Ecosystem wealth in the Barents Sea

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Abstract

We develop an inclusive wealth type index for natural capital in the Barents Sea that accounts for ecosystem services via trophic interactions. We consider three key fish species in the Barents Sea under stochastic growth dynamics. Compared to evaluation at market prices, the estimated wealth from the inclusive wealth approach is several times higher. Ecosystem wealth depends on the management scheme, and we consider both business as usual (BAU) and an optimized ecosystem-based management scheme (EBM). While BAU maintains wealth near its current level (5% increase in the long run), EBM increases wealth with almost 20% in the short run and more than 25% in the long run. Realized shadow prices suggest that prey species stocks are undervalued when evaluated at market prices.

Keywords

Natural capital, inclusive wealth, fisheries, Barents Sea

1. Introduction

Sustainability is central to modern natural resource management. Management of the Barents Sea cod, the world's largest cod stock today, is case in point (Olsen *et al.* 2007). Renewable natural resources exist in an intricate interplay with an ecosystem and the environment. Management of the resource hence influences the ecosystem, and human interventions in other parts of the ecosystem or environment influence the resource. Management grounded in sustainability must consider these interactive effects while maintaining the capacity for future resource needs (Polasky *et al.* 2015). Sustainable and ecosystem-based management poses, in other words, intricate and complex problems that require new tools to gauge resource scarcity, opportunity cost, and substitution opportunities (and limitations) between different capital stocks (Arrow *et al.* 2004, Fenichel and Abbott 2014). Yun *et al.* (2017) presented an inclusive wealth headline index for sustainable ecosystem-based management that made headway toward measuring resource scarcity and substitution opportunities. We further broaden the applicability of this index to acknowledge uncertainty in underlying dynamics and to capital stocks not directly utilized.

The economic literature on sustainable development has two veins (Arrow *et al.* 2012). One goes back almost hundred years and focuses on maintaining real income. The other, more recent vein takes intergenerational wellbeing as its objective. That is, social wellbeing is the wellbeing of the current generation and the potential welfare of future generations. The criterion function for sustainable development of intergenerational wellbeing is a weighted sum of all capital asset stocks in society. The weights are the marginal contributions of the stocks to intergenerational wellbeing – the assets' accounting prices. The weighted sum is proportional to societal wealth. Sustainable development is then development where societal wealth is nondecreasing.

A challenge for the wealth-approach to sustainable development is that natural capital stocks tend to be neglected or underrepresented in wealth assessments (Arrow *et al.* 2012). Official accounts of national wealth, for example, may significantly underrepresent natural capital stocks (Obst *et al.* 2016, Greaker *et al.* 2017). An issue with national wealth accounts in this regard, is that they tend to rely on market prices, and market prices fail to reflect the full marginal contribution of natural capital to national wealth (Barbier 2011). (Whether national wealth accounts aim to reflect intergenerational wellbeing is a different matter altogether.) A relevant example is a natural capital stock that is not directly utilized – say, juvenile herring in the Barents Sea – and thus fetches no market price. But certainly the herring in the Barents Sea is there, preying upon capelin larvae that otherwise could have been harvested when grown or served as prey for the Barents Sea cod. Also, herring in the Barents Sea is precious prey for the cod stock before it migrates to the Norwegian Sea to mature and spawn. Thus, in a multitude of ways, herring contributes to the ecosystem wealth in the Barents Sea, but none of it is captured by its nonexistent market price.

In the perspective of sustainable development, accurate measurement of natural capital asset prices is a key management problem (Smulders 2012). Flawed or missing measurements may lead to distorted decisions (Stiglitz *et al.* 2010), and while national accounts and budgets are incomprehensive in terms of natural capital, ecosystem-based management has limited traction with decision makers (Barbier 2011). And the management issue is significant; an estimated 28% of global wealth rests in ecosystems (UNU-IHDP and UNEP 2014). Thus, to establish accounting prices – in the literature often referred to as shadow prices – for ecosystem goods and services is a critical step in achieving sustainable development (Polasky *et al.* 2015).

Fenichel and Abbott (2014) derived the relevant asset price for a natural capital stock and demonstrated its relationship to net present value (that is, the value function, for example obtained via dynamic programming). A key insight is that when the decision space has a single point – one is committed to what Dasgupta and Maler (2000) calls an economic program – the costate or adjoint in the dynamic programming scheme is the relevant asset price. In the words of Fenichel and Abbott (2014), '[t]he adjoint equation reflects society's resource allocation choices associated with any economic program' (p. 3). Yun *et al.* (2017) extended the approach to consider a system of interacting capital stocks and presented the measure of ecosystem wealth as 'an attractive headline index' for ecosystem-based management (p. 6539). In particular, they studied three Baltic Sea fisheries (sprat, herring, and cod) and concluded that herring and sprat, both prey species for the cod, represent larger stores of wealth than suggested by their market prices. In contrast, the derived accounting price for cod was lower than what was implied by its commercial value.

We apply the approach to three key fish stocks in the Barents Sea; cod, capelin, and herring. The Barents Sea is one of the most productive ocean areas in the world and subject to extensive research. The cod fishery is commercially and historically important (Hannesson *et al.* 2010), and is – after the infamous collapse of the cod stock in the Northwest Atlantic – the largest cod fishery in the world. Capelin is the most important prey species for the cod and is also commercially exploited. Herring, on the other hand, is not fished for in the Barents Sea but has an important influence on the ecosystem, both as prey for cod and as predator on capelin larvae. Limiting our model to these three species has the advantage that the cod stock dynamics is reasonably well captured while the model remain tractable (Kvamsdal and Sandal 2015). To limit our scope to obtain a measure of the ecosystem wealth resting in these species and deriving relevant accounting prices for them, we adopt the bioeconomic model established by Poudel and Sandal (2015).

We compare outcomes from two economic programs; the current management regime, referred to as business as usual (BAU), and an ecosystem-based management program (EBM). BAU is based on maximum sustainable yield for the individual species and largely emulates the current management scheme (ICES 2017a, 2017b). EBM is, given the model structure, the optimal management plan and takes into account both ecological and economic tradeoffs. We find that continuing with BAU, ecosystem wealth is largely maintained at its current level, while wealth may increase significantly (20-25%) under EBM. Similarly to Yun *et al.* (2017), we find that more wealth rests in the prey species stocks than what their market prices suggest. When comparing our measure of inclusive wealth to a simple aggregate evaluated at market prices, we find that our measure is several times higher.

The reminder of this article is organized as follows. In section 2, we explain how we derive the ecosystem wealth measure and the relevant accounting prices. In section 3, we present the bioeconomic model for the key Barents Sea fish stocks. Section 4 is devoted to results (forecasts of the ecosystem state, wealth measures under differing economic programs, and derived accounting prices). Finally, we provide our concluding remarks in section 5.

2. Ecosystem wealth

Wealth is the price-weighted sum of all societal capital stocks valued at appropriate asset prices (Yun *et al.* 2017). This concept of wealth may be considered standard in the economic literature, and is by Fenichel and Abbott (2014) traced back to Jorgenson (1963). An index of wealth is then:

$$W(t) = \sum_{i} \lambda_i(t) x_i(t) \tag{1}$$

Here, $x_i(t)$ is the capital stock level at time t for capital stock x_i, while $\lambda_i(t)$ is its appropriate asset price, the accounting price (Dasgupta 2001), at the given time. The index – called inclusive wealth – sums over all capital stocks. $W(t)$ is a linear expression, but prices will depend on the state of the full system of capital stocks, making the inclusive wealth measure nonlinear in capital stocks (Yun *et al.* 2017). Changes in wealth over time can be measured as follows:

$$\Delta W = \sum_{i} \bar{\lambda}_i \Delta x_i \tag{2}$$

where the Δ-notation refers to discrete changes over the time span $\Delta t = t_b - t_a$ $(t_b > t_a)$ such that: $\Delta x_i(t_b) = x_i(t_b) - x_i(t_a)$. $\bar{\lambda}_i$ denotes the mean asset price over Δt. When Δt is small, it can be shown that (Dasgupta 2001, Arrow *et al.* 2004):

$$\frac{\Delta W}{\Delta t} \approx \frac{\Delta V}{\Delta t} \tag{3}$$

Here, ΔV are changes to the net present value of the flow of dividends. Equation (3) is essentially $\Delta W \approx \Delta V$. A necessary condition for sustainable development over Δt is that wealth is nondecreasing (Yun *et al.* 2017):

$$\Delta W \approx \Delta V \geq 0 \tag{4}$$

Equation (4) is thus our sense of sustainability in what follows. Nondecreasing wealth (4) corresponds to a weak requirement for sustainability, relating only to the aggregate development and where no particular capital assets are viewed as essential and irreplaceable (Barbier 2011, Polasky *et al.* 2015). A strong requirement goes beyond the aggregate level and protects essential assets from depletion. Thus, the different assets needs to be considered in terms of their essentiality, and strong sustainability further leads to constraints in the management problem. Presently, we abstract from these complications and follow Yun *et al.* (2017) in considering the weak sustainability requirement.

