; Gren et al. 2012). We follow this literature and apply chance-constrained programming for translating the restriction in (3) into a deterministic framework, which allows for relatively easy numerical solutions (e.g. Taha, 2007). The probability restriction in equation (3) can then be written as

$$prob\left[\frac{S_T^E - K_T^E - (\mu^{\phi,E} S_T^E - \mu^{\lambda,E} K_T^E)}{(\sigma^E)^{1/2}} \leq \frac{0 - (\mu^{\phi,E} S_T^E - \mu^{\lambda,E} K_T^E)}{(\sigma^E)^{1/2}}\right] \geq \beta^E \tag{3'}$$

where $\sigma^E = Var(\phi^E S_T^E - \gamma^E K_T^E) = S_T^{E^2} \sigma^{\phi,E} + K_T^{E^2} \sigma^{\gamma,E} - 2 S_T^E K_T^E Cov(\phi^E, \gamma^E)$. The term $\frac{S_T^E - K_T^E - (\mu^{\phi,E} S_T^E - \mu^{\lambda,E} K_T^E)}{(\sigma^{\phi,E} + \sigma^{\gamma,E})^{1/2}}$ shows the number of standard errors, ψ^E, that $S_T^E - K_T^E$ deviates from the mean values. By the choice of β^E, there is a level of acceptable deviation, $\psi^{\beta,E}$, and the expression within brackets in (3') then holds only if

$$\mu^{\phi,E} S_T^E + \psi^{E,\beta} \sigma^{E^{1/2}} \leq \mu^{\gamma,E} K_T^E \tag{4}$$

Expression (4) shows the effects on costsof climate change impacts through the nutrient pool constraints. The minimum cost can be reduced under climate change impacts, which occurs when $0 < \mu^{\phi,E} < 1$ and $\mu^{\gamma,E} > 1$, i.e. when the nutrient pools are reduced and the targets are revised upwards. On the other hand, the existence of uncertainty in one or both of the climate impacts results in increased cost when $\psi^{\beta,E} > 0$.

Following Bramoulle and Ohlsson (2005) endogenous technical change is described by accumulation of knowledge through abatement and an initial knowledge stock, H_0^i. It is assumed that knowledge is created by the sum of abatement of both nutrients, which is often the case for several technologies involving land use changes, such as cultivation of catch crops or construction of wetlands. The accumulated knowledge in period *t*, H_t^i, is then written as

$$H_t^i = H_0^i + \sum_E \sum_{\tau=0}^{t} A_t^{i,E} \tag{5}$$

Abatement cost in each period of time is assumed to exhibit economy of scope where the cost of simultaneous abatement of both nutrients, $A_t^{i,N}$ and $A_t^{i,P}$, for achieving specific nutrient targets is lower than separate abatement, i.e. $C^i(A_t^{i,N}, A_t^{i,P}) < C^i(A_t^{i,N}) + C^i(A_t^{i,P})$ (e.g. Panzar and Willig 1981; Baumol et al. 1988). Further, the cost depends on the accumulated knowledge described by equation (5). The cost function is thus written as

$$C_t^i = C^i(A_t^{i,N}, A_t^{i,P})(H_t^i)^{-\theta,i} \tag{6}$$

where $\theta^i = N(\mu^{\theta,i}, \sigma^{\theta,i})$ is the learning elasticity in absolute terms, which shows the percentage decrease in costs from one percentage increase in abatement accumulation.

3. Properties of cost-effective solutions

The decision problem is now specified as choosing the allocation of abatement among countries and time periods that minimises total control cost for achieving the targets defined by equation (4), which is written as

$$Min \quad \sum_t \sum_i \sum_E \rho_t \left(\overline{C}_t^i + \eta^i \sigma^{C^i} \right) \tag{7}$$

$$\text{s.t. (1)-(6)}$$

where ρ_t is the discount factor, $\overline{C}_t^{i,}$ is expected cost, and η^i is a measurement of risk aversion. The variance in costs is found from a second order Taylor expansion, which gives $\sigma^{C^i} = Var(C_t^i) = C^i(A_t^{i,E}, A_t^{i,-E})^2(-H_t^{-\theta}\ln H_t)^2\sigma^\theta$.

The first-order conditions for a cost effective solution are obtained by solving for S_T^E in equation (2), formulating the Lagrangian, and differentiating with respect to $A_t^{i,E}$, which deliver

$$\rho_t\left(\frac{\partial\overline{C}_t^i}{\partial A_t^{i,E}} + \eta^i\frac{\partial\sigma^{C^i}}{\partial A_t^{i,E}}\right) = \lambda_T^E\left(\frac{\mu^{\phi,E}\partial S_T^E}{\partial A_t^{i,E}} + \psi^{\beta,E}\frac{1}{2}\left(\frac{\partial\sigma^E)}{\partial A_t^{i,E}}\right)^{-1/2}\right) \tag{8}$$

where

$$\frac{\partial\overline{C}_t^i}{\partial A_t^{i,E}} = \frac{\partial C^i(A_t^{i,E}, A_t^{i,-E})}{\partial A_t^{i,E}}H_t^{-\theta,i} - \theta\left(\sum_t^T C^i(A_\tau^{i,E}, A_\tau^{i,-E})H_\tau^{-(\theta+1),i}\right), \tag{9}$$

$$\frac{\partial\sigma^{C^i}}{\partial A_t^{i,E}}\frac{1}{2\sigma^\theta} = \frac{\partial C^i(A_t^{i,E}, A_t^{i,-E})}{\partial A_t^{i,E}}(-H_{t,i}^{-\theta}\ln H_t^i)^2 + H_t^{-(\theta+1),i}\left(\theta\sum_t^T C^i(A_\tau^{i,E}A_\tau^{i,-E})^2(\ln H_t^i - 1)\right), \tag{10}$$

$$\frac{\partial\overline{S}_T^E}{\partial A_t^{i,E}} = -\mu^{\phi,E}\sum_t^T (1-\alpha^E)^{T-\tau+1}, \tag{11}$$

$$\frac{\partial\sigma^E}{\partial A_t^{i,E}} = -(2\sigma^{\phi^E}S_T^E + K_T^E Cov(\phi^E, \gamma^E))\sum_t^{T-1} (1-\alpha^E)^{T-\tau+1}, \tag{12}$$

