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Forecasting the Nature Index

A comparison of methods

Olav Skarpaas
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Abstract

Skarpaas, O. & Pedersen, B. 2012. Forecasting the Nature Index: a comparison of methods - NINA Report 794. 28 pp.

The Nature Index (NI) is an aggregate of many biodiversity indicators developed to give an overview of the state and trends of biodiversity. The NI is currently also being considered and implemented for other applications such as monitoring of national ecological sustainability and assessments of local management plans. For these and other applications of the NI, methods for forecasting future trends and responses to pressures and management actions are needed.

In this report we discuss the opportunities for systematic forecasting of the NI. Our goal is two-fold: First, to provide a basis for decisions regarding forecasting of the NI framework in general and, second, to provide specific advice for forecasting the current implementation of the Nature Index for Norway.

The report briefly describes the current NI framework and its implementation in Norway and then discusses alternative forecasting methods in relation to the various purposes of forecasting and the properties of the NI with consequences for forecasting. Finally, a selection of methods is tested using simulated data and real data for forest in Norway.

Ideally, we need a framework for forecasting that allows non-linear dynamics and covariates (mechanisms) and can handle missing values and short time series. Multivariate analysis may be necessary for certain applications. Automated forecasts may be necessary when there are many time series, and useful for on-the-fly updates and forecasts online. No forecasting method completely satisfies these requirements. For indicators that are known to follow standard population dynamics models, these models may be the best predictive tools. For certain parameter values the Ricker model may be a useful representation of the aggregated NI. The drawback is that these models must be specifically tailored to each case. Of the generic tools, ARIMA seems to be the most promising, as it includes common population dynamics models as special cases and a method to deal with non-stationarity (differencing), the incorporation of pressures is straightforward, modeling dependence among indicators is possible and procedures for automated model selection and forecasting exist.

Our tests on simulated time series and data for forest suggest that ARIMA is the best alternative (considering bias and precision) among formal methods when the underlying dynamics are unknown and the time series are sufficiently long. When the underlying dynamics are known, specific dynamic models may perform better. However, for the current low number of data points in time in the NI (4-5), simple naive forecasts perform better than formal methods. When forecasts are made at the NI level, disregarding individual indicators, the best approach seems to be to extrapolate the current state; linear extrapolation of the trend between the two last observations is better when forecasts are made at the level of individual indicators and then aggregated.

We conclude that different approaches are needed for different forecasting purposes. For the short-term updates of the NI, forecasts are needed for expert-based indicators which will only be updated every five years. We recommend linear extrapolation of the trend between the last two observations, unless experts recommend reusing the last observation. For the future, we recommend further work to develop a fully quantitative and automated forecasting system for the NI. This should be based on forecasts for individual indicators, which can then be aggregated to any level of the NI. For indicators where tailored models are available (e.g. lynx) these models should be used if possible, but for most indicators we will need a generic tool. Overall, ARIMA seems to be the most promising framework.

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Sammendrag

Skarpaas, O. & Pedersen, B. 2012. Framskriving av Naturindeksen: en sammenligning av metoder - NINA Rapport 794. 28 s.

Naturindeksen (NI) er sammensatt av mange biodiversitetsindikatorer og er utviklet for å gi en oversikt over tilstand og trender i biologisk mangfold. Naturindeksen vurderes også for andre formål, for eksempel som nasjonal bærekraftsindikator og som måleverktøy for lokale forvaltningsplaner. For disse og andre anvendelser trengs metoder for å framskrive trender og effekter av påvirkninger og forvaltningstiltak.

I denne rapporten diskuterer vi mulighetene for systematisk framskriving av NI. Rapporten har to formål: For det første å gi et grunnlag for beslutninger om framskrivinger av NI generelt, og for det andre å gi spesifikke råd om framskriving av den gjeldende utgaven av NI for Norge.

Vi beskriver kort rammeverket for NI og implementeringen for Norge, og diskuterer alternative framskrivingsmetoder i lys av ulike formål med framskriving og egenskaper ved NI av betydning for metodevalg. Deretter tester vi et utvalg relevante metoder med simulerte data og reelle data for skog.

Ideelt sett trengs et framskrivingsrammeverk som tillater ikke-lineær dynamikk og kovariater (mekanismer), og som kan håndtere manglende verdier og korte tidsserier. Multivariate metoder kan bli nødvendig for noen anvendelser. Automatisert framskriving kan bli nødvendig når mange tidsserier må analyseres parallelt, og er nyttig for øyeblikkelig oppdatering og framskriving på nett. Ingen eksisterende framskrivingsmetode tilfredsstiller alle disse behovene. For indikatorer hvor man kan godtgjøre at de følger standard populasjonsmodeller, kan slike modeller trolig gi de beste framskrivingene. For bestemte parameterverdier kan Ricker-modellen gi en nyttig representasjon av den aggregerte NI. Ulempen er at slike modeller må tilpasses hvert enkelt tilfelle. Blant mer generiske verktøy virker ARIMA mest lovende, fordi dette rammeverket inkluderer vanlige populasjonsmodeller som spesielle tilfeller, har en innebygget metode for håndtering av ikke-stasjonaritet, gir muligheter for å inkludere påvirkninger, kan modellere avhengighet mellom indikatorer, og har etablerte prosedyrer for automatisk modellseleksjon og framskriving.

Våre tester på simulerte tidsserier og data for skog antyder at ARIMA er det beste alternativet (med tanke på presisjon og forventingsfeil) blant formelle metoder når den underliggende dynamikken er ukjent og tidsseriene er tilstrekkelig lange. Når den underliggende dynamikken er kjent, kan spesifikke modeller fungere bra. Men for det lave antallet observasjoner i tidsseriene i den nåværende NI (4-5) gjør enkle, naive framskrivinger det enda bedre. Ved framskriving av den totale NI, uten hensyn til enkeltindikatorer, er den beste tilnærmingen å ekstrapolere dagens verdi, mens lineær ekstrapolering av trenden mellom de to siste observasjonene er best når framskrivingen gjøres på indikatornivå før aggregering.

Vi konkluderer at ulike tilnærminger bør brukes for ulike formål. For kortsiktige oppdateringer av NI trengs framskrivinger av ekspertbaserte indikatorer som bare oppdateres hvert femte år. Vi anbefaler lineær framskriving av trenden mellom de to siste observasjonene, med mindre ekspertene anbefaler å gjenta siste verdi. For framtidige framskrivinger anbefaler vi å utvikle et fullt kvantitativt og automatisert framskrivingssystem for NI. Dette bør baseres på framskriving av enkeltindikatorer, som så kan aggregeres til et hvilket som helst nivå. For indikatorer hvor spesialtilpassede modeller eksisterer (f eks gaupe), bør disse modellene brukes dersom det er mulig, men for de fleste indikatorer vil vi trenge et generisk verktøy. Samlet sett er ARIMA det mest lovende rammeverket.

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Contents

Foreword

This report is a part of the methodological development of the Nature Index at NINA. The conceptual and quantitative framework of the Nature Index is described in a series of NINA Reports (e.g. NINA Report 347, 542, 797), and other documents (see the web pages of the Directorate for Nature Management, www.dirnat.no/naturindeks).

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1 Introduction

The Nature Index (NI) is an aggregated measure of biodiversity (Certain et al. 2011) developed in response to the need for systems that synthesize scientific information on biodiversity across marine and terrestrial environments and communicate this information to provide a basis for public discussion of biodiversity and its management (Loreau 2006). The NI has recently been implemented in Norway, where more than 300 indicators were evaluated and reported by 125 experts on all major taxonomic groups and ecosystems (Nybø 2010a, Nybø 2010b).

An important application of the NI is the assessment of overall state and trends of biodiversity with respect to the 2010 and 2020 targets of the Convention on Biological diversity (http://www.cbd.int/2010-target/). However, the NI is currently also being considered for several other uses. For instance, because of its broad coverage of marine and terrestrial ecosystems, the NI has recently been approved as an indicator for biodiversity in the set of sustainable development indicators reported annually in the National Budget, replacing the previous sustainability indicators with a more limited coverage (Finansdepartementet 2011). Several studies are also considering the relevance of the NI for management, by linking its many indicators to human pressures such as land use, harvesting and pollution (Skarpaas et al. in prep) and to local management plans (Garnåsjordet et al. in prep.).

