Evaluating ecosystem indicators performance under climate change

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Background: The Ecosystem Considerations Chapter of the Alaska Fisheries Science Center's (AFSC) Stock Assessment and Fisheries Evaluation Report provides indicator-based ecosystem assessments and report cards for the eastern Bering Sea (EBS) and Aleutian Islands (Zador 2012). Ten broad, community-level indicators were chosen for the EBS by an interdisciplinary team, based on the indicators' potential to determine the current state and likely future trends of overall ecosystem productivity. Annual updates to the ecosystem assessment synthesize information based on indicator status to inform the North Pacific Fishery Management Council (NPFMC). The ecosystem assessment is presented to the Council in direct conjunction with the quota-setting process, and so has allowed the Council to make direct quantitative adjustments to Allowable Biological Catches in response to specific ecosystem-wide indicators. The next direct steps, identified by the Council, are to develop and test formal thresholds for these indicators to trigger specific management actions.

Risk analysis has been proposed as part of integrated ecosystem assessments (IEA) to determine the probability that an ecosystem indicator will reach or remain in an undesirable state (Levin et al. 2009). Previous studies (Fulton et al. 2004, Link et al. 2009) have tested ecological indicators under different fishing scenarios but constant climate conditions. Likewise, since most ecosystem indicators for the Alaska region are based on fisheries survey data, their behavior has only been tested under past climate conditions. Our interest lies in understanding and testing key ecosystem indicators under various future climate scenarios, so as to inform the development of management strategies that are resilient to climate variability and climate change. As first proposed by Hollowed et al. (2011), we will use outputs from the recently completed simulations of the high resolution ocean and lower trophic level models (Bering10K-NPZD), developed as part of the Bering Sea Project (bsierp.nprb.org) (Wiese et al. 2012) to explore these ideas and address both indicator development and risk analysis. We assume the Bering10K-NPZD model is a faithful representation of the EBS shelf ecosystem and propose to use this model as a platform to standardize the biophysical response to multiple climate projections, and provide a baseline variability in forecasts as processed by the biophysical system. To do this we will: i) assess the model's ability to replicate the time series of selected ecosystem indicators using a hindcast from 1970 through 2012 (Hermann et al. 2013); ii) evaluate 9 forecasts using forcing files extracted from multiple realizations of three IPCC climate models proven to perform best in the Eastern Bering Sea, based on their ability to capture decadal variability and ice dynamics (Wang et al. 2009, 2012). One Bering10-NPZD forecast realization, spanning a range of ice conditions, has already been performed for each of these three IPCC models: CGCM-t47 (low ice), ECHOG (high ice) and MIROCM (medium ice).

The Bering10K-NPZD model is part of a vertically integrated set that is used as the operating model for Management Strategy Evaluation as described in Aydin et al. (2010). ROMS-

Bering10K is a coupled ocean-sea ice circulation model whose spatial grid is a subset of the ROMS-NEP5 model described and evaluated by Danielson et al. (2011), which itself builds on a model described by Curchitser et al. (2005). The model has a spatial resolution of ~10 km, and the subgrid extends from the western Gulf of Alaska to the Russian coast and slightly past the Bering Strait. Danielson et al. showed ROMS-NEP5 closely reproduces ice cover and spring ice retreat onset. The Bering10K simulation includes modifications to the heat and salinity fluxes of NEP5, which were calibrated using extensive mooring data (Hermann et al. 2013). NPZD refers to a coupled lower trophic model specifically designed to incorporate the ice dynamics of the Bering Sea, and includes nutrients, phytoplankton, copepods, euphausiids and detritus. Model coupling now includes feedback from the NPZD to Bering10K through phytoplankton density, which affects shortwave penetration (heat absorption) in the upper water column. The NPZD model has been described and tested by Gibson and Spitz (2012) as well as reviewed by a team of field biologists as part of a synthesis project funded by the National Science Foundation (Mordy and Lomas 2012).

Based on the documented performance of the climate models, Bering10K-NPZD, and a review of the ecosystem indicator time series updated annually for the EBS (Zador 2012), we propose to evaluate the ecosystem physical structure and lower trophic levels of the EBS using three ecosystem indicators: i) sea ice retreat index, ii) extent of the cold pool, and iii) mean zooplankton biomass.