λ_T^E are Lagrange multipliers for the restrictions on nutrient concentrations, and –*E* denotes the other nutrient. The first-order condition in (8) states simply that a cost-effective solution occurs where the marginal cost of achieving the nutrient pool target is equal to λ_T^E for all countries. The terms at each side of (8) include marginal impacts on uncertainty; on future development of costs from accumulated abatement at the left-hand side and on the pool target at the right-hand side. The condition thus shows that a marginal abatement increases mean and variability in abatement but contributes with a reduction in mean and variance in nutrient pools.

The first term at the left-hand side of (9) is the marginal abatement cost without consideration of effects on technological development, which is positive. The second term is negative and shows the decline in future costs due to technological development from a marginal abatement in time *t*. However, the marginal effect on variance in costs is clearly positive, which can be seen from equation (10). The signs of marginal effects on the mean and variance in nutrient pools in equations (11) and (12) are also unambiguously negative, but the magnitude depends on the climate impact parameter $\mu^{\phi,E}$; the lower the parameter the smaller is the impact.

With respect to the derivation of optimal development of abatement over time, the full-fledged condition in (8) does not lend itself to an easy interpretation, and we therefore investigate the optimal paths under different simplifications. In the most simple case, without technological development and uncertainty, the optimal development of abatement over time is guided by

$$\frac{\partial C_{t+1}^{i}}{\partial A_{t+1}^{i,E}} \Bigg/ \frac{\partial C_{t}^{i}}{\partial A_{t}^{i,E}} = \frac{1}{\rho(1-\alpha^{E})} \tag{13}$$

According to (13), abatement is delayed because of the discount factor and of the self-cleaning capacity. The discount rate reduces future costs of abatement, and the self-cleaning capacity allows for the use of ‘free’ nutrient pool decrease. The inclusion of technological development, but not uncertainty, changes the condition to

$$\left(\frac{\partial C^{i}}{\partial A_{t+1}^{i,E}} H_{t+1}^{-\theta,i} - \theta\left(\sum_{t+1}^{T} C^{i} H_{\tau}^{-(\theta+1),i}\right)\right) \Bigg/ \left(\frac{\partial C^{i}}{\partial A_{t}^{i,E}} H_{t}^{-\theta,i} - \theta\left(\sum_{t}^{T} C^{i} H_{\tau}^{-(\theta+1),i}\right)\right) = \frac{1}{\rho(1-\alpha^{E})} \tag{14}$$

Let us for the moment assume that the derivative of $H_{t}^{-\theta}$ with respect to $A_{t}^{i,E}$ is zero. The first term in the numerator and denominator at the left-hand side of (14) is then positive, and for a given marginal abatement cost, a larger cost decrease is obtained from technological development in period *t+1* since

$H_{t+1}^{-\theta,i} < H_t^{-\theta,i}$ for $\sum_E A_{t+1}^{i,E}$>0. This, in turn, reinforces the delay in abatement caused by the discount rate and self-cleaning capacity shown at the right-hand side of (14). On the other hand, abatement is made earlier when including the second term in the numerator and denominator since $\partial H_t^{-\theta,i} / \partial A_t^{i,E} > \partial H_{t+1}^{-\theta,i} / \partial A_{t+1}^{i,E}$ because of the longer time period that the marginal abatement acts on cost decreases from technological development. Depending on the relative magnitude of these two forces, optimal abatement is either delayed or made earlier compared with the optimal abatement path without technological development.

Adding uncertainty in nutrient pools in time T does not affect the optimal path since the effect on $Var(S_T^E)$ makes no difference as shown at the right hand side of (13). Both $\partial \overline{S}_T^E / \partial A_t^{i,E}$ and $\partial Var(S_T^E) / \partial A_t^{i,E}$ are driven by the same time developments, see equations (11) and (12). However, since the target stringency increases by the risk discount in nutrient pool variability (eq. 4), there is a need for more abatement than under deterministic conditions when $\psi^{\beta,E} > 0$. This, in turn, implies larger abatement in the starting period under uncertainty. Uncertainty in target setting has the same impact; it will not affect the optimal rate of abatement during time but only the starting levels.

The introduction of uncertainty in the learning elasticity will affect the optimal rate of abatement during time. The expression for optimal development path then becomes quite involved. In order to develop some analytical result we therefor make the same assumption as above that $H_{t+1}^i - H_t^i = \sum_E A_{t+1}^{i,E}$, and then differentiate $\partial Var(C_t^i) / \partial A_t^{i,E}$ with respect to t in (12) which gives

$$d\left(\frac{\partial Var(C_t^i)}{\partial A_t^{i,E}}\right) / dt = 2\sigma^\theta H_t^{-(\theta+1),i}\left(\theta \sum_{t+1}^T C_t^{i\,2} H_t^{-(\theta-1),i}(1 - \theta \ln H_t^i \frac{dH_t^i}{dt}) - \frac{\partial C^i}{\partial A_t^{i,E}} 2(\frac{dH_t^i}{dt} + 1)\right) \quad (15)$$

$$< 0 \qquad for \qquad \theta \ln H_t^i \frac{dH_t^i}{dt} > 1$$

Thus, the effect of uncertainty in the development in learning rate is likely to delay abatement over time compared with the deterministic case. Relatively early abatement creates more abatement over a longer period of time during which costly uncertainty can act.