Taking intergenerational wellbeing as our objective for sustainable development, the potential present and future wellbeing stored in a set of capital stocks can, per equation (3), be expressed as the net present value of present and future dividend flows, also called the value function (Arrow *et al.* 2012):

$$V(x,t) = \mathrm{E}\int_t^{\infty} e^{-\delta(\tau-t)}\Pi(x,u,\tau)\mathrm{d}\tau \tag{5}$$

In (5), $\Pi(x,u,\tau)$ is the flow of dividends to society at time τ, with the vector x being a measure of capital stock levels and the vector u being a measure of control variables. Both x and u are functions of time, but we suppress the time argument to simplify the notation. We presume that management (that is, u) is committed to an economic program such that u is known for all future times (possibly and preferably as a feedback of x). An economic program that details the development of the control variables at all future times may sound unrealistically comprehensive, but the economic program typically consist of feedback rules where the controls essentially are functions of the capital stock levels x. Further in (5), δ is the rate of discount (5%) and the term $e^{-\delta(\tau-t)}$ discounts the value of dividends back to time t, and E is the expectancy operator. That is, capital stock levels are subject to stochastic developments. Moreover, capital stock levels are governed by some know stochastic differential vector equation:

$$\mathrm{d}x = f(x,u)\mathrm{d}t + \sigma(x)\mathrm{d}B \tag{6}$$

Equation (6) states that an incremental change $\mathrm{d}x$ results from the deterministic drift term $f(x,u)\mathrm{d}t$ and the stochastic diffusion term $\sigma(x)\mathrm{d}B$. The drift term is a function of both stock levels x and control variables u; $\mathrm{d}t$ is the time increment. The $\mathrm{d}B$ are Brownian increments with mean zero and variance $\mathrm{d}t$, that is, scaled to the time increment. The scale of diffusion ($\sigma(x)$) may in general depend on stock levels x.

Changes in the value function (5) ‘are the ultimate theoretical basis for assessing welfare’ (Yun *et al.* 2017, p. 6540), and given that we can derive the value function for any feasible economic program, we evaluate changes to the value function in our analysis below. We derive the value function by solving the stochastic Hamilton-Jacobi-Bellman (HJB) equation:

$$\delta V(x) = \sup_{u \in U} \left\{ \Pi(x,u) + \nabla V(x) f(x,u) + \frac{1}{2} tr\left(\Delta V(x) \sigma^2(x) \right) \right\} \tag{7}$$

In (7), $tr(\cdot)$ denotes the trace-operator, and $\Delta V(x)$ denotes the Hessian of $V(x)$. The HJB equation governs the solution of the problem of maximizing (5) subject to the constraint (6), where $u \in U$ is the decision variable and U is the set of feasible controls. As is well known, the HJB equation represents – under standard assumptions of smoothness and concavity – a contraction mapping that converges to a unique solution. However, under an economic program – a management scheme – the set of feasible controls consists of a single control, essentially making the supremum operator superfluous. The contractive property of the HJB equation is nevertheless maintained and may provide the relevant value function for the given economic program.

Assuming an economic program, where the set of feasible controls (U) contains a single control, simplifies the HJB equation and its solution procedure. This simplification enables the solution procedure for application to high-dimensional problems that otherwise is out of reach because of the curse of dimensionality. The simplification also short-cuts the derivations in Fenichel and Abbott (2014) and Yun *et al.* (2017) that show how the accounting price can be expressed in terms of (7). Put simply, the simplification is essentially to construct a problem where the given economic program is the optimal solution, and given its solution, the relevant shadow price is available in terms of the value function directly.

The accounting price (the shadow price) of a stock is the change in the net present value to society from an increase in the stock level (Fenichel and Abbott 2014), that is, the price is the marginal value. In a deterministic problem formulation, this price is identical to the adjoint variable that is governed by the adjoint equation. When considering a stochastic problem formulation, as below, the adjoint variable may vary from the marginal value. That is, solving the adjoint equation to derive the accounting price may lead astray when considering stochastic systems. A comprehensive account of the technical details would take us too far afield; interested readers may consult Yong and Zhou (1999, pp. 115-117). Below, we avoid this potential pitfall by considering marginal values directly, which conveniently is computationally simpler.

3. A bioeconomic model for the Barents Sea

The model comprise the three main species in the Barents Sea; cod, capelin, and juvenile herring (Durant *et al.* 2008). Cod and capelin are commercially targeted and are, as such, managed, whereas herring migrate to the Norwegian Sea before maturation (age 3 or 4) and is not targeted in the Barents Sea. Herring has nonetheless an important role in the Barents Sea ecosystem, both as predator for capelin larvae and as prey for cod. Cod is demersal and preys on capelin, herring, and other species, while capelin and herring are both pelagic.

We adopt the model used in Poudel and Sandal (2015), which is a stochastic formulation in continuous time. The model is formulated in terms of biomasses and is essentially a surplus production model with trophic interactions and stochastic drivers. The model thus abstracts from age-structure effects, selectivity issues, and further details that may or may not be of interest or relevance. For our analysis, these simplifications are both useful and acceptable (Link 2010, Kvamsdal and Sandal 2015).

Let x, y, and z represent stock levels for the capelin, cod, and herring stock. The stochastic stock dynamics are specified as follows:

$$\begin{aligned}
\mathrm{d}x &= (\rho_1 x(1-x) - \phi_1 x(y+\theta_1 z) - u)\mathrm{d}t + \sigma_1(x)\mathrm{d}B_1 \\
\mathrm{d}y &= \left(\rho_2 y(1-y) + \phi_2 y\sqrt{z}(1+\theta_2 x) - v\right)\mathrm{d}t + \sigma_2(y)\mathrm{d}B_2 \\
\mathrm{d}z &= \left(\frac{\rho_3}{y+\theta_3 x} z(1-z) + \frac{\phi_3 z x}{\theta_4 + z} + \phi_4\right)\mathrm{d}t + \sigma_3(z)\mathrm{d}B_3
\end{aligned} \tag{8}$$

In (8), the ρ_i, ϕ_i, and θ_i are all positive constants. Parameter values are listed in the appendix (Table A1). The state variables x, y, and z are scaled such that the values of main interest are in the unit interval (the carrying capacity, when stock interactions are ignored, is unity for each of the stocks). u and v are harvest rates for capelin and cod. The latter term in each equation is the stochastic drift term, where B_i ($i \in [1,2,3]$) are independent Brownian motions and $\sigma_i(\cdot)$ are scale functions. The scale functions are linear, for example, $\sigma_1(x) = s_1 x$, such that the stochastic driver is more prominent at high stock levels. In our base case, the pelagic stocks (capelin and herring) are subject to a stronger stochastic drive ($s_1 = 0.4$, $s_3 = 0.4$), while the cod stock is subject to a more moderate stochasticity ($s_2 = 0.2$).

The first terms in each equation in (8) are the deterministic drift terms and specifies how the three stocks grow and interact. For both capelin (x) and cod (y), the basic growth follows a logistic growth function. Capelin is prey for both cod and capelin; this interaction is captured in the capelin dynamics equation by terms inspired by the crude Lodka-Volterra form of predator-prey interaction. This type of interaction is not unusual in this type of model

(May *et al.* 1979, Kvamsdal and Sandal 2015). The interaction terms in the cod equation are similar, but are modified by the presence of herring ($\sqrt{z}$). Herring has both a different basic growth pattern, where the growth rate is reduced inversely proportional to a measure of the competing biomass ($y+\theta_3 x$), and a simplified interaction term with capelin only. The positive constant (ϕ_4) captures the inflow of herring larvae from the Norwegian Sea. For further details and discussion on the specification of the stock dynamics equations, see Poudel and Sandal (2015) and references therein.