We chose the seasonal ice retreat index because it has not performed well in very warm years, but it tracks variability important to current commercial fisheries. Mueter and Litzow (2008) found sea ice extent influences the biogeography of the groundfish community and explains 57% of the variability in commercial snow crab (Chionoecetes opilio) catch. The index is defined as the number of days past March 15 when sea ice coverage on the southern Bering Sea shelf is greater than 10% in a 2^o x 1^o box (bounded by 56.5 ^{o} to 57.5 ^{o} N, 165 ^{o} to 163 ^{o} W) on the southern EBS shelf, as calculated with a bootstrap algorithm from satellite imagery for 1978-present. From 2000 to 2005 sea ice coverage was less than 10% by March 15, so the index did not provide any information about ice retreat in those years.

The second index, cold pool extent, is defined by bottom temperatures less than 2°C. This cold pool has been shown to influence the latitudinal and longitudinal distribution of the groundfish community, including several important commercial species (Kotwicki et al. 2005; Spencer, 2008; Meuter and Litzow 2008, Stevenson and Lauth 2012). This in turn changes the spatial distribution of fishing effort (Haynie and Pfeiffer 2012). The cold pool also influences vertical mixing and stratification of the water column (Stabeno et al. 2012). We chose this index because given the decreasing trend in EBS ice extent estimated from various IPCC model forecasts (Wang et al. 2012) for the EBS, the cold pool is expected to change both in size and spatial location.

The third index, mean zooplankton biomass, is the mean of four regional zooplankton biomass survey estimates: basin, outer shelf, middle shelf and coastal waters as measured on stations by the T/S Oshoro Maru during summer. Greater consumption of high energy density zooplankton such as large copepods and euphausiids during cold years has been linked to increased survival of pollock recruitment (Heintz et al. 2013), hence a zooplankton-based indicator has good potential for use in management. Copepods and euphausiids from the NPZD can be used as-is to test different ways of measuring secondary productivity. This index is presently being explored under separate support for use in short-term (9 mo.) forecasts of pollock recruitmnent.

Objectives:

1. To evaluate our current ability to reproduce actual ecosystem indicator time series using output from an existing hindcast of the Bering10K-NPZD model. These indicators include sea ice retreat, extent of the cold pool, and mean zooplankton biomass.

2. To evaluate the ability of these ecosystem indicators to remain sensitive and informative under climate change using forcing files derived from forecast realizations of three different climate GCMs.

3. To compare and analyze forecast outputs of the GCMs with those from Bering10K-NPZD and develop where possible downscaling algorithms/proxies that directly relate global forcing to regional indicators.

Approach Objective 1: For sea ice retreat and cold pool extent, our primary interest is to quantify the accuracy of the model values, so as to define a baseline variability that will help evaluate the forecasts. For the zooplankton biomass index, our main focus is to establish its usefulness as a proxy for secondary production. We will first use the output from the 1970-2012 hindcast (already stored within the AFSC network), to reproduce the time series for the three ecosystem indicators using two methods: 1) the proxy/operating model method (index based on spatial integrals of the model output) and 2) the estimator/sampling method (index based on the present data collection and calculation process, applied to model output). For each index we will then perform a correlation analysis (Pearson and/or Spearman) and pattern similarity (Taylor diagrams) of modeled vs. data-driven time series. These comparisons will provide a quantitative assessment of the ability of the Bering10K-NPZD to reproduce observed patterns in the ecosystem indicators time series and the ability of the indicator to capture the dynamics of interest under present conditions. The table below summarizes the attributes and indicators to be tested.

Index/ Attribute	Proxy / operating model value	Estimator/sampling model value
Sea ice retreat/ Surface physical habitat	No. days after onset of ice retreat when sea ice coverage > 10% on the southern EBS shelf calculated from ice cover estimates on the Bering10K 10km grid over the simulated period	No. days past Mar-15 when sea ice coverage > 10% in a 2^{o} x 1^{o} box (56.5^{o} to 57.5^{o} N, 165^{o} to 163^{o} W) on the southern EBS shelf
Cold pool extent/ Bottom physical habitat	area with temperatures < 2^{o}C, extended down the middle shelf to the AK Peninsula and into Bristol Bay as measured on the bottom layer of the Bering10K 10km grid in summer	area with temperatures less than 2^{o}C, as measured on stations of the RACE bottom trawl survey sampled during summer
Zooplankton mean biomass/ Secondary production	wet weight (mg/m^3) of copepod and euphausiid biomass in the EBS basin, outer, middle shelf and coastal water during summer from Bering10K grid	mean wet weight (mg/m^3) of zooplankton biomass in the EBS basin, outer, middle shelf and coastal water as sampled on surveys