The main conclusions from this theoretical analysis are thus that the introduction of climate change increase or decrease total abatement cost depending on the impact on nutrient pool, and technological development reduces overall costs. The optimal timing of abatement is either delayed or made earlier depending on climate change impact, and on the relation between cost reductions of technological development from implemented and future abatement. The effects of introducing uncertainty are unambiguous; total costs are increased and abatement made earlier because of climate change uncertainty and delayed due to technological development uncertainty. Uncertainty in nutrient pools and targets increase costs through the need of more abatement in order to reach a minimum probability of achieving average targets. An uncertain learning elasticity increases the variation in future costs and thereby total cost for risk-averse agents.

4. Application to the Baltic Sea

The Baltic Sea is the largest brackish water sea, but also the sea with the largest areas of dead sea bottoms caused by eutrophication (Conley et al., 2009). This is not a new finding; signs of damages from eutrophication were detected already in the 1960s, and an international administrative body Helcom was established in 1974 in order to monitor status of the sea and coordinate mitigation actions. Since then, three international governmental agreements on nutrient load reductions have been signed (Helcom 1988; 2007; 2013). All agreements are supposed to be based on desired improvements in the functioning of the sea, such as less frequency of toxic algal blooms, larger populations of commercial fish, and water transparency, but only one of them presents required reductions in the nutrient pools (Helcom, 2007), which are reported in Gren et al. (2013). We therefore apply out model to this agreement. The latest agreement from 2013 contains only modest changes in nutrient load reductions, and the calculations will therefore be valid also for this agreement.

4.1 Data retrieval

The study makes use of data on abatement costs from Gren et al. (2008) and on nutrient transports in the sea from Gren et al. (2013). The Gren et al. (2008) study includes data on nutrient loads from different sources (atmospheric deposition, agriculture, industry, and households) in each country, and on abatement costs for different measures reducing loads from these sources. More precisely, the abatement measures are: increased nutrient cleaning capacity at sewage treatment plants, catalysts in cars and ships, flue gas cleaning in stationary combustion sources, and reductions in the agricultural deposition of fertilisers and manure, change in spreading time of manure from autumn to spring, cultivation of so called catch crops, energy forests, ley grass, and creation of wetlands. A change of spreading time from autumn to spring implies less leaching since, in spring, there is a growing crop which utilises the nutrients. Catch crops refer to certain grass crops, which are drilled at the same time as the ordinary spring crop but the growth, and thereby the use of remaining nutrients in the soil, is concentrated to the period subsequent to the ordinary crop harvest.

A pseudo-data approach is used for obtaining parameter values on quadratic abatement cost functions, where data on abatement costs and nutrient reductions are obtained by Monte Carlo simulations with cost effective solutions of 500 random combinations of nitrogen and phosphorus reductions for each of the riparian countries. The cost-effective solutions are calculated by use of the programming model described by Gren et al. (2008). The ordinary least square estimator is then applied for the estimation of coefficients in a quadratic cost function for nitrogen and phosphorus for each country, see Appendix. This approach for deriving cost functions in each time period assumes that cost effective reductions of nitrogen and phosphorus are implemented in each country.

There are no data on risk aversion in abatement costs for the riparian countries, which are needed for calculating cost of uncertainty in technological development. It is, however, generally agreed that the constant relative risk aversion (CRRA) for market risks ranges between 1 and 10, although it can be lower and higher (eg. Azar, 2010). We assume an average CRRA of 5 and calculate a constant absolute risk aversion (CARA) for each country, which is evaluated at the mean GDP/capita.

Table 1: BAU loads of nitrogen and phosphorus loads, abatement cost functions, and risk premium in riparian countries.

Country	Nitrogen, kton[1]	Phos Phorus, kton[1]	Parameter values[2] in the cost function $C^i = a^i A_t^{i,N\,2} + b^i A_t^{i,P\,2} - c^i A_t^{iN} A_t^{i,P}$ a^i	b^i	c^i	CARA[3]
Sweden	74	1.6	3.57	1576.63	20.89	$0.019 * 10^{-3}$
Poland	318	22.0	0.35	94.01	3.18	$0.091 * 10^{-3}$
Finland	49	1.7	5.65	2089.23	16.68	$0.020 * 10^{-3}$
Denmark	44	1.1	0.29	1945.18	58.83	$0.016 * 10^{-3}$
Germany	46	0.5	4.95	11836.62	149.80	$0.023 * 10^{-3}$
Estonia	56	1.6	1.27	1394.43	31.44	$0.068 * 10^{-3}$
Latvia	44	3.0	3.61	1021.82	45.30	$0.093 * 10^{-3}$
Lithuania	93	*3.5*	0.78	511.14	13.15	$0.094 * 10^{-3}$
Russia	83	4.0	2.90	340.17	17.36	$0.116 * 10^{-3}$
Total	824	38.9				

[1] Gren et al. (2008) Table 1; [2]Appendix, Table A2; [3]Constant absolute risk aversion calculated from an assumed relative risk aversion of 5 and evaluated at the mean GDP in 2008.

There is a relatively large body of literature estimating learning elasticities which is applied on manufacturing and energy technologies (e.g. McDonald and Schrattenholzer, 2001, Rasmussen, 2004; Jamasb, 2007). However, there is no study considering all the different abatement technologies included in Gren et al. (2008), which constitute a mix of mature, emerging and new technologies with different learning elasticities. Jamasb (2007) carried out estimates of a combination of different technologies for electricity provision, with a range of 0.03 to 0.21. We use an average of 0.12 in this study, and by assumption of a normal distribution, the standard deviation for a confidence interval of 0.95 is 0.045. The coefficient of variation is then 0.38.