For the model of the flow of dividends to society, we once more adopt the model used in Poudel and Sandal (2015), who again bases their model on Sandal and Steinshamn (2010):

$$\Pi(x, y, u, v) = p_1 u - c_1 u^{\alpha} + p_2 v - p_3 v^2 - c_2 v/y \tag{9}$$

In (9), the p_i, c_i, and α are all positive constants, also listed in the appendix (Table A2). Capelin harvests, largely used for fish oil and meal production, faces a constant real price (p_1). There is no stock effect on capelin harvesting costs, based on its schooling nature, but costs are nonlinear in the rate of harvest (α). Cod harvests faces a downward sloping price schedule ($p_2 v - p_3 v^2$). Cod harvesting costs has a stock effect such that costs are inversely proportional to the stock level; the costs are otherwise linear in the harvest rate. The herring stock is not exploited in the Barents Sea and thus generate no direct flow of dividends. Again, for further details and discussion of equation (9), see Poudel and Sandal (2015) and references therein.

We calculate the ecosystem wealth for the Barents Sea system under three different management scenarios (economic programs). The first we call business-as-usual (BAU) and is an approximation of the current management regime (ICES 2017a, 2017b). The BAU harvesting policies aims at maximum sustainable yield (MSY) for the individual species without considering trophic interactions. Indeed, this is a simplification of todays' management, but captures the main tendencies of the management plans well enough for our model. For the cod, for example, the fishing mortality of the management advice from the International Council for the Exploration of the Sea (ICES) is close to the MSY fishing mortality, in fact closer than the other potential management plans considered (ICES 2017a). Notably, the maximum harvest rate is set below the theoretical maximum of the growth function because we have a stochastic model subject to what is called downward drag induced by stochasticity (Poudel *et al.* 2015); the harvest rate is also limited to rates that generate revenue.

The second management scenario under investigation is called ecosystem-based management (EBM) and is simply the harvest policies established by solving the optimization problem in equation (7), subject to equations (8) and (9). The resulting policies are three-dimensional surfaces (manifolds) that take account of species interactions, stochastic drivers, and economic conditions. These optimal policies have surprising features, such as nonmonotone changes in the capelin harvest rate along the cod stock axis (Sandal and Steinshamn 2010, Poudel and Sandal 2015). The EBM-policies are qualitatively identical to the policies discussed in Poudel and Sandal (2015), but are recalculated for our grid and variable scaling.

The BAU and EBM regimes are the main management scenarios that we study below. We also study outcomes from the single-species management (SSM) regime, where the harvesting policies are optimal but constrained to not consider trophic interactions. That is, as if interaction terms in (8) were set to zero. SSM amounts to consider the optimal policy (EBM) along its boundaries on the axis as valid throughout the state space. Admittedly, the SSM regime is simplistic; a more elaborate single-species management approach would adjust remaining parameters to partly take account of the missing interaction terms. Thus, the results reported for SSM below is perhaps not entirely worst case, but certainly not the best case for single-species management.

The BAU and SSM harvesting policies are plotted in Figure A1 in the appendix. The four-dimensional EBM-policies cannot be comprehensibly plotted in any reasonably limited space, but Poudel and Sandal (2015) provide several illustrations of key parts of the manifolds. Poudel and Sandal (2015) also discuss long-run stock and harvest levels, stability issues (resilience), interaction effects, and effects of the stochastic drivers.

4. Ecosystem wealth in the Barents Sea

Figure 1 shows the observed development in stock levels until 2016 (ICES 2016, 2017a, 2017b, Mehl *et al.* 2016), and predicted stock levels from 2016 and over a fifty year period. The curves show the mean paths from 1000 predicted paths under the two main management regimes (EBM and BAU). See appendix for predictions also for the SSM-regime, as well as plots showing 50% probability intervals around the predicted expected levels (Figures A2, A3). Cleary, long run predictions are subject to considerable uncertainty.

The predicted mean paths in Figure 1 do in no way represent the far more stochastic behavior that any realized path displays. Rather, the predicted mean paths indicate at what levels the stocks are expected at with time. The historical figures (2000-2016) illustrate the level of stochasticity that the system is subject to. For example, both the pelagic species varies over the lower half of their ranges in a matter of years.

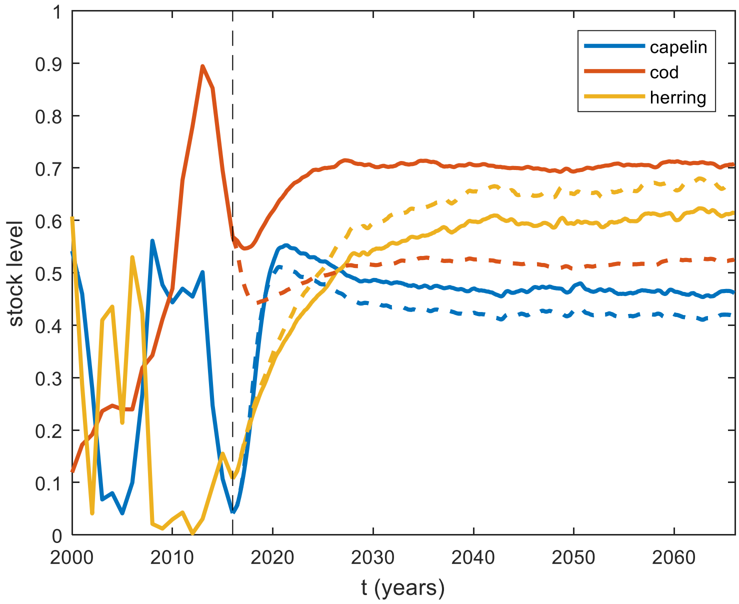

Figure 1: Observed and predicted (smoothed mean paths) stock levels under EBM (solid curves) and BAU (dashed curves). Figures up until 2016 are observed levels. The vertical line separates observed and predicted figures.

There are some discrepancies in the expected stock levels under the two different regimes displayed in Figure 1. While the discrepancies in the pelagic stocks (capelin and herring) are relatively small, discrepancies are more significant for the cod stock. Under both regimes, the cod stock is initially brought down, but under EBM (solid curves) cod is depressed for a brief period only before it is brought up to a relatively high expected level near its historic highs. Under BAU (dashed curves), the initial depression of cod lasts longer and slightly overshoots the expected BAU long run level near the MSY target level at 0.5. Capelin is initially (2016) at a very low level, and it recovers quickly under both regimes, in part aided by reduced predation from the depressed cod stock. After some slight overshooting, capelin settles down near the MSY target level under both regimes, but admittedly at a somewhat higher level under EBM despite predation from a larger cod stock. Also the initial (2016) herring level is relatively low. Not being directly utilized, it grows slowly to levels near its historic highs, albeit to a somewhat lower level under EBM where the predation pressure from cod is higher. A key difference in the pelagics is that capelin is expectedly higher under EBM than under BAU, while herring is expectedly higher under BAU. That is, the optimized EBM scheme clearly prioritizes capelin over herring.

As noted above, recovery of capelin is in part facilitated by suppression of its main predator under both EBM and BAU. Under EBM, the suppression of cod must be understood as aiding the capelin recovery, which quickly is manifested such that the cod suppression is brief. Under BAU, the cod is suppressed because the initial (2016) stock level was above the implicit target stock level. In an early foray into co-management plans for interacting species, Sandal and Steinshamn (2010) discussed conditions under which a prey species can recover while the predator is suppressed.

Again, we observe several instances of overshooting: capelin under both EBM and BAU, and cod under BAU. The reason for this overshooting is the herring which slowly – over a period of twenty years – reaches a stable level (in expectation at least; as the probability intervals displayed in figures in the appendix shows, deviations from the expected level are substantial).

A final aspect about the predicted stock levels in Figure 1 is the high long-run levels of herring that seem incompatible with near-term history (2000-2016). Unquestionably, the predictions are simply reflections of the modelled dynamics (8), and a natural question may be whether our model is a relevant representation of the Barents Sea ecosystem. For one thing, the system is subject to substantial stochasticity, and as the probability intervals shown in Figure 2A in the appendix reveal, herring stock levels well below historic highs have significant probabilities. Furthermore, the Barents Sea herring are, as discussed above, residues – so to speak – from herring spawning along the Norwegian coast. In the future, it is not unlikely that the Norwegian Sea spring-spawning herring will reach higher than today's levels – with better ecosystem-based management plans or better cooperation between the various fishing nations pursuing the large pelagics in the Norwegian Sea (Ekerhovd and Steinshamn 2018). Under such scenarios, more juvenile herring would mostly likely end up in the Barents Sea. Thus, high long-run levels of herring in the Barents Sea may conflict with near-term historical levels, but aligns with credible future scenarios.