For these and other applications of the NI, methods for forecasting future trends and responses to pressures and management actions are needed. So far the NI index incorporates and presents the current state and historical trend of biodiversity, with the bulk of information coming from expert assessments of indicators to be updated every five years. Such information is useful for evaluation of long-term trends and goals like the 2020 target, but is less well suited for reporting of short-term changes (such as the annual sustainability indicators in the National budget) and for devising management goals and options for the future.

In a study addressing how to improve the knowledge basis for precautionary approaches to biodiversity policy, Aslaksen et al. (2012) illustrate how the NI can be supplemented with information on “early warnings” of biodiversity from scientific experts providing data for the NI. The experts were asked to give a “forecast” of the state of their indicators 10 years ahead and give their considerations of the need for implementing management measures. The results indicate a potential for eliciting experts in assessing future trends and the need and potential for precautionary action. However, several of the experts reported that the forecasts were highly uncertain, and for 37% of the indicators, no forecasts were reported. The reasons for non-reporting range from ecological processes that make forecasts difficult (natural fluctuations) to practical reasons (lack of time and communication with surveyors) and science-policy reasons (the role of the expert as scientific advisor vs independent researcher). This suggests that to achieve a complete coverage of indicators and unbiased forecasts of the NI a more systematic approach to forecasting is needed.

In this report we discuss the opportunities for systematic forecasting of the Nature Index. We first briefly describe the current Nature index framework and its implementation in Norway (Chapter 2). We then discuss the various purposes of forecasting and the properties of the Nature Index with consequences for forecasting methods (Chapter 3), and review alternative forecasting methods in relation to the purposes of forecasting and the properties and context of the Nature Index (Chapter 4). Many forecasting methods are available (see e.g. Box & Jenkins 1976, Chatfield 1996, Hyndman & Khandakar 2008), but the number of techniques that are applicable in this context will be greatly limited by the task at hand. We briefly discuss the most common methods, and then test a selection of methods that we find particularly relevant (Chapter 5).

Our goal is twofold: First, to provide a basis for decisions regarding forecasting of the Nature Index framework in general and, second, to provide specific advice for forecasting the current implementation of the Nature Index for Norway.

2 The Nature Index: the state of biodiversity

In this chapter we review the Nature Index framework (Certain et al. 2011, Nybø 2010b) and further develop the notation (in accordance with Pedersen & Skarpaas 2012) to prepare for the discussion of forecasting in the following chapters.

The Nature Index (NI) is a composite measure of the state of biodiversity for a given area at a given time. The Nature Index is composed of a large set of indicators (308 in the current implementation for Norway) that represent various aspects of biodiversity across the major ecosystems, and respond to different human pressures. In principle, the indicators can represent any aspect of biodiversity from genes to ecosystems. In the current implementation for Norway, the indicators are mainly species, because species also partly reflect genetic diversity and the state of ecosystems, and because most knowledge and data are available at the species level (for further details on the indicator set and the selection process, see Certain et al. 2011, Nybø 2010a, Nybø 2010b).

To combine the indicators to produce an index, the indicators are scaled by a reference value, *i.e.* their value in a reference state (Certain & Skarpaas 2010, Certain et al. 2011, Nybø et al. 2008). This serves two purposes: First, the reference state, for each indicator, is supposed to reflect an ecologically sustainable state for the indicator, and the scaled value measures the deviation from this state: a value of 1 means that the indicator is in the reference state, whereas a value of 0 means a seriously degraded state. Second, because the scaled values are all dimensionless numbers between 0 and 1, they can be averaged across, for instance, municipalities, ecosystems, or taxonomic groups. Thus the use of a reference value facilitates a flexible combination of indicators expressed in different measurement units, such as abundance or species richness. This also facilitates the use of expert judgment, where values may typically be given on a relative scale (e.g. Scholes & Biggs 2005).

The Nature Index framework can be expressed mathematically as follows (Certain et al. 2011, Pedersen & Skarpaas 2012). Let NI_{kt} be the Nature index for location (e.g. municipality, county) *k* in year *t*. NI_{kt} is a weighted sum of the scaled biodiversity indicators S_{ikt}

$$NI_{kt} = \sum_i S_{ikt} W_{ikt} \ , \qquad (1)$$

where S_{ikt} are stochastic variables with domain [0,1], and W_{ikt} are the corresponding weights satisfying $\sum_i W_{ikt} = 1$.

The weights are introduced to correct for imbalances in the indicator set. With all weights equal to 1/n (where n is the number of indicators), the NI is a plain average of the indicators. Plain averaging of scaled indicators implies a “complete equivalence” assumption, *i.e.* that no municipality, no ecosystem, and no indicator is more important than another. This assumption is not always true. Moreover, despite efforts to balance the indicator set to represent different aspects of biodiversity, the indicators are not homogeneously distributed among taxonomic groups, pressures, or major ecosystems in Norway (Certain et al. 2011, Nybø 2010b).

The scaled indicators are functions of unscaled indicators U_{ikt}

$$S_{ikt} = f_i\left(U_{ikt}; U_{ik}^{ref}\right) \qquad (2)$$

where U_{ikt} are stochastic variables with domain [0,*u*], where for most cases *u* is in [1,∞), and U_{ik}^{ref} is a “reference value” (a scalar parameter) representing the value of the indicator in the reference state (Certain et al. 2011, Nybø 2010b). Scaling functions f_i generate values in [0,1] and belong to one of three families (OPT, LOW, MAX) of functions:

OPT:

$$f_i(x) = \begin{cases} \frac{x}{U_{ik}^{ref}}, & 0 \le x \le U_{ik}^{ref} \\ 2 - \frac{x}{U_{ik}^{ref}}, & U_{ik}^{ref} < x \le 2U_{ik}^{ref} \\ 0, & x > 2U_{ik}^{ref} \end{cases}, \tag{3a}$$

LOW:

$$f_i(x) = \begin{cases} \frac{x}{U_{ik}^{ref}}, & 0 \le x \le U_{ik}^{ref} \\ 1, & x > U_{ik}^{ref} \end{cases}, \tag{3b}$$

MAX:

$$f_i(x) = \begin{cases} 1, & 0 \le x \le U_{ik}^{ref} \\ 2 - \frac{x}{U_{ik}^{ref}}, & U_{ik}^{ref} < x \le 2U_{ik}^{ref} \\ 0, & x > 2U_{ik}^{ref} \end{cases}. \tag{3c}$$

NI_{kt} may be calculated from various sets of indicators resulting in indexes for e.g. all nature types or major habitats present at the location jointly, for each major habitat separately, or for single trophic levels within or across major habitats, i.e. NI_{kt} may be calculated from any set of indicators relevant for a specified purpose (Certain et al. 2011, Nybø 2010b, Nybø & Skarpaas 2008).

In the current implementation for Norway, data on the indicators were collected from 125 experts who reported means and quartiles of the indicators based on monitoring, models or expert judgment. Expert assessments were important because monitoring data are lacking for many important indicators, and because existing data are often biased towards problem areas (e.g. polluted waters). NI was calculated using Monte Carlo methods, sampling from distributions fitted to the reported mean and quartiles of each unscaled indicator (see Certain et al. 2011 for details). The indicators were then scaled using one of the three scaling functions (eq. 3a-c) as determined by the expert. The reported NI values are the median of the simulated, scaled and averaged indicator values. Weights were applied across the spatial axis, to keep the index area-representative, and across the indicator axis, to solve issues concerning the ecological significance of the various indicators (Certain et al. 2011).

In this report, we test forecasting methods for the NI on both real and simulated data (chapter 5). For the real data, we calculate the NI as described in (Certain et al. 2011). For the simulated data, we omit weights, and randomize the selection of scaling functions. The forecasting tests are described in chapter 5, after a discussion of purposes of forecasting (chapter 3) and the methodological options available (chapter 4).