Data on nutrient pools and carry over rates are obtained from simulations with an oceanographic model (Savchuk and Wulff 2007, 2009) for consistent estimates of nutrient pools and self-cleaning capacities, which are reported in Gren et al. (2013). The carry-over rates vary for different marine basins of the Baltic Sea. We calculated a weighted average for the entire Baltic Sea from the basin specific carry-over rates and nutrient pools reported in Gren et al. (2013), where the pools constitute weights. In a similar vein, targets as measured in average nutrient pools reductions are calculated as the weighted average of reductions in Gren et al. (2013).

Quantification of impacts on nutrient pools from climate changes is not readily available. Instead, there is a relatively large body of literature on the estimation of impacts on nutrient discharges from single drainage basins in the catchment (see compilation of studies in Lindqvist et al., 2013). The general approach is to use a regional Baltic Sea model, the so-called Rosby Centre Atmosphere Ocean Model (RCAO), for simulating impacts of different climate change scenarios obtained from two global circulation models, at the Hadley Centre, United Kingdom and Max Planck Institute for Metrology in Germany which are used for setting the boundary conditions which drive the regional RCAO-model.

Each global model applies two different CO_2 emission scenarios, high and low emissions, obtained from the Intergovernmental Panel on Climate Change (IPCC). This results in four different climate change scenarios with a high or a low future CO_2 level and with boundary conditions from one of two different global general circulation models. The results show different impacts on nutrient loads in different parts of the Baltic Sea. The loads of nutrients are expected to decrease for the largest marine basin, Baltic Proper, between 15% and 61% for nitrogen and between 14% and 49% for phosphorus (Lindqvist et al., 2013 Table 2). On the other hand, loads are expected to increase between 8% and 31% for all other marine basin. Ranges in impacts on total Baltic Sea are calculated by weighting the impacts calculated for each marine basin with its nutrient pools.

With respect to climate change impacts on the targets, there exist no studies on their quantification. Changes in temperature are likely to affect the anoxic sea bottom areas, and the CO_2 uptake by oceans cause acidification which impacts biological activities (e.g. Kabel et al., 2012). It is therefore quite likely that, for given nutrient pools, the damages can be higher and thus counteract the calculated climate change effects on reduction in nutrient pools. However, since there exists no number on expected changes on settled targets, we simply assume that μ^{γ^E} is the same for both nutrient targets and amounts to 0.9 and that the coefficient of variation is 0.1.

Table 2: Nutrient pools, carry over rates, targets, and uncertainty quantification in pools and targets

	Pools, kton [1]	Carry over rate, $(1-\alpha^E)$ [2]	Target, % reduction[3]	Average climate impact on pools, $\mu^{\phi,E}$ [4]	CV in $\mu^{\phi,E}$ [5]	Average target effect, $\mu^{\gamma,E}$	CV in γ^E
Nitrogen	2567	0.76	8.62	0.89	0.13	0.9	0.1
Phosphorus	558	0.94	41.50	0.84	0.14		

[1]Bioavailable nutrients in Gren et al., (2013), Table 1 with shares of total N of 0.844 and total P of 0.943;
[2] Weighted average from nutrient pools and self-cleaning rates in in Gren et al. 2013 Table 1,
[3] Weighted average from nutrient pools and target reductions in Gren et al., 2013 Table 1
[4] Weighted average from nutrient pools in Gren et al., 2013 Table 1 and climate change effects in Lindkqvist et al., (2013) Table 2;
[5]CV, coefficient of variation calculated from the data obtained under [4]

Finally, there is a need for defining the target time when the improvements are to be achieved, and the discount rate. The target times are determined by implementation of abatement measures and response time of the sea basins. Helcom BSAP suggests 2021 to be the deadline for implementation of nutrient load reductions. However, the suggestion contains no discussion on when the targets are supposed to be achieved. We therefore follow Gren et al. (2013) and apply a time period of 60 years. We choose a relatively low discount rate of 1.5.

4.2 Results

Minimum costs are calculated for the impacts of learning and the two climate change impacts, separately and in combination, with and without uncertainty. The GAMS Conopt2 solver is used for the numerical solutions (Rosenthal et al., 2008).

4.2.1 No uncertainty

The total cost for achieving the targets in the reference case, without any impacts, amounts to 307 billion SEK. This corresponds to an average annual cost of approximately 5.2 billion SEK, which is considerably lower than the cost of 15 billion SEK for achieving the same targets calculated by Gren et al. (2013). The reason for the difference is the focus on the entire Baltic Sea in this study which makes the average nutrient carry-over rates smaller. Gren et al. (2013) assign targets for each of the seven marine basins, where the self-cleaning capacity of the largest basin is 2/3 of the rate used in this paper. However, the minimum cost can be even lower, in particular when the favourable condition of climate change impacts on pools and learning act simultaneously, see Figure 1.