Based on the predicted stock levels in Figure 1, we can calculate the level of ecosystem wealth in the Barents Sea under the different management scenarios (BAU, EBM, SSM). That is, we solve (7) while – in the case of BAU and SSM – constraining the set of feasible harvest schedules U to only consist of the BAU or SSM-policies (Figure A1). In the case of EBM, U is constrained to the set of nonnegative and bounded controls. Solving (7) yields a value function for each of the management scenarios that we thus evaluate along the predicted paths. We report the results in Figure 2, with expected wealth levels (solid curves) and 95% probability intervals (shaded areas). To ease comparisons, all curves in Figure 2 are scaled to the BAU 2016-level (50.6 billion NOK).

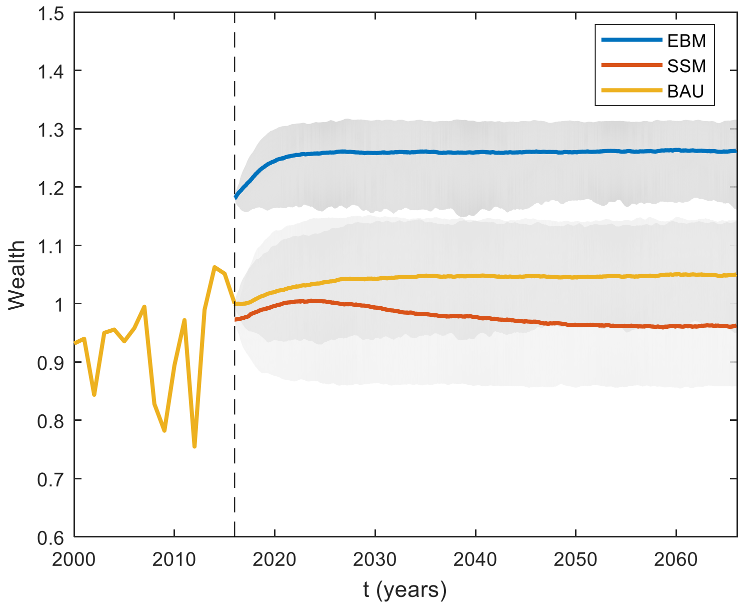

Figure 2: Expected ecosystem wealth in the Barents Sea (with 95% probability intervals) under EBM (dark shaded area), BAU (medium shaded area), and SSM (light shaded area). Estimates for 2000-2016 are shown in the same color as BAU. All figures are scaled to the BAU 2016-level.

The BAU-regime is expected to keep the level of wealth near today's level. The development is more or less flat initially, before it slowly increases to some 5% above the 2016 level. Wealth stabilizes notably faster – within five to ten years – than the underlying resource stocks that under BAU takes more than twenty years before their expected levels settle down for all stocks. Another notable feature is the relatively narrow probability interval when compared to probability intervals for the stock levels (Figure A2). The reason wealth varies less is that the value function is relatively flat near the long-run state. Wealth has also increased over the years 2000-2016, although with substantial variations. Importantly, wealth is nondecreasing in expectancy and, per our definition in (4), sustainable under BAU. If we estimate wealth simply by market prices multiplied with stock levels and aggregating, we get approximately 0.30 on the scale used in Figure 2 (15.0 billion NOK). Thus, considering inclusive wealth results in more than three times as much wealth as the simple aggregate.

Wealth under EBM behaves similar to wealth under BAU, but at a significantly higher level and with a shorter stabilization period (five years). Expected wealth is nondecreasing also under EBM. A switch to EBM in 2016 would immediately increase the level of ecosystem wealth in the Barents Sea with more than 18%. In the long run, wealth is expected to be approximately 26% higher than in 2016. Given that the EBM-policies resulted from the optimization procedure, improvement in wealth was to be expected, but an increase of 18-26% is significant. The EBM probability interval is narrow when compared to stock level probability intervals (Figure A2), and also somewhat narrower than under BAU. The 95% probability interval for long run wealth under EBM is roughly $(1.18, 1.31)$, while under BAU it is roughly $(0.96, 1.14)$. There are several reasons for more variability in wealth under BAU, but a key factor is the higher herring levels under BAU. The stochastic scaling factors increase linearly with the stock levels, such that a stock at a higher level is subject to a stronger stochastic driver.

Finally, considering ecosystem wealth under SSM reveal a somewhat different scenario. A shift from BAU to SSM in 2016 would not change wealth more than a few percent in the short run. Wealth under SSM is expected to increase for almost 10 years before it slowly regresses below its initial level. That is, SSM is not sustainable. Wealth under SSM is also much more uncertain; the long-run 95% probability interval is $(0.86, 1.14)$, notably encompassing the BAU long-run probability interval. Taken at face value, SSM has the same probability (2.5%) of generating wealth more than 14% above the 2016-level as under BAU. SSM has considerable downside risk, however. Wealth under SSM is more uncertain because the value function is steeper in the area of the SSM long-run state. Moreover, under SSM, capelin fails to recover and cod would increasingly rely on a volatile herring stock (Figure 3A). That wealth regresses after its initial increase is connected to this collapse of capelin, in expectancy (initially, some paths predict recovery, but eventually most paths collapse to near the 2016 level).

5. Shadow prices

In the literature, as discussed above, shadow prices are promoted as highly relevant for ecosystem-based management by reflecting ecosystem services through trophic interactions and as measures of scarcity and limits to substitutions. We understand shadow prices here as marginals (value function gradients), and not necessarily as identical to the adjoint variable in the optimization problem (in stochastic problems, as ours, the gradient of the value function is not always identical to the adjoint). While shadow prices will reflect the value of ecosystem services, they also reflect commercial potential, and these effects are not trivially separated. Thus, shadow prices need to be interpreted with some care. The value function – the wealth measure – is what matters. Furthermore, shadow prices present a largely static picture in the sense that they presume all other stocks being kept constant (or some; we return to considering variations over several dimensions below). But this, staying constant, is not how an ecosystems functions, and perhaps a more pertinent consideration would be to consider marginals along a given path (that is, subject to some management regime).

These reservations aside, we follow Yun *et al.* (2017) in that studying shadow prices may add to our understanding of how the different resource stocks contribute to ecosystem wealth in different parts of the state space (in different situations). For example, Figure 3 displays the shadow price for capelin under EBM (left panel) and BAU (right panel) and in two different situations: where cod and herring both are kept fixed at their 2016-level and where cod and herring are kept at their expected long-run level. The figure also indicates the relevant net market price (harvest market value minus harvest costs, per harvested kilogram), and the capelin levels in the respective situations (2016 and long run). The net price varies as the relevant harvest level varies with the capelin level (that is, along the horizontal axis); when the harvest level is zero, the net price is constant and identical to the highest attainable market price (no harvest costs are subtracted).

As expected, the capelin shadow price (Figure 3) is positive and downward sloping in own stock under EBM. In 2016, the shadow price was higher than the net market price, while lower at the expected long run level. That the shadow price is higher than the net price suggests that capelin is more valuable as prey in the ecosystem than on the market. Under BAU, the shadow price is not downward sloping everywhere. That the shadow price is not downward sloping everywhere in own stock is because the harvest profile is not adapted to the multidimensional growth functions. Under BAU, the shadow price is just below the net market price in 2016, but considerably above (approximately three times as high) in the long run. A long run shadow price above the net market price suggests that evaluation at market undervalues the social worth of capelin. Generally, the price curves are steep at low levels and flatter at high stock levels, and close to zero at very high levels. That is, they are strongly nonlinear, notably in contrast to the corresponding curves presented in Yun *et al.* (2017), whereas in agreement with recent theoretical work (Nævdal and Skonhoft 2018).