3 Forecasting the Nature Index: methodological requirements

The first step towards forecasting is to develop a dynamic model for the Nature Index, i.e. shift from the current focus on state at time t to the development over time. Such a dynamic model may be constructed in different ways, as will be clear in the review of forecasting methods below (chapter 4). However, dynamic models are always constructed around one or more state variables, i.e. the variables that characterize the properties of the system that we are interested in forecasting.

In the case of the Nature Index, we may be interested in the state and development of the system at (at least) two levels: the aggregated index and the individual indicators. A dynamic model with NI as a state variable will give a picture of the aggregated development of biodiversity, but will not give any information on the underlying indicators. Dynamic models of individual indicators give more detailed information, and can always be scaled and aggregated to provide forecasts for the aggregated index. Thus while the indicator approach is computationally more demanding, it provides more information.

3.1 Methodological requirements for different forecasting purposes

The choice of state variable(s) and forecasting method(s) will depend on the purpose of the forecasting. In the preceding and ongoing development of the Nature Index for Norway, several general purposes of forecasting have emerged. For each of these, we have listed the corresponding requirements regarding methodology (**Table 1**).

One of the main purposes of the Nature Index is to measure the progress towards the goal of halting the loss of biodiversity – initially by 2010, now by 2020. If the single purpose of forecasting is to evaluate progress towards the 2020 goal at the national level, given a continuation of past conditions, the only requirement of a forecasting method is that it can produce a 10-year forecast (with minimal bias and maximal precision).

However, if one wants to know how underlying processes and mechanisms, such as human pressures and management actions, might affect future values, the forecasting method must also account for these processes. This can be done by including pressures or management covariates when fitting models to time series of the nature index or indicators, or by including such relationships known a priori.

Table 1*. Purposes of forecasting and methodological requirements following from each purpose.*

Purpose	Methodological requirements
Evaluate progress towards the 2020 goal	10-year forecast
Evaluate effects of management and pressures	Include covariates and mechanisms (dose-response relationships)
Evaluate local development (municipality, county)	Local forecasts
Validate individual indicators	Forecasting at indicator level
On-the-fly updates and forecasts online	Automated modeling and forecasting

While some pressures act over large areas (e.g. climate change), most pressures affect biodiversity locally or regionally (e.g. harvesting, land use, pollution). Similarly, some management actions are taken at the national level (e.g. establishment of national parks and the distribution of management resources), but most actions with direct effects on biodiversity are local. Therefore, there is a need to make local forecasts, with spatial resolution corresponding to the geographical scale of important pressures and management actions. In Norway, this means forecasts at the municipality level. Such local forecasts will make the Nature Index more useful as a planning tool.

In principle, local forecasts require no other methods than national forecasts, but the number of forecasts increases dramatically. In Norway there are more than 400 municipalities and marine regions. Developing models manually for each of these will be time-consuming and costly. Automated modeling and forecasting will greatly reduce costs.

Similarly, modeling individual indicators rather than the aggregated index implies that a great number of model-fitting and forecasting exercises must be carried out. This may be desirable for indicators of particular interest, such as large predators, harvested species and rare and threatened species. It may also be useful to compare such quantitative forecasts with those made by experts (Aslaksen et al. 2012). Forecasting all indicators individually gives great flexibility: the indicators can be aggregated in any way to produce forecasts for thematic indexes. However, if every indicator is to be forecast for each municipality, we are talking thousands of time series. With this number of time series, automated procedures for model-fitting, model selection and forecasting are absolutely necessary.

3.2 Methodological requirements and constraints of the Nature Index

In addition to methodological requirements arising from the purposes of forecasting (**Table 1**) there are several requirements and constraints related to technical properties of the Nature Index (**Table 2**).

First, the Nature Index (eq. 1) takes a value between zero and one. This means that forecasts of the aggregated index should be based on a dynamic model with the same domain. However, strict boundaries on the domain may not be that important in practice because the index will usually take intermediate values and remain relatively stable when there are many indicators. Moreover, if the NI forecast is an aggregate of forecasts for individual indicators, the scaling and aggregation of the indicators (eq. 1-3) will ensure that the forecasts are within [0,1].

Ideally, forecasting of individual indicators should be based on a solid knowledge of the dynamics of individual indicators, preferably in the form of calibrated and validated dynamic models. Validated dynamic models are presently not available for most indicators (Nilsen et al. 2011). This means that we will be forced to rely on the observed time series patterns for model development. The patterns in the current indicator set of the Nature Index for Norway range from invariant to linear and highly non-linear (Nybø 2010b). Any framework aiming to forecast individual indicators must take all of these forms into account. In many cases the dynamics are likely to be non-linear. Log-linear dynamics are easily adapted to linear frameworks by transformation or link functions, as they are linear on a log scale. More complex non-linear relationships may require non-linear dynamical systems approaches.

The observed trends in individual indicators and in the aggregated index (Certain et al. 2011, Nybø 2010b) imply that the time series are non-stationary (their mean changes with time). While there are modelling frameworks and forecasting methods that can handle non-stationary time series, many approaches assume stationarity (see below). To obtain reliable forecasts for the NI, the method must handle non-stationarity, either by not assuming stationarity in the first place, or by a reliable approach for achieving stationarity in non-stationary time series (e.g. differencing; see below).

Each indicator in the NI comes with a specified uncertainty, which is used to fit error distributions and compute uncertainty in the aggregated index (Certain et al. 2011). In the current implementation for Norway, different distributions may be used to simulate variability at different times at the same locality (e.g. Elg, Førde: Gamma in 1990, Lognormal in 2010). Thus, if forecasts are to be made at the indicator level, the distributions of the individual indicators should be properly represented. With a large number of indicators, the aggregated index (a sum) approaches a symmetric distribution (Pedersen & Skarpaas 2012) that should be well approximated by a normal distribution.

Several methodological requirements and constraints are related to the number of indicators and spatiotemporal resolution of the data. The NI for Norway has a large number of indicators and many spatial units, suggesting that automated modeling and forecasting may be useful or even necessary, as discussed above (chapter 3.1). In contrast, the indicators are currently reported for just a few points in time (1950, 1990, 2000, 2010), and several indicators have missing values at some of these times. Time series methods are most reliable for time series with a complete set of several observations at regular time intervals. This suggests that if formal forecasting methods are to be applied, techniques for data replacement may be needed. Alternatively, one may consider “naive” forecasts using the current state or a linear extrapolation of the last trend (see chapter 4).

The last challenge we will mention here is dependence among observations and indicators. Observations of a single indicator may be spatially autocorrelated, because of internal population processes (e.g. dispersal) or environmental factors (e.g. climate). Furthermore, several of the indicators in the NI are related through interactions such as trophic chains (Pedersen & Eide 2010). Thus, the development of indicators over time may depend on the states and development of the same or other indicators in neighboring spatial units. Such interdependence may influence the development of the NI. To properly account for interdependence, multivariate methods are needed (Buckland et al. 2007, Ives et al. 2003).

***Table 2**. Properties of the Nature Index for Norway and methodological requirements and constraints imposed by these properties.*

Property	Methodological requirements and constraints
Nature Index value between 0 and 1	Dynamic index model with domain [0,1]
Indicators with different dynamics	Flexibility in dynamic indicator models
Trends in indicators and index	Handling of non-stationarity
Indicator uncertainty	Proper representation of uncertainty
Many indicators	Automated modeling and forecasting
Many local units (municipalities, counties)	Automated modeling and forecasting
Observations every 10 (5) years	Multi-annual time steps
Short time series	Few model parameters
Missing values	Deletion or replacement technique
Dependence among indicators	Multivariate models

3.3 Conclusion: methodological requirements and constraints

To go beyond the simple purpose of evaluation progress towards the 2020 target, we need a framework for forecasting that allows non-linear dynamics and covariates (mechanisms) and can handle missing values and short time series. Multivariate analysis may be necessary for certain applications. Automated forecasts may be necessary when there are many time series, and useful for on-the-fly updates and forecasts online.