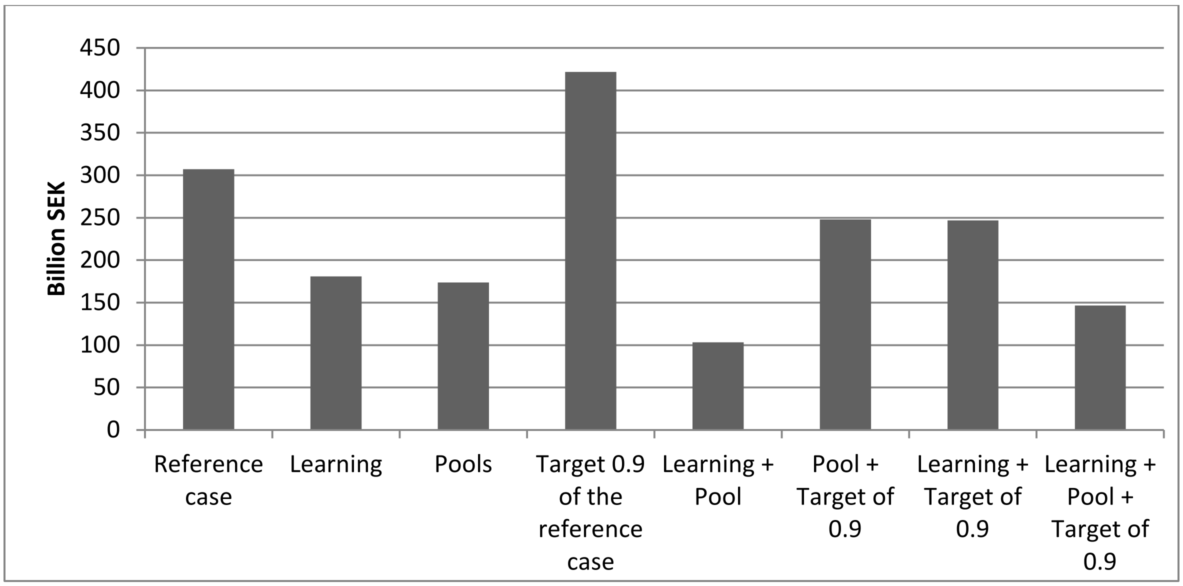

Figure 1: Minimum cost for achieving 41.5% reduction in phosphorus and 8.62% reduction in nitrogen pools in 60 years. 'Learning' impact of technological change from learning; 'Pools' decrease in nutrient pools; 'Target' decrease in pool targets.

As shown in Figure 1, impacts of technological change from learning and decrease in initial nutrient pools from climate change have similar effects on total cost, reducing it by approximately 50% compared with the reference case. When these factors act simultaneously the cost is decreased by approximately 2/3. As expected, the cost increases from future needs of tightening the targets. It is interesting to note that when this climate change impact acts in combination with the any or both of the other factors the cost always decrease compared with the reference case.

With respect to timing of abatement costs, all scenarios show three phases; *i)* an initial period of about 30 years with low annual costs, *ii)* increasing cost for a period of 15 to 25 years, and *iii)* a plateau followed by a decline. The first part is explained by the cost savings made from delaying abatement due to the discount rate and the self-cleaning capacities as shown by equation (13) in Section 3. The second phase arises from the combination of stationary maximum cleaning of phosphorus in order to reach the target in period 60 and the abatement of nitrogen, which has a much faster turnover rate. In the third phase, abatement of both nutrients is at the maximum level, and the costs are declining because of the discount rate. The main difference in optimal paths between the scenarios is the timing of these three phases.

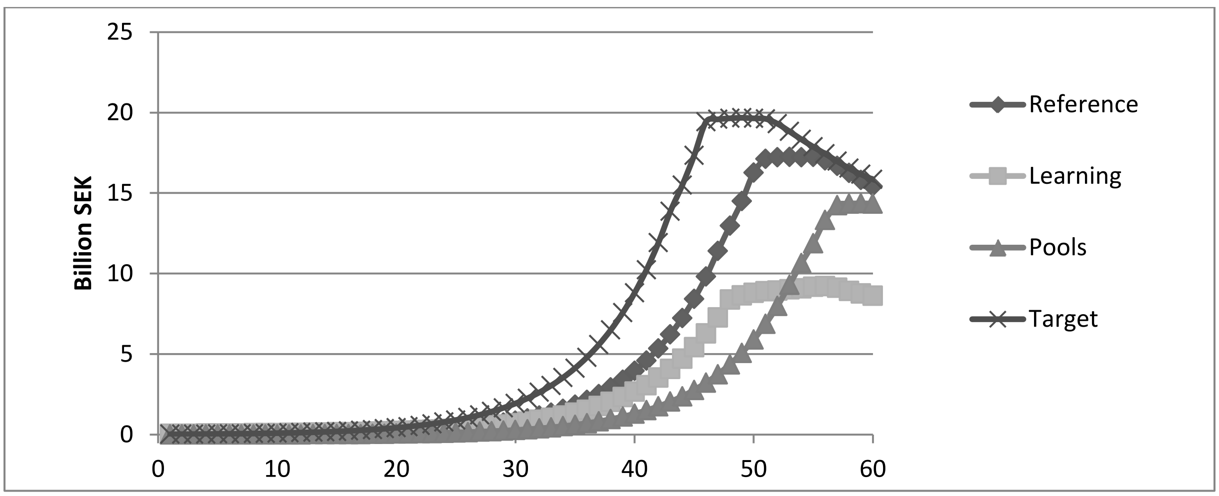

Figure 2: Optimal paths of annual discounted abatement costs under four different scenarios of technological development and climate change impacts. (See Figure 1 for description of legends)

The main difference in optimal time paths occurs between the highest cost, 'Target' and the lowest cost 'Learning'. Due to the higher target stringency, the cost outlays occur earlier because of the need to obtain, in particular, the phosphorus target. The main implication of technological development from learning can be seen by comparing ''Learning' and 'Pools'. Although the total costs are in the same order of magnitude for these scenarios, the patterns during time differ where the outlays occur about 10 years earlier for the 'Learning' scenario because of the subsequent gains made from cost decreases as shown by equation (14) in Section 3.

Recall from the data retrieval Section 4.1 that Poland accounts for the largest loads of both nutrients. This, in combination of the large reduction requirement of phosphorus, implies that the abatement costs are highest for Poland in all scenarios, see Figure 3.