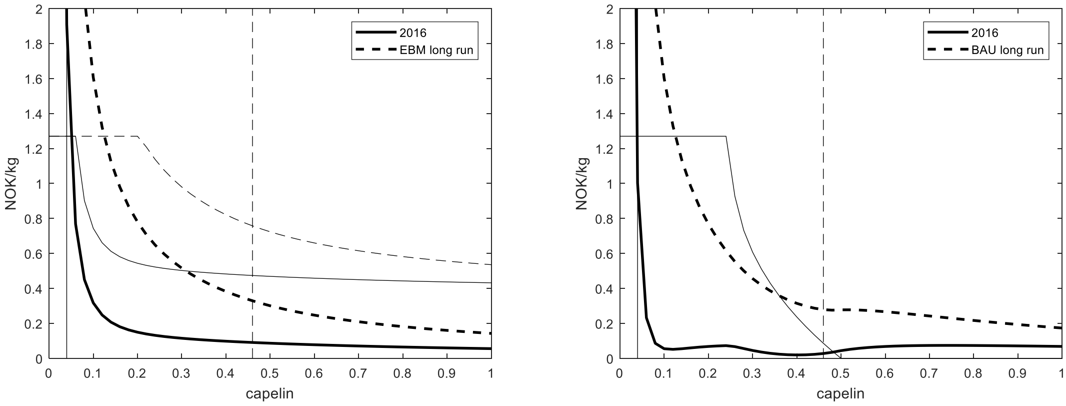

Figure 3: Shadow price (gradient of the value function) for capelin under EBM (left panel) and under BAU (right panel) with cod and herring at their 2016 levels (bold solid curve) and at their long-run levels (bold dashed curve). Indicated are the net price in 2016 (solid curve) and in the long run (dashed curve), and the capelin level in 2016 (solid vertical line) and in the long run (dashed vertical line). Under BAU (right panel), the net price is identical in 2016 and in the long run.

In a similar way as for capelin above, Figure 4 displays the shadow and net prices for cod under EBM (left panel) and BAU (right panel), and in the 2016-situation (solid curves) and in the expected long run (dashed curves). Relevant stock levels are also indicated on the figure. Different from the capelin case, the net prices vary also when the harvest level is zero because harvest costs are density dependent. As for capelin, the cod shadow price is positive and downward sloping in own stock under EBM, both in 2016 and in the long run. The general shape and level is similar under BAU, but the shadow price is not downward sloping everywhere; near the MSY target level (0.5), the price is briefly upward sloping in own stock. This upward sloping near the MSY target level reflect anticipation of the kink in the net price; the kink reflects the kink in the harvest rate (see Figure A1). In both scenarios, the shadow price is significantly smaller than the net price everywhere but at low stock levels, where the shadow price is high while the net price goes to zero. Again as for capelin, the shadow price approaches zero at very high stock levels.

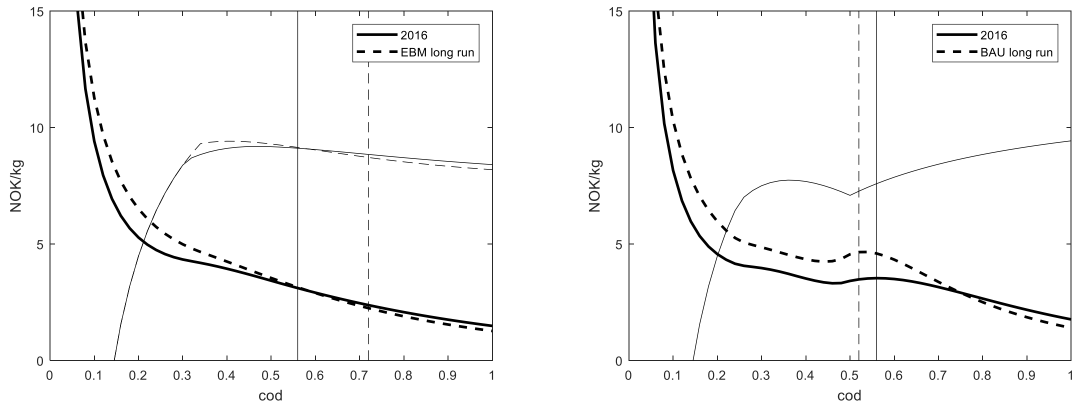

Figure 4: Shadow price (gradient of the value function) for cod under EBM (left panel) and under BAU (right panel) with capelin and herring at their 2016 levels (bold solid curve) and at their long-run levels (bold dashed curve). Indicated are the net price in 2016 (solid curve) and in the long run (dashed curve), and the cod level in 2016 (solid vertical line) and in the long run (dashed vertical line). Under BAU (right panel), the net price is identical in 2016 and in the long run.

Figure 5 shows the herring shadow price under EBM (left panel) and BAU (right panel) in the 2016-situation (solid curves) and in the expected long run (dashed curves). The shadow price behaves similarly across all scenarios and situations: monotonously downward sloping; steeply at low levels and essentially flat at high levels. At low levels, the shadow price is positive; herring is valuable as prey for cod. At higher levels, the shadow price is negative under EBM and herring becomes a liability (on the margin) for the Barents Sea ecosystem. It varies at what levels the herring shadow price turns negative, but notably close to the expected long run level under EBM. That is, under EBM, the system is managed in such a manner that in the long run, herring is in expectancy exhausted of its potential for social worth. In the 2016 situation, the shadow price turns negative at relatively low levels because of its negative effect on the then very small capelin stock. Further, the shadow price is generally higher in the long run situation in both scenarios. But our analysis fails to account for the value herring from the Barents Sea represents when it enters the Norwegian Sea to spawn. Notwithstanding, at low levels, where herring was in 2016 and where it has been in many recent years, we find that herring has a positive shadow price and embodies considerable ecosystem wealth. In contrast, evaluated at its nonexistent (zero) market price significantly underrepresents ecosystem wealth.

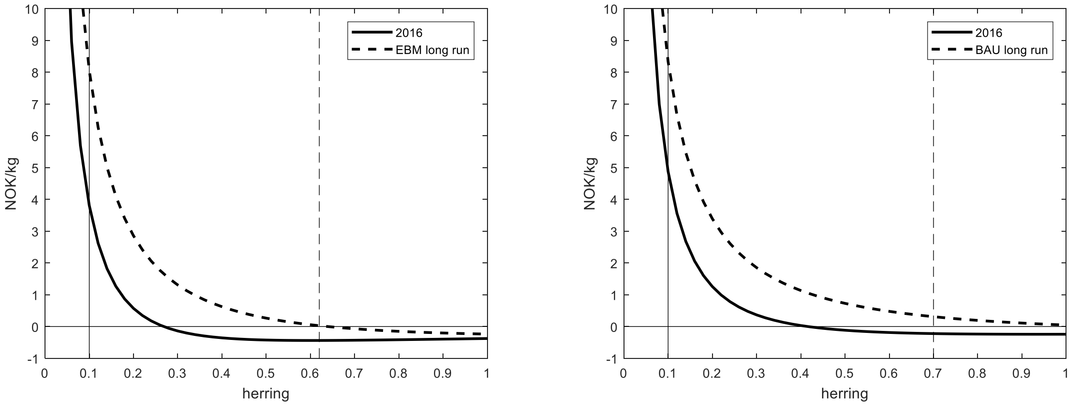

Figure 5: Shadow price (gradient of the value function) for herring under EBM (left panel) and under BAU (right panel) with capelin and cod at their 2016 levels (bold solid curve) and at their long-run levels (bold dashed curve). Indicated are the herring level in 2016 (solid vertical line) and in the long run (dashed vertical line).

Shadow prices reflect scarcity and account for cross-stock interaction effects and behavioral feedbacks (Yun *et al.* 2017). A question that emerges is whether stocks are substitutes or complements, something that depends on trophic interactions, how changes in abundance affect harvest policies, and how the stocks contribute to the flow of dividends (Yun *et al.* 2017). A way to study substitutability and complementarity between resource stocks is to examine shadow price contour plots where two stocks vary while the third stock is kept constant. When the shadow price of a given stock decreases with an increase in another stock, the second stock acts as a substitute for the first; when the shadow price increases, the second stock acts as a complement. We here presuppose that stocks are goods with positive shadow prices rather than liabilities with negative shadow prices. In an evidently simpler model where shadow prices are monotonic and close to linear (Yun *et al.* 2017), it suffices to check whether shadow price contours are downward or upward sloping to establish if stocks are substitutes (downward) or complements (upward).