4 Forecasting methods

4.1 An overview

Forecasts are needed in many areas, including economy, demography, engineering, meteorology and biology. A wide range of forecasting methods have been developed for different applications (see e.g. Box & Jenkins 1976, Chatfield 1996, Hyndman & Khandakar 2008). The methods vary in several respects. Here we will be most concerned with how different methods meet the methodological requirements for forecasting of the Nature Index (**Tables 1 and 2**).

A large number of the indicators in the Nature Index for Norway are biological populations. In population biology, there is a long tradition for modeling population dynamics. **Table 3** summarizes a set of growth models that are often used in theoretical and applied population biology. These models come in continuous and discrete time versions, but because the Nature Index is updated in discrete time steps, we only present the latter.

A basic growth model is the exponential, which is a useful approximation for many ecological processes (Holmes et al. 2007). The trends in many of the (unscaled) indicators in the Nature Index resemble exponential growth or decline (Nybø 2010b). This suggests that the exponential may be a useful parsimonious model at the indicator level. However, without checks, the exponential model increases to infinity, while most (if not all) real biological populations experience some kind of density-dependent growth. Thus the exponential model is mainly relevant for declining processes or processes in early stages of growth.

Density dependent growth can be modeled in different ways. In the Gompertz model, the log growth rate is proportional to the log of population size ("weak" density dependence), whereas in the Ricker model, the log growth rate is directly proportional to population size ("strong" density dependence) (**Table 3**). These models can produce a variety of dynamics, ranging from stable equilibria via cycles to chaos, depending on the parameter values. We note that the Ricker model with parameters $\alpha \leq 1$ and $\beta \leq -\alpha$ is bounded by 0 and 1 (for $0 < X_0 < 1$ and deterministic growth), and therefore may be a suitable model for the aggregated Nature Index and indicators with domain [0,1]. Both Gompertz and Ricker contain the exponential model as a special case (with parameters $\beta = 1$ and $\beta = 0$ respectively).

Table 3*. Selected growth models with a basic formulation, a corresponding linear representation suitable for parameter estimation with e.g. linear regression, and a representation suitable for estimation and forecasting with the ARIMA framework. The following substitutions are made to obtain the linear representations from the basic formulations: $Y_t = log(X_t)$, $Z_t = Y_t – Y_{t-1}$. . In the ARIMA(p,d,q) representations of the linear models, p denotes the order of the autoregressive component, d denotes the order of differencing and q denotes the order of moving averages.*

		Linear representations	
Model	Basic formulation	Regression model	ARIMA(p,d,q)
Exponential	$X_t = \exp(\alpha) X_{t-1}$	$Z_t = \alpha$	ARIMA(0,1,0)
Gompertz	$X_t = \exp(\alpha + (\beta - 1) \ln X_{t-1}) X_{t-1}$	$Y_t = \alpha + \beta Y_{t-1}$	ARIMA(1,0,0)
Ricker	$X_t = \exp(\alpha + \beta X_{t-1}) X_{t-1}$	$Z_t = \alpha + \beta X_{t-1}$	-

For all of the models in **Table 3** it is straightforward to include covariates in the linear representation, such as pressures (e.g. human population size, built areas, etc). Furthermore, parameter estimation is simple because the models can all be written as linear equations for which parameters can be estimated by ordinary linear regression (**Table 3**). (Dennis & Taper 1994 showed that the maximum likelihood estimates are identical to the least squares estimates, see also Ponciano et al. 2005). However, note that because of the time-dependence, the standard errors estimated by linear regression are not correct. Instead, confidence intervals for parameters can be estimated using parametric bootstrap (see e.g. Ponciano et al. 2005). Alternatively, the parameters of the exponential and the Gompertz models may be estimated with the ARIMA time series approach (see below), which explicitly accounts for dependence in time.

Once the growth models are parameterized, it is straightforward to produce forecasts using the equations in **Table 3**. However, in so doing, one assumes that the model structure is appropriate and that the parameters estimated from the past dynamics remain valid in the future.

As already noted, there are no validated dynamic models for most of the indicators in the Nature Index. Furthermore, some indicators (e.g. community indexes, surrogates) cannot necessarily be expected to follow the dynamics of standard population models. Thus for a number of indicators, more open-ended approaches to time-series analysis and forecasting may be needed. Three common general-purpose approaches are spectral analysis, exponential smoothing and integrated autoregressive-moving average (ARIMA) time series analysis.

The basic idea of spectral analysis is to represent the time series using harmonic functions. This is particularly useful for cyclical time series, which are quite common in ecology (Kendall et al. 1998). The classical single spectrum (Fourier) analysis (SSA) applies to single time series and assumes stationarity. Cross-spectrum analysis allows comparison of multiple time series (i.e. covariates). Recent developments in wavelet analysis allow non-stationary cyclical patterns (Cazelles et al. 2008). However, long-term trends must still be removed from the data before analysis and the results may depend strongly on the detrending technique (Chatfield 1996). This limits the potential for this technique for the Nature Index. Besides, many of the indicators in the Nature Index do not behave cyclically (although some might). In one clearly cyclical case, small rodents (including lemmings), the indicator is the amplitude of the cycles rather than population size.

Exponential smoothing (ETS) is a technique that is well suited to handle non-stationary and non-linear processes. However, it includes no representation of mechanisms (although some overlap with ARIMA models). Exponential smoothing is also parameter intensive: 2 parameters are estimated per level and growth (with no seasonality). On a large data set of time series, exponential smoothing performed best on seasonal data, whereas ARIMA performed best on annual data (Hyndman et al. 2002).

The ARIMA framework combines autoregressive (AR) and moving average (MA) models (see e.g. Chatfield 1996, Kendall & Ord 1990). AR and MA models assume stationarity; in the integrated framework this is achieved by differencing. Various modifications of the framework allow incorporation of covariates (ARMAX, VARX), seasonal patterns (SARIMA), etc. The exponential and Gompertz models are special cases of the ARIMA framework (**Table 3**). Multivariate modeling is also possible (Buckland et al. 2007, Gilbert 2009, Holmes & Ward 2011, Ives et al. 2003). Finally, an important technical advantage of ARIMA is an established framework for automated modeling and forecasting (Hyndman & Khandakar 2008).

Time series methods are most reliable with many observations. For time series with few observations in time one may consider “naive” forecasts using the current state or a linear extrapolation of the last trend. The last state may be a good predictor of the next state for stable indicators. Extrapolation of the last trend may be a reasonable approach if growth rates change throughout the time series and there is no strong-density dependence or other factors causing regular or abrupt fluctuations.

4.2 Conclusion: relevant forecasting methods

No forecasting method completely satisfies the wish list of desirable properties discussed above (chapter 3, **Tables 1 and 2**). For indicators that are known to follow standard population dynamics models, these models may be the best predictive tools. For certain parameter values the Ricker model may be a useful representation of the aggregated Nature Index. The drawback is that these models and the computing tools for forecasting must be specifically tailored to each case.

Overall, ARIMA seems to be the most promising generic tool: this is a well established framework which includes common population dynamics models as special cases. A method to deal with non-stationarity (differencing) is built into the framework, the incorporation of pressures is straightforward, modeling dependence among indicators is possible and procedures automated model selection and forecasting exist. However, for short time series, as in the case of the Nature Index, one needs to limit differencing (which further reduces time series length) and the orders of autoregressive/moving average components (which require an increasing number of parameters).

With extremely few observations in time, formal methods are likely to fail. In such cases naive forecasts, e.g. extrapolating the current state or trend, may be a reasonable alternative.

5 Testing and comparing forecasting methods

We used simulations to explore how different forecasting methods (selected on the basis of the discussion in chapter 4) perform for different underlying dynamics (chapter 5.1). We also applied the methods to real Nature Index data for forest (Nilsen et al. 2010, Storaunet & Gjerde 2010) to test the forecasting procedures under realistic conditions (chapter 5.2). We concentrate on univariate methods, as multivariate methods require specification of relationships among indicators that are too many and too complex to go into in the time frame of the current project, but we return briefly to the issue of indicator interdependency in the discussion below.