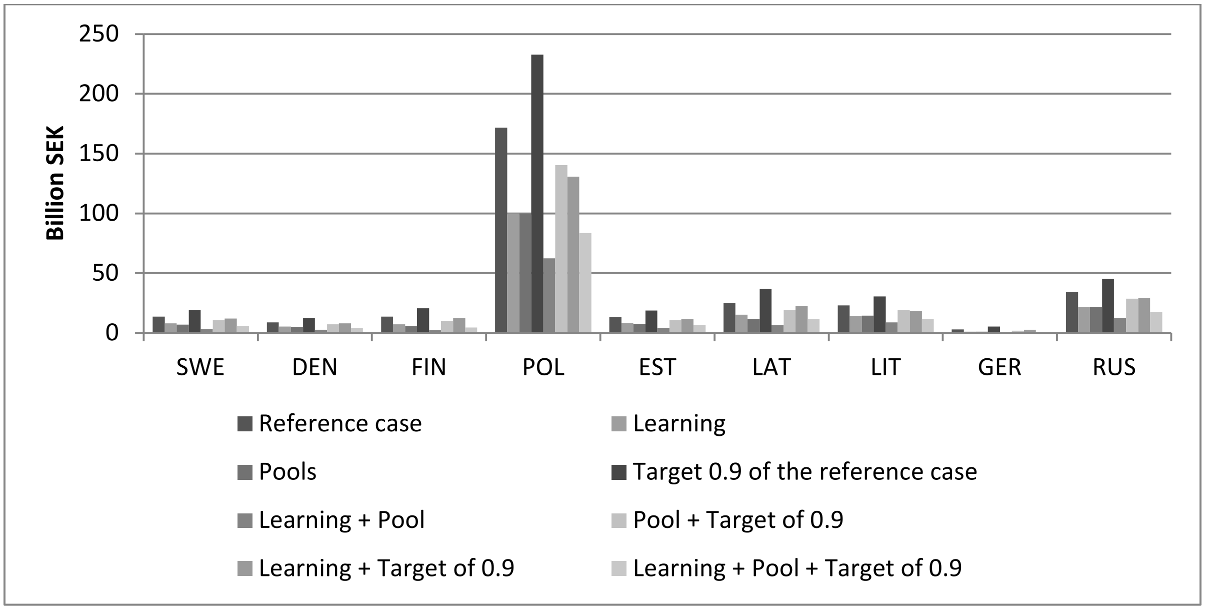

Figure 3: Total cost of abatement per country, under different technological development and climate change scenarios. (SWE Sweden; DEN Denmark; FIN Finland; POL Poland; EST Estonia; LAT Latvia; LIT Lithuania; GER Germany; RUS Russia)

The impacts of different scenarios on total abatement costs are similar for all countries, and follows that on total costs displayed in Figure 1. For Poland, the most costly scenario (Target) is approximately 5 times more expensive than the least costly scenario (Learning + Pools). Poland bears a least 50% of total cost in all scenarios.

4.2.2 Uncertainty

When calculating costs of the different scenarios under uncertainty we need to decide about the reliability levels for achievement of the targets, which we set at β=0.9 for both nutrient targets. As expected, costs under all scenarios increase when uncertainty is included, see Figure 5.

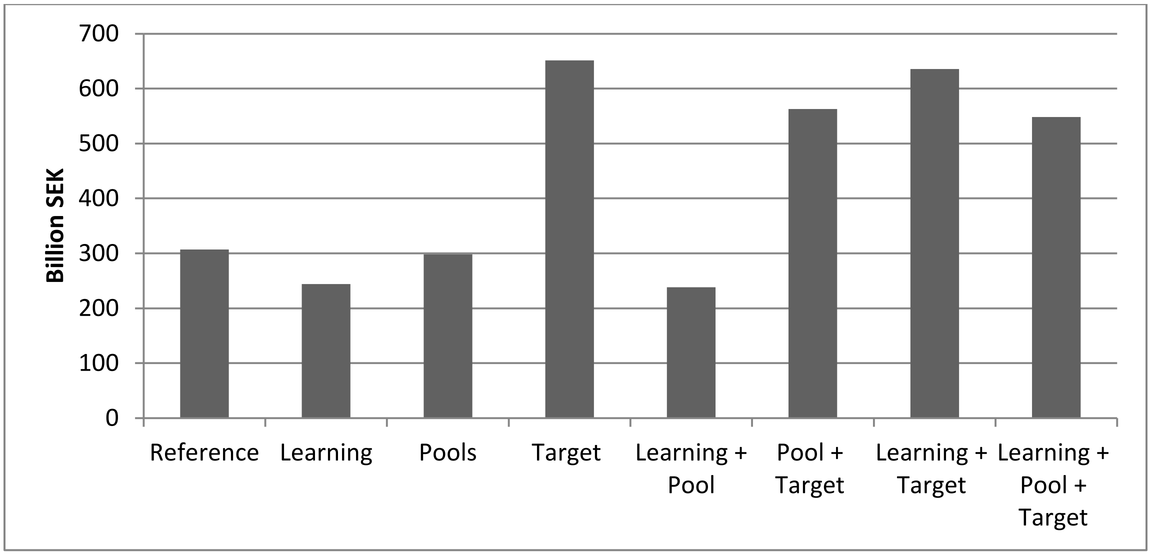

Figure 5: Minimum cost for achieving 41.5% reduction in phosphorus and 8.62% reduction in nitrogen pools after 60 years under conditions of uncertain technological change and climate impacts ('Learning' impact of technological change from learning; 'Pools' decrease in nutrient pools; 'Target' decrease in targets to 0.9 of the reference case)

There is now only three scenarios, 'Learning', 'Pools', and 'Pools + Learning' that are lower or equal to the cost in the reference case. Costs in all other scenarios increase by at least 50%, and in all cases but one, 'Learning', the outlays are made earlier than in the certainty cases because of the need to obtain more stringent targets, se Figure 6