As an example, figure 6 shows shadow price contours for capelin (left panel) and cod (right panel), under BAU, with herring at the expected long-run level. The capelin shadow price (left panel) varies substantially with changes in cod. When the cod stock level is relatively low (approximately below 0.6), the capelin shadow price increases with increases in cod and cod acts as a complement to capelin. Given that cod preys on capelin, the complementarity must lie in the increased ecosystem service as prey that capelin offers. At higher cod levels, on the other hand, the capelin shadow price decreases with increases in cod. The strength of both these effects vary substantially along the capelin axis. The contours also shows that the capelin shadow price is non-monotonic in own stock under BAU, as seen above (Figure 3). The cod shadow price (right panel) also varies with the capelin level although the effects from changes in capelin are less dramatic than effects observed in the capelin shadow price (left panel). That cod has greater impact on capelin than vice versa is because cod is the main predator on capelin while capelin is one of several food sources for cod. When cod is relatively low (again approximately below 0.6), the cod shadow price increases with increases in capelin and capelin acts as a complement to cod. At higher cod levels, the cod shadow price decreases with increases in capelin. Also for cod does the contours show that the cod shadow price is non-monotonic in own stock under BAU, as seen above (Figure 4). All of these results depend in various degree on the level of herring. A comprehensive account, including consideration of several plots of the type in Figure 6 is beyond our current scope.

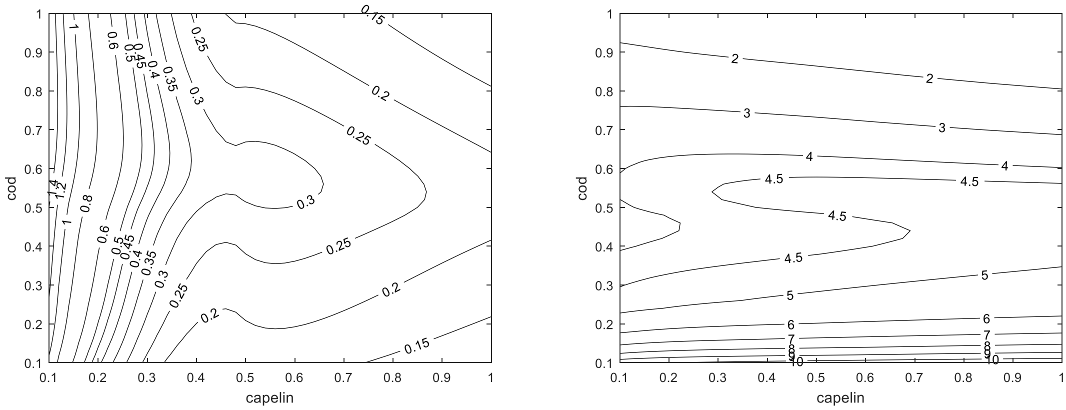

Figure 6: Shadow price contour plots for the capelin (left panel) and cod (right panel) shadow prices, under BAU, evaluated with herring at the expected BAU long-run level. The numbers on the curves indicate the shadow price (NOK/kg) along the contour.

The capelin-cod example in Figure 6 is interesting because both stocks are directly utilized and thus contributes to the flow of dividends. Another example is capelin and herring shadow prices. Capelin and herring are both pelagic species and prey for cod, and given that the interaction with cod most likely are the most important ecosystem service of both stocks, investigating substitution effects is of interest. In Figure 7, we display shadow prices for capelin (left panel) and herring (right panel), under EBM and with cod at its long-run expected level. Both stocks have decreasing shadow prices in own stock, with varying rates depending on the relative stock levels. Further, the stocks are complements; the shadow prices increase with increases in the other stock. That herring is a complement to capelin is somewhat surprising, given that it preys on capelin larvae. The complementary effect is stronger when the complement is at low levels. Conversely, when the own stock is at high levels, the complementary effect is essentially one-sided. For example, when capelin is high, an increase in herring increases the shadow price of capelin, but an increase in capelin has little impact on the herring shadow price.

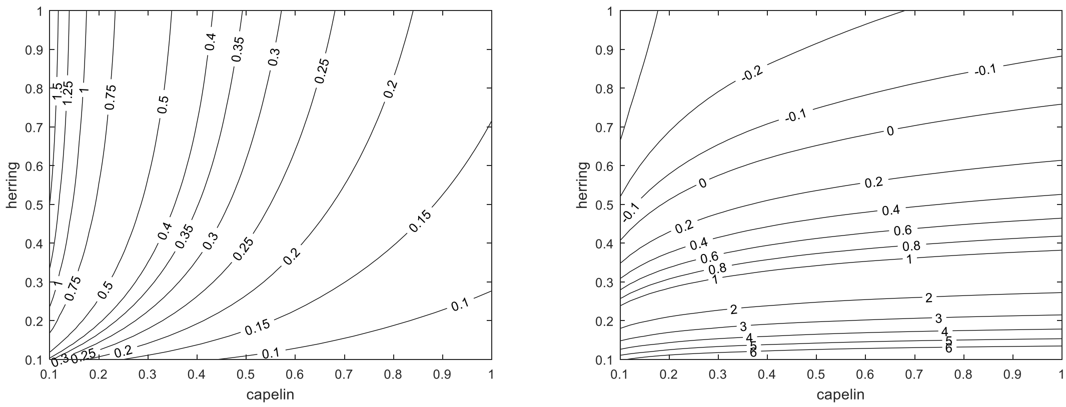

Figure 7: Shadow price contours for the capelin (left panel) and herring (right panel) shadow prices, under EBM and evaluated with cod at the expected EBM long-run level.

Table 1 summarizes and complements our key results. In particular, it states 50% probability intervals for long run shadow prices. These intervals are not contingent on keeping all but one dimension constant, as in figures 3 - 5, but are evaluated over the ensemble of predicted paths. That is, the listed shadow price probability intervals account for uncertainty both in own stock and other capital stocks. All listed intervals are 50% probability intervals, thus complementing Figure 2 that displayed 95% intervals for the wealth index. Further, the table lists both means and medians for the long run expectancies, and these differ somewhat in various cases.

Table 1 shows that, in contrast to the finding in Figure 5, the expected long run shadow price for herring differs from zero when full uncertainty (that is, both in own and other stocks) is accounted for. Still, zero is part of the 50% probability interval. Another result complementing earlier findings is that the 50% probability interval for long run wealth under BAU and SSM does not have the same upper limit. In Figure 2, we saw that the upper limit of the 95% intervals was similar. Whether it is the 50% or the 95% interval one wants to put more emphasis on is not necessarily obvious, but clearly, this choice may affect comparisons of the different management scenarios. Finally, all listed shadow prices for herring under SSM in Table 1 are negative, indicating that SSM fail to benefit from the presence of herring in the manner that both EBM and BAU does. Herring is wholly a liability under SSM.

Long run predictions are riddled by uncertainty, and how important the scaling of the stochastic drivers are, is a relevant question. Thus, we provide a summary results table (Table

A3, appendix) also for a model with weaker stochastic drivers for the pelagic species ($s_1 = 0.2$, $s_3 = 0.2$). The first conclusion we can draw from comparing tables 1 and A3 is that uncertainty is costly. The reduction in the scaling of stochastic drivers results in approximately 8% more wealth under both EBM and BAU. Somewhat surprisingly, SSM fares much worse with the reduced stochasticity, yielding approximately 12% less wealth. Mainly, this is caused by a much more certain collapse in the capelin stock. Notwithstanding, the results for EBM and BAU – the management regimes in focus – are as expected, and we would rather err on the side of too large stochastic scaling terms.

Table 1: Results summary for stock levels, shadow prices, and wealth index in the 2016 state and long run (with 50% probability intervals) for EBM, BAU, and SSM. Shadow prices and wealth index evaluated over predicted paths.