5.1 Simulations

Simulations were used to explore the performance of forecasting methods when the underlying dynamics are governed by the exponential model (density-independent) vs. the Ricker model (density-dependent) (**Table 3**).

For each of the models, we ran 2000 simulations, each with 10 indicators with randomly selected scaling models (LOW, OPT or MAX, eq. 3a-c, selected with equal probability). The parameters of the models, the initial state U_0 and the reference value U_{ref} were set as follows to capture realistic variation in the NI indicators. For the exponential model: α ~ uniform(-0.2,0.2), U_{ref} = 100, U_0 ~ uniform(0,2*U_{ref}). For the Ricker model: α ~ uniform(-0.2,0.2), $\beta = -\alpha$, U_{ref} = 0.5, U_0 ~ uniform(0,2* U_{ref}). The chosen interval of α gives growth rates $R_0 = \exp(\alpha)$ in the interval (0.82, 1.22). In other words, the growth rates span from about 20% annual decrease to 20% annual increase in population size, which seems to cover most realistic average growth rates for the NI indicators.

In all simulations normally distributed process noise was then added to α when calculating the new indicator value in each annual time step. We show the results for a level of noise that corresponds to a fairly stochastic system (mean = 0, sd = 0.1), but also comment on how the results change for smaller levels of noise (i.e. closer to deterministic dynamics).

The indicators were simulated for 30 time steps (years). To the 20 first steps of each of these time series we fitted four models (Exponential, Gompertz, Ricker and ARIMA). The remaining 10 time steps were used to validate model forecasts.

A realization of the simulations of the exponential model and the forecasting process is illustrated in **Figure 2**, and the results of 2000 simulations with various fitted models are summarized in **Figure 3**.

We see that the estimates based on the aggregated NI (left panels in **Figure 3**) were not as precise as those based on individual indicators (right panels). There was also a weak tendency towards a negative bias, especially for long-term forecasts. This seems to be related to the relationship between starting values and the distribution among scaling models; the bias was smaller when the simulations were repeated with values $U_0 < 0.5^* U_{ref}$, which may correspond better to an “equilibrium” value for the NI when the scaling models are equally probable. However, the bias was generally small compared to the overall variability (imprecision) of the forecasts. The forecasts of the density-dependent models, i.e. the Gompertz and the Ricker, were less biased, but not as precise as the exponential and ARIMA forecasts. In sum, the best forecasts for the aggregated NI were obtained with ARIMA.

For individual indicators, the exponential model gave the best forecasts. This was expected, given that the exponential is the underlying simulation model for each of the indicators. However, all of the other methods also perform well. This is also expected, as all models contain the exponential as a special case. However, the ARIMA framework seems to be better at capturing the exponential dynamics than the Ricker and Gompertz models.

With smaller amounts of noise, all models performed better; with no noise, the fit was perfect for the forecasts based on individual indicators. But for the aggregated NI, the forecasts were imprecise even with no noise. This is because of the scaling process, which is not captured perfectly by the models.

In the simulations with the Ricker model (**Figure 4**), the forecasts were slightly less precise than for the exponential simulations (compare **Figures 5 and 3**), but the main results are the same: forecasts based on the individual indicators were more precise than those based on the aggregated index, and the results for the alternative models were quite similar (**Figure 5**). Again, the ARIMA framework provides the best long-term forecasts.

When the noise is reduced, the models performed better, in particular the Ricker model. With no noise, the parameter estimates and forecasts are perfect for the Ricker, but still imprecise for the other models. This suggests that when the underlying dynamics is density dependent, knowing the precise form of density dependence will be important for the ability to make precise forecasts.

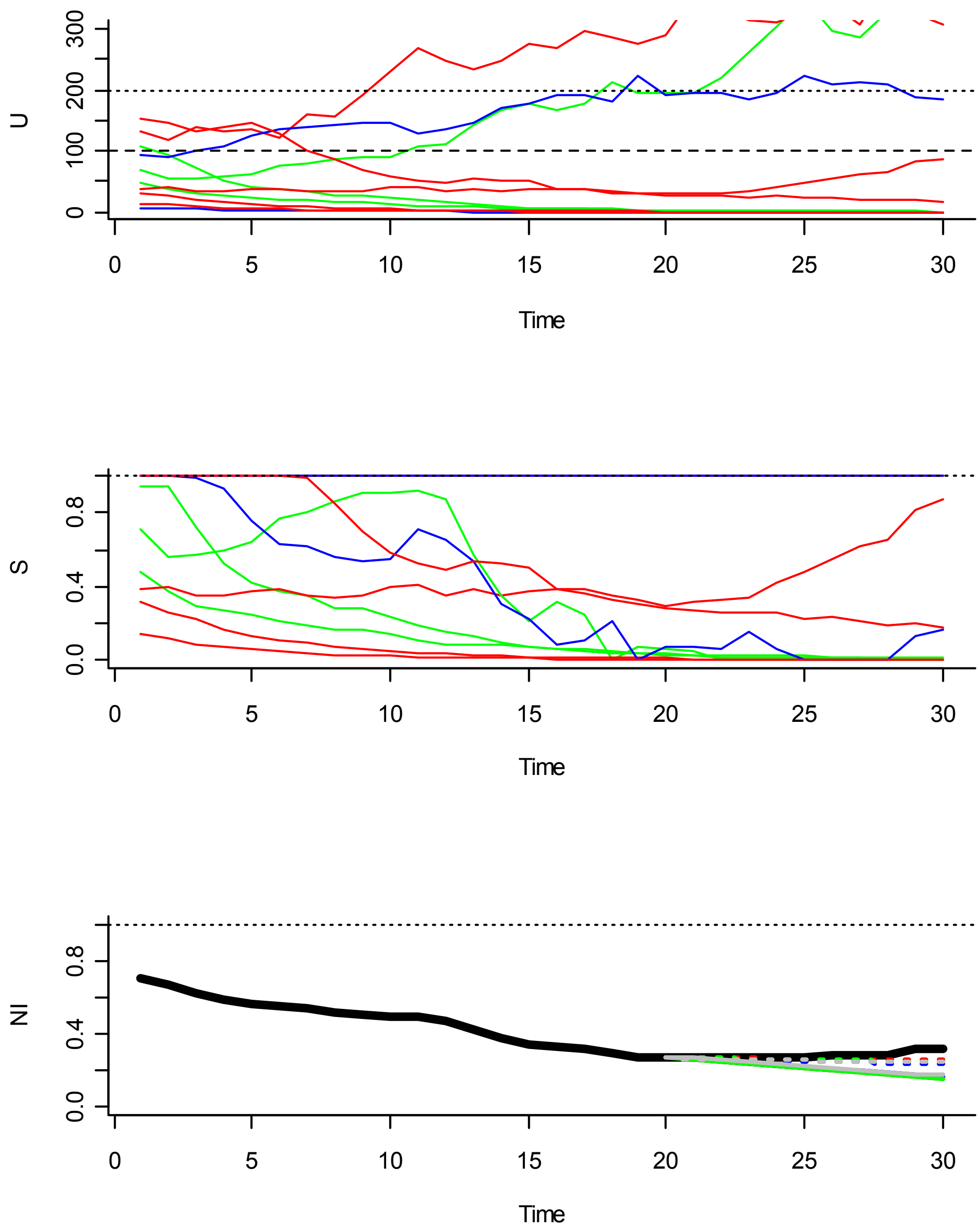

Figure 2. *Simulation and forecasts of the nature index based on the exponential model (**Table 3**) for individual indicators. The top panel shows time series of unscaled indicators (U) with colors according to their scaling model (LOW: red, OPT: green, MAX: blue). The horizontal lines indicate Uref (dashed) and 2Uref (dotted). The middle panel shows the scaled values (S) of the indicators in the top panel. The bottom panel shows the aggregated nature index (mean of Si, with equal weights; solid black line) and forecasts with the exponential model (blue), Riker (red), Gompertz (green) and ARIMA (gray). The solid colored lines represent forecasts based on the aggregated index and the dashed lines represent the corresponding forecasts based on individual indicators.*