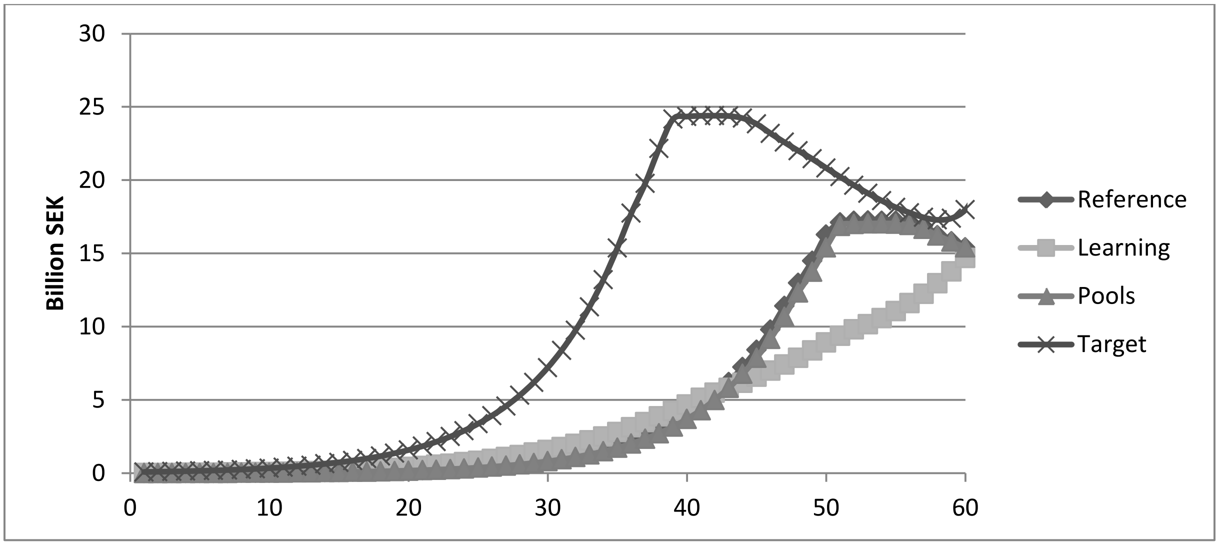

Figure 6: Optimal paths of annual discounted abatement costs under four different scenarios of uncertain technological development and climate change impacts. (See Figure 1 for description of legends.)

A fourth phase is now introduced in the 'Target' scenario where a crook appears in the last five years. The reason is the delay of nitrogen abatement, where the increased abatement requirement is postponed because of the discount rate and the relatively high nitrogen pool turnover rate. The 'Pools' scenario shows the same time pattern as the reference scenario since the cost of uncertainty in pools outweighs the decline from lower pools. As expected from the theoretical analysis, the 'Learning' scenario shows a delay in abatement costs due to delay in costs of the uncertainty in cost decline.

However, in all scenarios the costs are sensitive to the assumption of the chosen reliability level. Under assumption of normal probability distributions, a reliability level of 0.5 corresponds to the deterministic case. The costs increase relatively slowly from this level up to a level of 0.95 in all scenarios, after which there are rapid increases, in particular for all scenarios involving 'Target', see Figure 7.

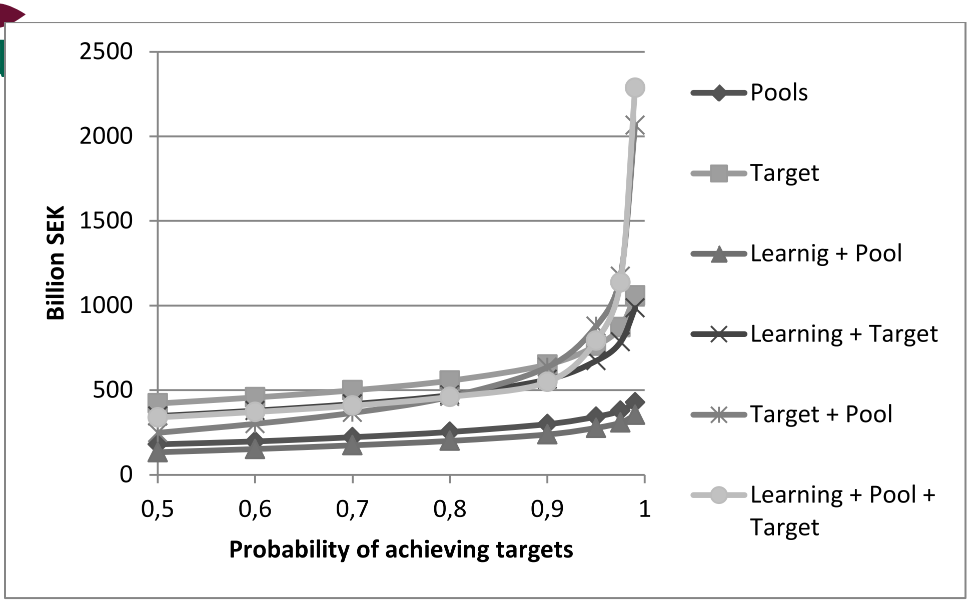

Figure 7: Total discounted abatement costs under different scenarios of uncertain technological change and climate impacts for different probability levels of achieving the nutrient targets in 60 years.

The main difference in abatement costs between the scenarios appears at high reliability levels where targets including both ‘Pools’ and ‘Targets’ now become most expensive. The reasons are the risk discount of both uncertainties and that the cost of uncertainty in the decline in nutrient pools is higher than the reduction in costs from the reduction in nutrient pools.

5. Conclusions

Climate change is likely to result in several and uncertain impacts on a eutrophied sea, and this study investigated the implications for cost-effective solutions of two of them; effects on nutrient pools and target setting. Depending on the direction of impacts, total abatement cost for reaching certain future nutrient pool targets can either increase or decrease. Unlike this ambiguous result, the introduction of technological development from learning by doing results in a cost decrease. Another unambiguous result is the increase in abatement cost from considering uncertainty, irrespective of its origins in nutrient pools, target setting or technological development. However, the combined impact on total abatement cost of all impacts depend can be either a decrease or an increase depending on the magnitude of the effects, and on risk aversion against non-attainment of targets and variability in costs.