	State	Stock level			Shadow price			Wealth
		x	y	z	$\partial V/\partial x$	$\partial V/\partial y$	$\partial V/\partial z$	V
EBM								
	2016	0.04	0.56	0.10	1.95	3.07	3.45	1.18
	long run (mean)	0.45	0.71	0.61	0.374	2.44	1.94	1.26
	long run (median)	0.44	0.69	0.53	0.310	2.43	0.181	1.27
	50% interval	(0.33, 0.57)	(0.59, 0.80)	(0.30,0.85)	(0.18, 0.46)	(1.92, 2.98)	(-0.213, 1.29)	(1.25, 1.29)
BAU								
	2016	0.04	0.56	0.10	1.10	3.55	4.11	1.00
	long run (mean)	0.41	0.53	0.67	0.347	4.03	1.40	1.05
	long run (median)	0.39	0.48	0.61	0.301	4.24	0.301	1.05
	50% interval	(0.30, 0.49)	(0.42, 0.58)	(0.37, 0.91)	(0.204, 0.426)	(4.02, 4.44)	(-0.025,1.16)	(1.03, 1.08)
SSM								
	2016	0.04	0.56	0.10	7.39	3.16	-5.23	0.973
	long run (mean)	0.16	0.61	0.76	3.07	2.85	-0.594	0.963
	long run (median)	0.05	0.60	0.74	2.95	2.87	-0.576	0.923
	50% interval	(0.03, 0.23)	(0.52, 0.69)	(0.51, 0.99)	(1.74, 4.14)	(2.34, 3.39)	(-1.30, -0.295)	(0.894, 1.04)

6. Concluding remarks

Our basic result is our solution of (7) subject to (8) and (9) under various assumptions upon the set of feasible controls U. All our findings follow from these solutions. The solutions provide value functions and, in the cases of EBM and SSM, where U is not limited to a single control, feedback control policies. The value functions and the feedback policies take account of the dynamic uncertainty in the system, and this uncertainty is as such reflected in all our results. In particular, derived accounting (shadow) prices embody uncertainty over how the ecosystem may develop over time. When we report probability intervals for long run shadow prices, it is not because the prices are uncertain, but because the prices depend on the stock levels, which are uncertain.

The feedback policies are used to predict how the system will evolve over a fifty year period (Figure 1). The value functions then yield the development in ecosystem wealth under the different management scenarios (Figure 2). Our finding that a 2016 switch to EBM increases wealth with 20-25% is similar in magnitude to the findings in Yun *et al.* (2017). In absolute terms, our results are on par with recent investigations of value creation in the Barents Sea (Hänsel *et al.* 2018). We further derive accounting prices (shadow prices) for the various natural capital stocks by considering marginal changes in the value functions (Figures 3-7). The general finding is that our derived accounting prices differ from relevant net market prices. Because accounting prices are the appropriate measures of contributions to social worth (Dasgupta 2001), accounts and decisions based on market values may lead astray. In particular, accounting practices tend to undervalue natural capital because market prices mostly misrepresents scarcity and substitution opportunities for ecosystem components (Obst *et al.* 2016, Greaker *et al.* 2017). Our study make a novel contribution in relation to these concerns because we consider a resource stock (juvenile herring) that is not directly exploited and thus has no market value at all. We find that herring has a positive accounting price at historically observed stock levels.

A fundamental feature of the accounting prices that we report, are their strong nonlinearity. This feature allow our prices to become increasingly steeper at low stock levels, in line with recent theoretical results (Nævdal and Skonhoft 2018), while leveling off at high stock levels. It is only the unexploited herring stock that has negative accounting prices in relevant parts of the state space, reflecting that – at very large herring levels – its preying on capelin becomes more harmful than its role as prey for cod. As mentioned above, our model fail to account for the value the herring represents once it departs for maturity in the Norwegian Sea.

This latter point leads to a more general discussion of sustainability. Yun *et al.* (2017) expressed concern over declining ecosystem wealth in the Baltic Sea even under EBM. But such concerns are only of significance when considering a closed system, which neither our nor the Baltic Sea model represents. For one thing, it may in principle make sense to draw down wealth in natural capital stocks if substituted for more productive capital of a different kind. Also, the value function may be monotonically increasing in a given stock, but this does not imply that investing continually in a higher stock level is rational. Rather, one trades off potentially higher wealth with what it takes to attain it, in terms of time and resources. In our model, we only observe declining wealth under SSM, but further investigations are required to establish whether this is a real concern. Under SSM, the expected long run herring stock level is higher than what it is under either EBM or BAU (Figures A2, A3), and depending on the value this represents for the herring fishery in the Norwegian Sea, declining wealth in the Barents Sea ecoregion may or may not be a concern. In their concluding discussion, Yun *et al*. (2017) points to this need for assessing tradeoffs beyond the bioeconomic model to ultimately facilitate fully developed ecosystem-based management.

References

Arrow, KJ, P Dasgupta, LH Goulder, G Daily, P Ehrlich, G Heal, S Levin, K-G Maler, S Schneider, D Starrett, B Walker (2004). Are we consuming too much? *Journal of Economic Perspectives* 18(3): 147-172.

Arrow, KJ, P Dasgupta, LH Goulder, KJ Mumford, K Oleson (2012). Sustainability and the measurement of wealth. *Environment and Development Economics* 17: 317-353.

Barbier, EB (2011). *Capitalizing on Nature*. Cambridge University Press, New York.

Dasgupta, P (2001). *Human Well-Being and the Natural Environment*. Oxford University Press, New York.

Dasgupta, P, K-G Maler (2000). Net national product, wealth, and social well-being. *Environment and Development Economics* 5: 69-93.

Durant, JM, DØ Hjerman, PS Savarros, NC Stenseth (2008). Northeast Arctic cod population persistence in the Lofoten-Barents Sea system under fishing. *Ecological Applications* 18(3), 662-669.

Ekerhovd, N-A, SI Steinshamn (2018). Three species and three agents on a common ground. Manuscript.

Fenichel, EP, JK Abbott (2014). Natural Capital: From Metaphor to Measurement. *Journal of the Association of Environmental and Resource Economists* 1(1-2): 1-27.

Fenichel, EP, JK Abbott, SD Yun (2018). The nature of natural capital and ecosystem income. In *Handbook of Environmental Economics*, doi.org/10.1016/bs.hesenv.2018.02.002.

Greaker, M, K Grimsrud, L Lindholt (2017). The potential resource rent from Norwegian fisheries. *Marine Policy* 84: 156-166.

Hannesson, R, KG Salvanes, D Squires (2010) Technological Change and the Tragedy of the Commons: The Lofoten Fishery over 130 Years. *Land Economics* 86(4): 746-765.

Hänsel, MC, JO Schmidt, MH Stiasny, MT Stöven, R Voss, MF Quaas (2018). Ocean services for the Barents Sea – socio-economic effects of ocean warming and acidification on the Northeast Arctic cod fishery. In *AMAP Assessment 2018: Arctic Ocean Acidification*, pp. 91-99, Arctic Monitoring and Assessment Program (AMAP), Tromsø, Norway.

ICES (2016) Stock Annex: Herring (Clupea harengus) in subareas 1, 2, and 5, and in divisions 4.a and 14.a (Norwegian Spring Spawning). *ICES Stock Annex.* www.ices.dk

ICES (2017a). *ICES Advice on fishing opportunities, catch, and effort (cod.27.1-2).* International Council for the Exploration of the Seas, Copenhagen, DK. DOI: 10.17895/ices.pub.3092.

ICES (2017b). *ICES Advice on fishing opportunities, catch, and effort (cap.27.1-2).* International Council for the Exploration of the Seas, Copenhagen, DK. DOI: 10.17895/ices.pub.3272.

Jorgenson, DW (1963). Capital theory and investment behavior. *American Economic Review* 53(2): 247-259.

Kvamsdal, SF, LK Sandal (2015). The Ensemble Kalman Filter for Multidimensional Bioeconomic Models. *Natural Resource Modeling* 28(3): 321-347.

Link, JS (2010). *Ecosystem-Based Fisheries Management: Confronting Tradeoffs.* Cambridge University Press, New York.

May, RM, JR Beddington, CW Clark, SJ Holt, RM Laws (1979). Management of Multispecies Fisheries, *Science* 205: 267-277.

Mehl, S., A Aglen, B Bogstad, G Dingsør, K Korsbrekke, E Olsen, A Staby, TdL Wenneck, R Wienerroither, AV Amelkin, AA Russkikh (2016). Fish investigations in the Barents Sea winter 2016. *IMR/PINRO Joint Report Series* 4/2016, Institute of Marine Research (IMR), Bergen, Norway.

Nævdal, E, A Skonhoft (2018). New insights from the canonical fisheries model – Optimal management when stocks are low. *Journal of Environmental Economics and Management* 92, 125-133.

Obst, C, L Hein, B Edens (2016). National accounting and the valuation of ecosystem assets and their services. *Environmental and Resource Economics* 64: 1-23.

Olsen, EHG, I Røttingen, A Dommasnes, P Fossum, P Sandberg (2007). The Norwegian Ecosystem-Based Management Plan for the Barents Sea. *ICES Journal of Marine Science* 64(4): 599-602.