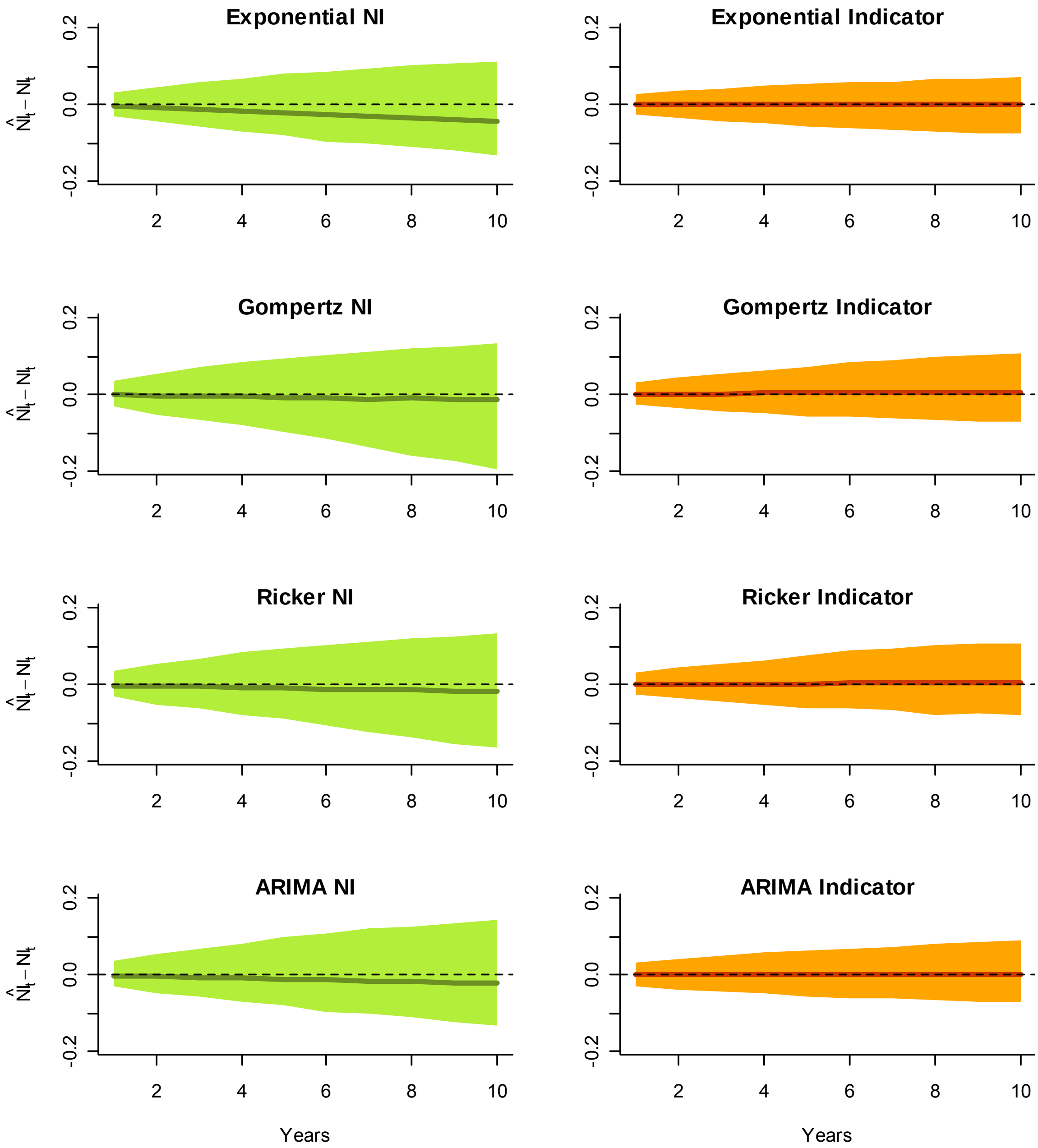

***Figure 3**. Bias and precision of forecasts of a simulated Nature Index (NI) for different methods when indicators were simulated using the exponential model (**Table 3, Figure 2**). Each panel shows the true value (dashed line), the median forecast of 2000 simulations (solid line) and the 95% quantiles of the forecasts (shaded area). The left panels show forecasts from models fitted to the aggregated NI; the right panels show the corresponding forecasts from models fitted to the individual indicators, which were then scaled and aggregated to produce a forecast for the NI.*

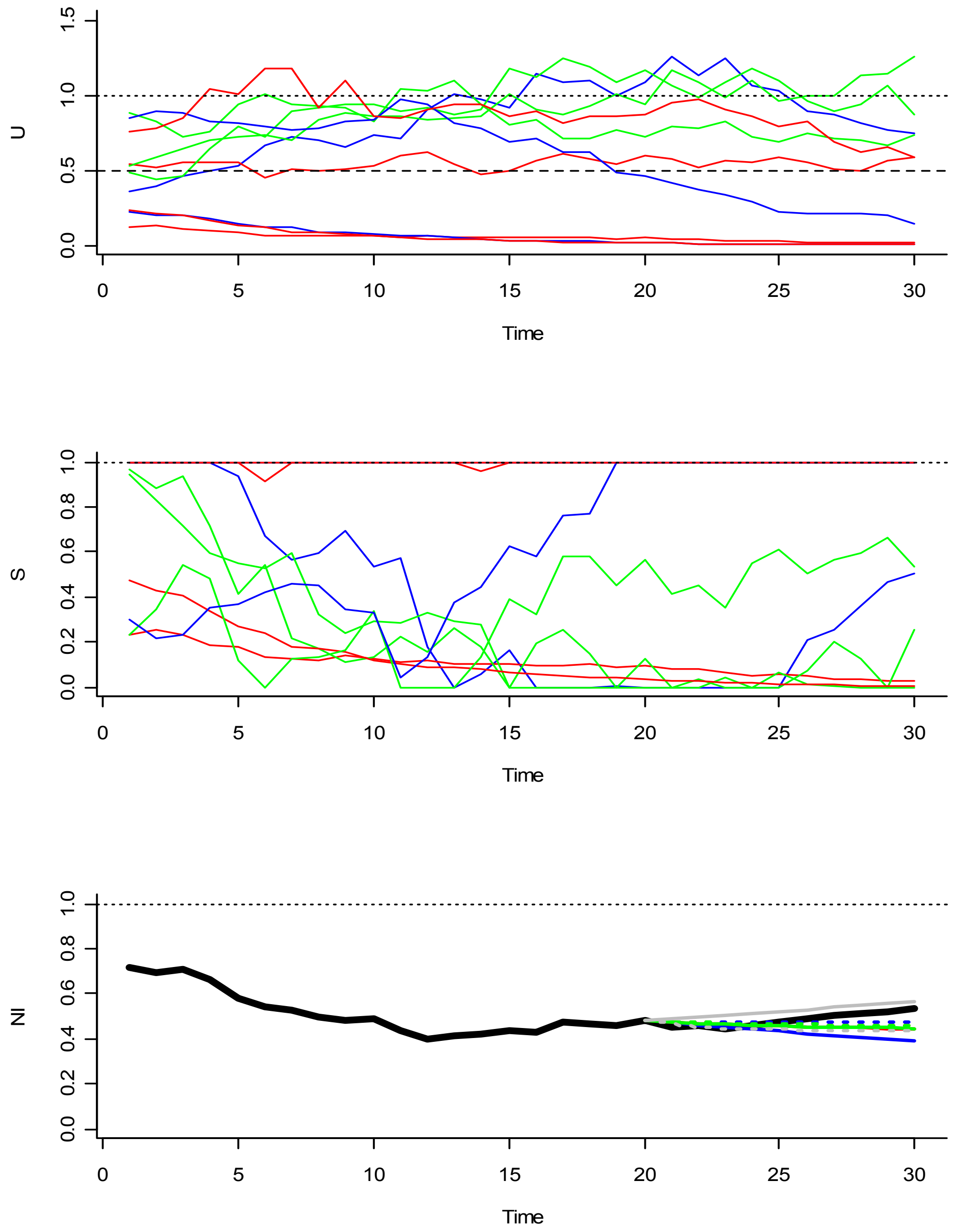

Figure 4. *Simulation and forecasts of the nature index based on the Ricker model (**Table 3**) for individual indicators. The top panel shows time series of unscaled indicators (U) with colors according to their scaling model (LOW: red, OPT: green, MAX: blue). The horizontal lines indicate U_{ref} (dashed) and $2U_{ref}$ (dotted). The middle panel shows the scaled values (S) of the indicators in the top panel. The bottom panel shows the aggregated nature index (mean of Si, with equal weights; solid black line) and forecasts with the exponential model (blue), Riker (red), Gompertz (green) and ARIMA (gray). The solid colored lines represent forecasts based on the aggregated index and the dashed lines represent the corresponding forecasts based on individual indicators.*