The model was applied to the most recent intergovernmental agreement for combatting eutrophication in the Baltic Sea, which requires an average of 41.5% reduction in the phosphorus and 8.62% in the nitrogen pool. The minimum cost for achieving these targets in 60 years amounts to approximately 310 billion SEK in the reference case without any technological development or climate change. However, the cost can either decrease by 2/3 or increase 2.5 times depending on assumptions on the combination of impacts. The most favourable condition occurs for the combination of technological development and climate impact on nutrient pools. The latter are expected to decrease by approximately 15% due to climate change. However, if climate change instead requires a target reduction increase by 10%, the cost can increase considerably. The range in minimum cost becomes even larger when considering uncertainty, between 248 and 2011 billion SEK, because of the risk discount and variability in climate change effects and technological development.

Undoubtedly, our results show that the existence of uncertainty, and the aversion against it, increase abatement costs for all type of combinations of technological development and climate change. However, the results also show that climate change may facilitate implementation of nutrient abatement strategies because of the expected reduction in nutrient pools. In this case, the cost may be below current abatement costs even under conditions of uncertainty and no technical development. These results point to the importance of analysing and quantifying different climate change impacts and in particular their combined effect on environmental problems, since, in isolation they may under- or overestimate minimum cost solutions to pre-specified targets.

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Appendix: Estimation of nutrient abatement cost functions

Data on costs, nitrogen and phosphorus abatement are abatement from calculations of cost effective solutions to 500 random combinations of nitrogen abatement between 1 and max 60% BAU nitrogen loads, and of phosphorus combinations between 1 and 80% a of BAU phosphorus loads. The restrictions are determined by the capacity constraint imposed in Gren et al. (2008). The reason for the differences in maximum percent abatement of BAU loads is that relatively much of the nitrogen emission sources are located upstream in drainage basins with low impact nitrogen loads to the sea, and that part of nitrogen loads come from airborne emission sources located outside the catchment of the Baltic Sea. For some countries, the maximum reductions are not attainable, and the number of observations are then below 500, see Table A1 for descriptive statistics.

The data are used to estimate the regression equation

$$C^i = a^i (A^{i,N})^2 + b^i (A^{i,P})^2 + c^i A^{iN} A^{i,P} + \varepsilon^i \tag{A1}$$

where $A^{i,N}$ and $A^{i,P}$ are abatement of nitrogen and phosphorus, respectively, and ε^i is the error term. Ordinary least square estimator is used, and the results are presented in Table A2.

Table A1: Summary statistics, costs in million SEK and abatement of nitrogen and phosphorus in kton

Variable	*Observations*	*Mean,*	*Standard deviation*	*Mean*	*Max*
TC^{Poland}	500	11183	8558	61	39231
TC^{Sweden}	500	3243	2395	50	10096
$TC^{Denmark}$	500	2412	2088	59	9973
$TC^{Finland}$	500	2895	1892	25	8652
$TC^{Estonia}$	470	830	571	7	2850
TC^{Latvia}	451	1702	1235	9	5228
$TC^{Lithuania}$	455	1446	1145	3	6810
$TC^{Germany}$	500	1443	1291	22	5916
TC^{Russia}	500	2735	2930	15	18782
$A^{N, Poland}$	500	98	58	3.83	206
$A^{N, Sweden}$	500	23	14	0.89	47
$A^{N, Denmark}$	500	14	8.06	0.53	29
$A^{N, Finland}$	500	15	8.98	0.59	32
$A^{N, Estonia}$	470	17	10	0.66	36
$A^{N, Latvia}$	451	14	8.07	0.53	29
$A^{N, Lithuania}$	455	29	17	1.12	60
$A^{N, Germany}$	500	14	8.43	0.56	30
$A^{N, Russia}$	500	26	15	1.00	54
$A^{P,Poland}$	500	8.91	5.09	0.24	18
$A^{P,Sweden}$	500	0.65	0.37	0.02	1.28
$A^{P,Denmark}$	500	0.45	0.26	0.01	0.88
$A^{P,Finland}$	500	0.69	0.39	0.02	1.36
$A^{P,Estonia}$	470	0.65	0.37	0.02	1.28
$A^{P,Latvia}$	451	1.18	0.67	0.03	2.32
$A^{P,Lithuania}$	455	1.42	0.81	0.04	2.80
$A^{P,Germany}$	500	0.20	0.12	0.01	0.40
$A^{P,Russia}$	500	1.62	0.93	0.04	3.20

Table A2: Results from OLS estimation of joint abatement cost functions for the Baltic Sea riparian countries.

Country	*Nitrogen* a^i	*p-value*	*Phosphorus²:* b^i	*p-value*	*Joint N and P:* c^i	*p-value*	*Adj.* R^2
Sweden	3.577	0.000	1576.631	0.000	20.894	0.000	0.99
Poland	0.347	0.000	94.010	0.000	3.179	0.000	0.99
Finland	5.648	0.000	2089.229	0.000	16.680	0.000	0.99
Denmark	0.293	0.000	1945.179	0.000	58.831	0.000	0.98
Germany	4.946	0.000	11836.620	0.000	149.799	0.000	0.96
Estonia	1.274	0.000	1394.426	0.000	31.437	0.000	0.99
Latvia	3.610	0.000	1021.817	0.000	45.296	0.000	0.99
Lithuania	0.776	*0.000*	511.138	0.000	13.150	0.000	0.95
Russia	2.904	0.000	340.171	0.000	17.361	0.000	0.86

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