Polasky, S., B Bryant, P Hawthorne, J Johnson, B Keeler, D Pennington (2015). Inclusive Wealth as a Metric of Sustainable Development. *Annual Review of Environment and Resources* 40: 445-466.

Poudel, D, SF Kvamsdal, LK Sandal (2015). Stochastically induced critical depensation and risk of stock collapse. *Marine Resource Economics* 30(3), 297-313.

Poudel, D, LK Sandal (2015). Stochastic Optimization for Multispecies Fisheries in the Barents Sea. *Natural Resource Modeling* 28(3): 219-243.

Sandal, LK, SI Steinshamn (2010). Rescuing the prey by harvesting the predator: Is it possible? In *Energy, Natural Resources, and Environmental Economics*, E Bjørndal, M Bjørndal, PM Pardalous, M Rönnqvist (eds.), Springer, Berlin-Heidelberg.

Smulders, S (2012). An arrow in the Achilles' heel of sustainability and wealth accounting. *Environment and Development Economics* 17: 368-372.

Stiglitz, JE, A Sen, J-P Fitoussi (2010) *Mis-Measuring Our Lives: Why GDP Doesn't Add Up. The Report by the Commission on the Measurement of Economic Performance and Social Progress*, New Press, New York.

UNU-IHDP, UNEP (2014). *Inclusive Wealth Report 2014. Measuring progress toward sustainability.* Cambridge University Press, Cambridge, UK.

Yong, J, XY Zhou (1999). *Stochastic Controls: Hamiltonian Systems and HJB Equations*. Springer-Verlag New York, Inc.

Yun, SD, B Hutniczak, JK Abbott, EP Fenichel (2017). Ecosystem-based management and the wealth of ecosystems. *Proceedings of the National Academy of the Sciences* 114(25): 6539-6544.

Appendix

Table A1: Parameter values, equation (8)

Parameter	Value
ρ_1	1.8515
ρ_2	0.5490
ρ_3	0.4326
ϕ_1	0.6583
ϕ_2	0.072e-3
ϕ_3	8.3950
ϕ_4	0.0154e-3
θ_1	1.019
θ_2	3.191e3
θ_3	2.472
θ_4	3.252e3

Table A2: Parameter values, equation (9)

Parameter	Value
p_1	1.0
p_2	4.2638
p_3	4.5124
c_1	1.9777
c_2	0.6168
α	1.4

Note: Original values are scaled such that the leading parameter (p_1) is unity.

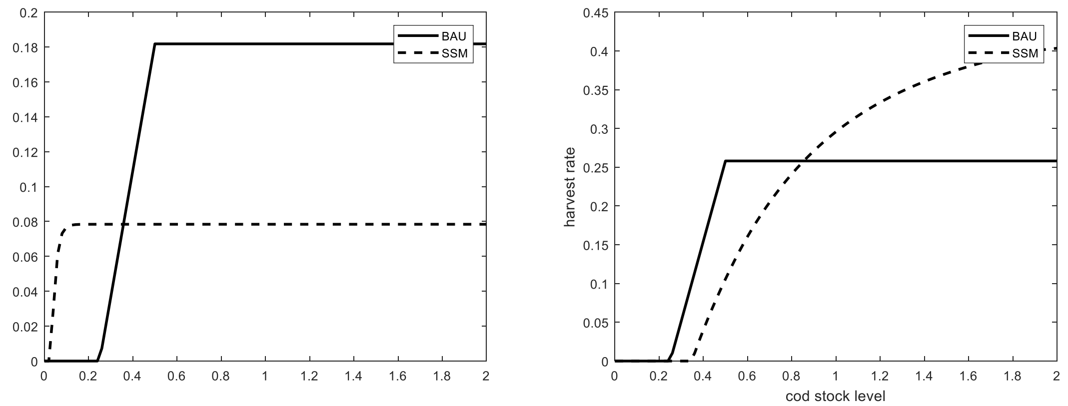

Figure A1: Harvest rate profiles as functions of stock levels, under BAU (solid curves) and SSM (dashed curves), for capelin (left panel) and cod (right panel).

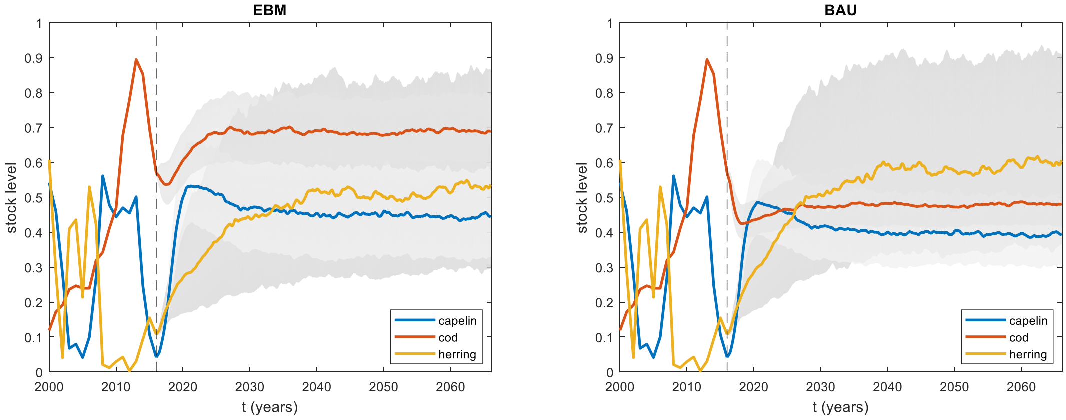

Figure A2: Observed and predicted stock levels (smoothed median paths) with 50% probability intervals (shaded areas) under EBM (left panel) and BAU (right panel).

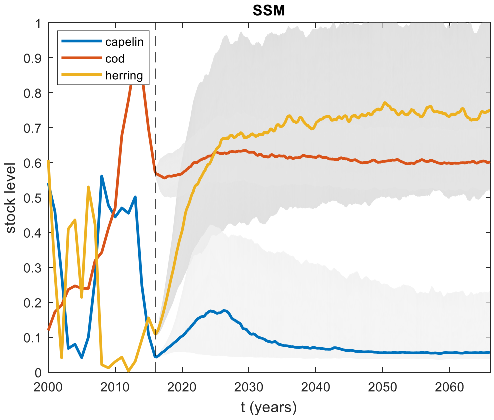

Figure A3: Observed and predicted stock levels (smoothed median paths) with 50% probability intervals (shaded areas) under SSM.

Acknowledgement

We acknowledge financial support from the Research Council of Norway (project no. 257630).

Table A3: Alternative model (reduced scaling of stochastic drivers) results summary for stock levels, shadow prices, and wealth in the 2016 state and long run (with 50% probability intervals) for EBM, BAU, and SSM. Shadow values and wealth index evaluated over predicted paths. Wealth uses same base as figures in Table 1.

State		Stock level			Shadow price			Wealth
		x	y	z	$\partial V/\partial x$	$\partial V/\partial y$	$\partial V/\partial z$	V
EBM								
	2016	0.04	0.56	0.10	1.86	3.16	2.22	1.26
	long run (mean)	0.39	0.73	0.90	0.46	2.21	-0.31	1.33
	long run (median)	0.38	0.71	0.89	0.44	2.18	-0.36	1.34
	50% interval	(0.32, 0.45)	(0.62, 0.82)	(0.72, 1.06)	(0.364, 0.544)	(1.72, 2.67)	(-0.390, -0.316)	(1.32, 1.35)
BAU								
	2016	0.04	0.56	0.10	0.764	3.67	3.65	1.08
	long run (mean)	0.35	0.56	0.92	0.413	4.03	0.0077	1.14
	long run (median)	0.35	0.51	0.91	0.385	4.36	-0.051	1.13
	50% interval	(0.31, 0.40)	(0.44, 0.64)	(0.75, 1.08)	(0.300, 0.495)	(4.02, 4.55)	(-0.130, 0.089)	(1.11, 1.16)
SSM								
	2016	0.04	0.56	0.10	18.7	2.93	-2.73	0.852
	long run (mean)	0.02	0.56	0.96	0.938	3.54	-0.0387	0.834
	long run (median)	0.02	0.55	0.95	0.902	3.57	-0.0322	0.834
	50% interval	(0.02 ,0.03)	(0.48 ,0.63)	(0.85, 1.06)	(0.842, 0.995)	(3.16, 3.98)	(-0.037, -0.027)	(0.816, 0.850)