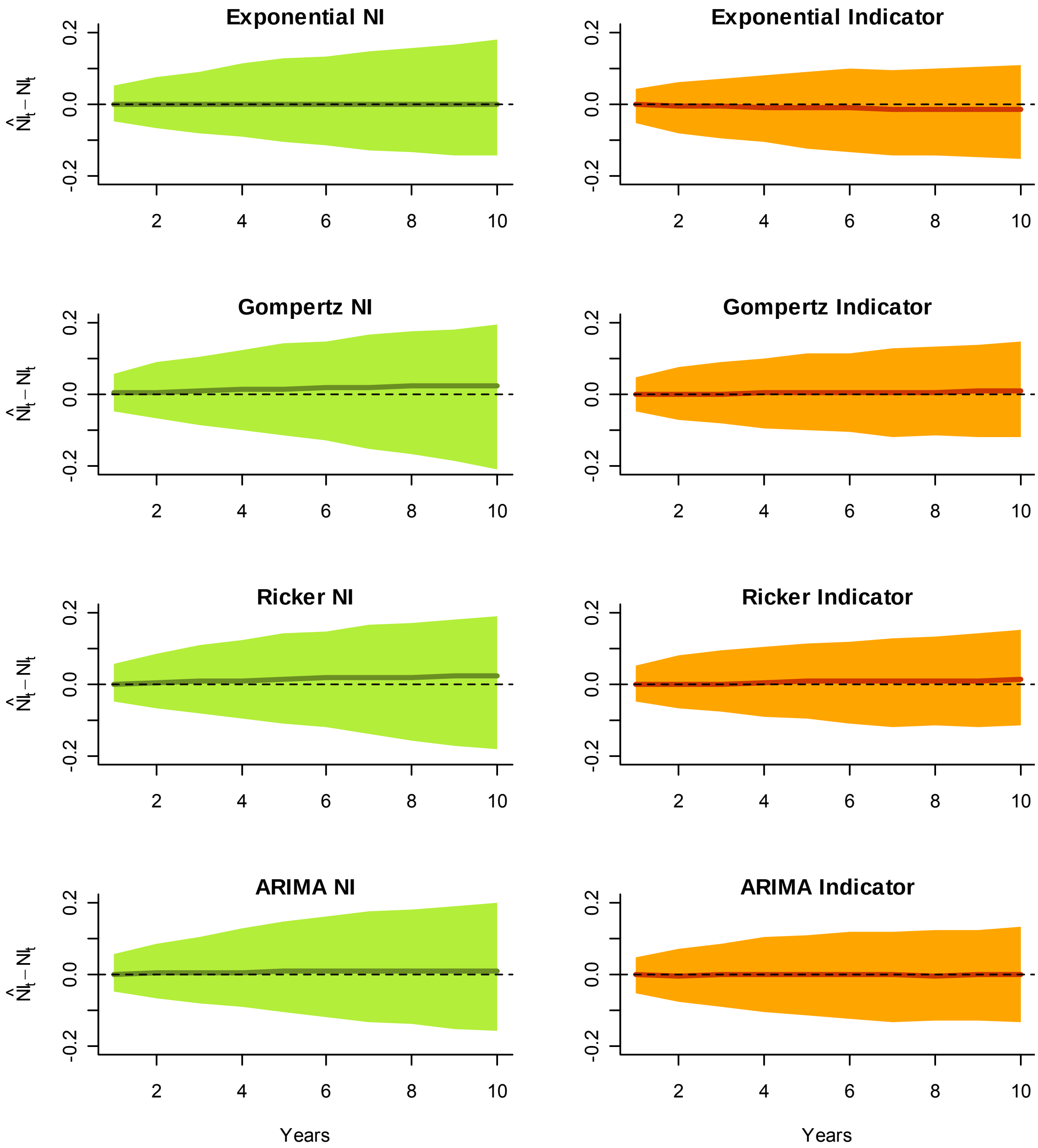

Figure 5*. Bias and precision of forecasts of a simulated Nature Index (NI) for different methods when indicators were simulated using the Ricker model (****Table 3, Figure 4****). Each panel shows the true value (dashed line), the median forecast of 2000 simulations (solid line) and the 95% quantiles of the forecasts (shaded area). The left panels show forecasts from models fitted to the aggregated NI; the right panels show the corresponding forecasts from models fitted to the individual indicators, which were then scaled and aggregated to produce a forecast for the NI.*

5.2 Data for forests in Norway

To test the forecasting procedures on realistic data sets, where the underlying dynamics are unknown, and the available time series are short, we applied the methods to real Nature Index data for forest in Norway (Nilsen et al. 2010, Storaunet & Gjerde 2010). We selected this ecosystem because it has the largest number of indicators among the major ecosystems (72), and because forecasting is considered as a tool for linking the NI to local forest management (Garnåsjordet et al. in prep.).

We used data for 1950-2000 to parameterize the models, and data for 2010 to validate the forecasts. For the 1950-2000 period the NI database has values for 1950, 1990 and 2000 only. Several of the methods require continuous time series with observations at regular time steps. We therefore used linear interpolation between 1950 and 1990 to fill in the data for 1960, 1970 and 1980.

We considered data replacement necessary to test the formal methods for these data (3 observations is hardly enough for any time series analysis method), but data imputation may distort the results and lead to biased estimates of growth rates and variability. Therefore, we also tested two simple, “naive” forecasting methods, which only use the last observations: (1) naive state approach: repeating last state, i.e. $x_{t+1} = x_t$, and (2) naive trend approach: linear extrapolation of last trend, i.e. $x_{t+1} = x_t + (x_t – x_{t-1})$.

We tested the methods at the aggregated index level, and at the level of individual indicators. In each case, we estimated model parameters for each of the 430 municipalities.

For the aggregated NI the best forecasts (in terms of bias and precision) for 2010 were provided by the naive state approach (**Figure 6**, green boxplots). The naive trend approach clearly underestimated the state for forest in 2010. The forecasts of the formal methods were somewhere in between the two types of naive forecasts. On average, all of the formal forecasts were negatively biased, and the density dependent models had many extreme deviations in both positive and negative directions. ARIMA performed best of the formal techniques for the aggregated NI.

When forecasts were made at the level of individual indicators, the naive trend approach performed best (**Figure 6**, orange boxplots). The naive state approach tended to overestimate NI in 2010. The exponential model performed best of the formal methods. The ARIMA forecasts were slightly too low, but much better than the density dependent models (Ricker and Gompertz), which both severely underestimated the NI for forest in 2010.

5.3 Conclusion: method performance

From the two tests on simulated time series (chapter 5.1) and real data for forest (chapter 5.2) it seems reasonable to conclude that ARIMA is the best alternative among formal methods when the underlying dynamics are unknown and the time series are sufficiently long. One needs more observations in time than the number of parameters to be estimated. In practice at least 5-10 observations will probably be needed for relatively stable indicators and 10-20 (or more) for fluctuating indicators. When the underlying dynamics are known, specific dynamic models may perform better. However, for the current short time series of real data in the Nature Index, simple naive forecasts perform better than formal methods. When forecasts are made at the NI level, the best approach seems to be to extrapolate the current state; linear extrapolation of the trend between the two last observations is better when forecasts are made at the level of individual indicators.

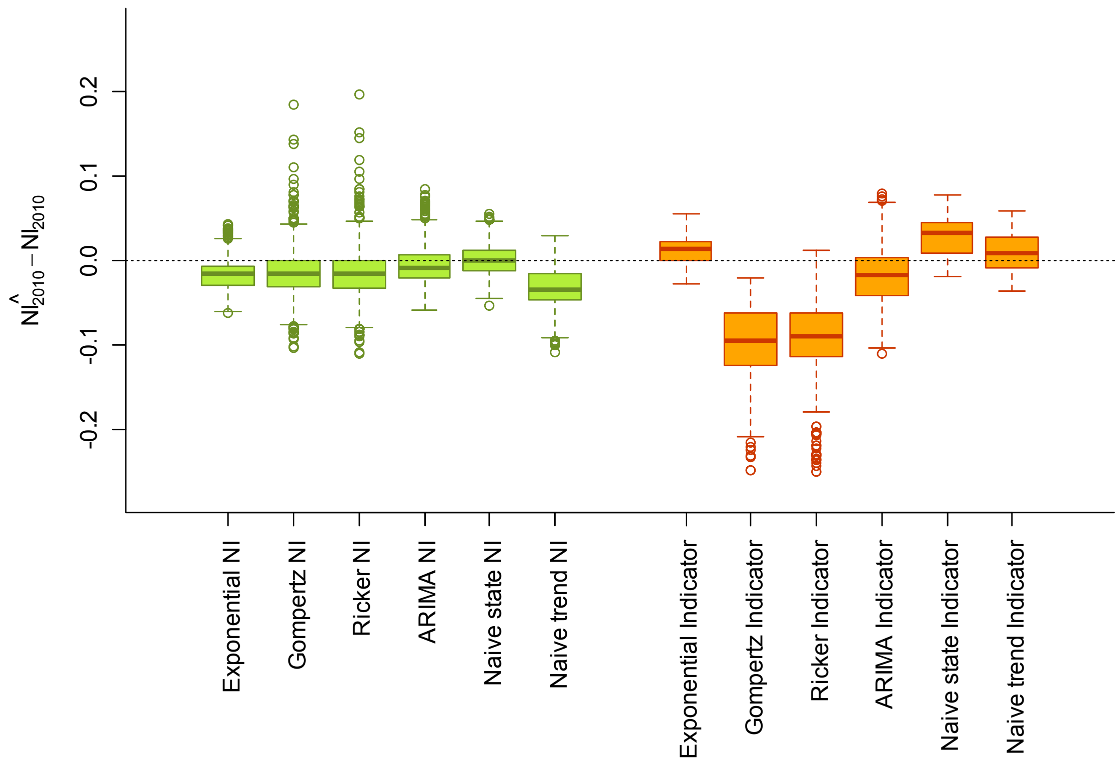

***Figure 6**. Bias and precision of forecasts of the Nature Index 2010 for forest, using different population models (**Table 1**), naive forecasts (**Table 2**) and applied to the aggregated NI (green) and individual indicators (orange). For each method, the boxplot shows the distribution of the difference of forecasts from the true value for 430 municipalities: solid horizontal line: median, box: inter-quartile range. The whiskers extend to the most extreme value that is at most 1.5 times the inter-quartile range away from the box; outliers are indicated by dots.*

6 Discussion

The results of the previous chapters of this report provide a basis for decisions regarding forecasting of the Nature Index framework with the current data for Norway, as well as in future cases or implementations elsewhere with longer time series.

It seems clear that for the current NI data, simple naive forecasts perform as well as or better than formal methods that make more or less strict assumptions regarding the underlying dynamics. When the time series are sufficiently long for more formal techniques, the ARIMA framework seems to perform best. This framework is the most flexible in terms of representing different kinds of dynamics of the methods tested here. It is also the most developed framework for including covariates, dependence among indicators and automated modeling and forecasting (Hyndman & Khandakar 2008), which makes it useful for many purposes.

Although we believe our results are fairly robust, there are a few caveats, both regarding the simulations (chapter 5.1) and the tests for the forest data (chapter 5.2).

Our simulations were relatively simple, with the same dynamic model for all indicators and a limited setup for simulating parameter values and scaling models. With different models for individual indicators, we still expect ARIMA to perform best, unless the underlying dynamic models are (assumed to be) known. In the latter case, a suite of tailor made dynamic models may perform better than ARIMA. We did not simulate effects of environmental covariates (e.g. pressures), but expect that any model including relevant covariates would perform better than models without, and that this would apply equally to all formal approaches. There was a relatively high variability in the simulated indicators compared to real indicators, so the forecasts for real data may be better than suggested by our results, as long as the forecasting model corresponds well with the underlying dynamics. In our simulations scaling models were selected at random. In the data for Norway there are more LOW models than OPT and MAX. This may affect the results for forecasts of the aggregated NI, but when forecasts are made at the individual indicator level the scaling models should not matter as they are accounted for in the aggregation process.

In the tests on real data, we focused on forests. Results for other ecosystems may differ. For instance, simple extrapolation of the current state of the NI may be less successful in ecosystems with a stronger negative trend (e.g. open lowland), positive trend (e.g. freshwater) or degree of stochasticity (e.g. ocean pelagic). In highly stochastic systems, forecasting at the aggregated indicator level may still be most successful because the variability of individual indicators is reduced by averaging. On the other hand, forecasting at the aggregated index level may be less successful compared to forecasting at the indicator level when the index is closer to 1 than in the forest case. This may be expected because the combination of non-linearities in the scaling functions near the reference states and uncertainty in indicator values induce bias in the NI (Pedersen & Skarpaas 2012). Compared to the other major ecosystems, forest has few indicators near the reference state and hence few local index values near 1, suggesting that forecasting at the index level may be less successful in other ecosystems. The poor performance of density-dependent models for individual indicators in forest may be partly due to linear interpolation of values between 1950 and 1990. This gives the relatively uncertain observations from 1950 a strong bearing on the time series. In this context an advantage of the naive indicators is that they consider only the more reliable recent observations. However, with additional historical information, and future updates of the Nature Index, the length and resolution of the time series will increase. Thus, missing values is mainly a problem of the past, and should therefore not be given too much weight in the choice of method. When time series on the indicators are longer, increased information on covariates and interdependence among indicators may also improve the predictions of formal methods compared to the naive forecasts. We expect correlation to affect several of the indicators through e.g. common pressures (land use, pollution, etc) and trophic interactions (e.g. herbivores and large predators). Accounting for correlations may reduce bias and increase precision of forecasts, particularly at the individual indicator level. As discussed above, information on interdependency is currently most easily incorporated in the ARIMA framework.

Should forecasting be carried out at the level of the aggregated index or at the level of individual indicators? Our results for simulated data and real data from forests seem to support opposite conclusions: For the simulated data, the most precise and least biased results were obtained with forecasts at the indicator level, whereas for forest data, the best results were obtained for the aggregated index. However, as discussed above, the forest data may give undue credit to forecasting at the aggregated index level. Other aspects also speak for the indicator level, such as the flexibility to include covariates and to aggregate to any level (e.g. ecosystem or thematic index) without redoing the forecasts.

7 Conclusion

On the basis of our discussion of the methodological requirements and constraints of the Nature Index (chapter 3), overview of available forecasting methods (chapter 4) and tests of relevant forecasting methods (chapter 5), we conclude that different approaches are needed for different forecasting purposes.

For the updates of the Nature Index in the next few years, forecasts are needed for expert-based indicators which will not be updated with new information until 2015. We recommend linear extrapolation of the trend between the last two observations, unless experts recommend extrapolation of the last state. This is because the current time series contain too few observations for formal methods, and because little information is yet available to assess the relationship between indicators and covariates quantitatively. Experts may be able to consider such information qualitatively and thereby judge the relevance of a constant state vs. a trend.

For the future, we recommend further work to develop a fully quantitative and automated forecasting system for the Nature Index. This should be based on forecasts for individual indicators, which can then be aggregated to any level of the NI. For indicators where tailored models are available (e.g. lynx) these models should be used if possible, but for most indicators we will need a generic tool. Overall, ARIMA seems to be the most promising framework.

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794

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