Approach Objective 2: We will run six additional forecast realizations of Bering10K-NPZD (3 are readily available) using IPCC climate model output, for application as forcing and boundary conditions. This forcing procedure has been described in Hermann et al. (2013). We will then generate time series of the indicators from the available forecast outputs (2012-2035), using both the operating model and the sampling model as developed from our examination of the hindcast. The performance of both the operating model and sampling model values under different climate scenarios will then be evaluated using regression analysis and pattern similarity analysis. We will also estimate the trend for each of the indicators and compare both trends and correlations across climate scenarios. We will evaluate the shortcomings of the indices and suggest complementary information/ modifications. The ice retreat index may require complementary information to be informative under warmer climate conditions; as the cold pool is expected to shift in size and location over time; we will evaluate the adequacy of the standard sampling grid under warmer climates and propose additional candidate stations. For the third index, we will test combinations of euphausiid-copepod biomass to complement or as alternatives to the current zooplankton biomass index.

Utilizing these improved indices, we will provide a range of forecast variability which will serve as context to the state of the ecosystem in view of the projected climate scenarios. We plan to choose conditions below and above the historical mean for each ecosystem indicator (e.g. one standard deviation above and below historical mean) and provide the frequency and magnitude of such events in the forecasted time series so as to inform how often these events can be expected in the future. While nine forecast time series are not enough to properly estimate the likelihood of these events, this exercise will provide a basis whihch can be refined as more forecasts become available. Both the ensemble mean of the forecasts and the expected frequency of events can provide a baseline to anchor risk analysis given climate change. The ensemble means with its associated variance for each indicator can then be used as proxies of climate change and associated uncertainty to be incorporated in stock assessments or other population dynamics models. Quantification of forecast uncertainty is further strengthened by objective 3.

Approach Objective 3: As an extension of the statistical analysis in Objective 2, we will compute the covariance between the large-scale forcing patterns of the GCMs and the regional indices generated by Bering10K-NPZD, subjected to the nine realizations of that large-scale forcing. This analysis – a model-based form of statistical downscaling – will proceed using both simple regression and multivariate EOF analysis (Hermann et al. 2013) of the output from global and regional models. Ideally this will enable the direct use of forecast realizations of the IPCC climate models to predict the regional indices, without the need to rerun simulations with Bering10K-NPZD for each global realization. At a minimum, this method will provide an economical way to estimate forecast uncertainty and other statistics of the regional indices, given the large number of global realizations which have emerged under the IPCC Assessments Reports. Such EOF-based methods– sometimes referred to as "regression on the pattern level" – have in fact been widely used in both global and regional climate prediction (van den Dool, 2007, Chapter 8, and references therein).

Benefits: 1) This constitutes a baseline assessment of model performance for future ecosystem tools using the Bering10K-NPZD model outputs. Its use as a platform to replicate these ecosystem indicators is a first step into incorporating the fish and fisheries modules into forecast models fully coupled to the biophysics of the EBS ecosystem. 2) The forecast time series of the indicators can be used as proxies of future climate in stock assessment and other statistical models. Their joint analysis will provide a quantitative estimate of variability and trends under different future climate scenarios, providing a first approach to uncertainty in climate change as processed by a biophysical system. Having these time series is the first step to developing and testing formal thresholds for these indicators to trigger specific management actions, as directed by the NPFMC. The time series will be part of the Ecosystem Considerations chapter for Alaska. 3) The suite of nine forecasts would be amongst the very few available worldwide with high spatial resolution and lower trophic levels. These may serve as data for analyses based on other scales and variables, and to create forcing files for general and *ad hoc* applications, including but not limited to stock assessments. Information derived from these forecasts will inform the development of better indicators that will remain informative despite climate variability. 4) The covariance analysis will provide a way to estimate forecast uncertainty, or potentially a way to use forecast realizations of the IPCC climate models to predict the regional indices directly, which greatly reduces high performance computing/storage needs as well as model run/data processing time. 5) The estimates of forecast uncertainty derived from this project and future analyses of the suite of forecasts directly address indicator development and risk analysis, two of the steps proposed for an IEA by Levin et al. (2009) and expected to be incorporated into the developing Alaska IEA.

It is of primary importance to test the response and information content of ecosystem indicators under future climate scenarios because the eastern Bering Sea is particularly vulnerable to warmer climate conditions. We may be able to improve those indices or qualities of the indices that currently fail to respond under warmer conditions by testing them under forecasted conditions; any improvements will be incorporated into future ecosystem assessments. The cold-warm variability of ice retreat and bottom temperature in the last 10 years in the eastern Bering Sea has proven to have short-term consequences for management and economic impacts (Meuter and Litzow 2008; Haynie and Pfeiffer 2012). Evaluating the different forecasts in terms of the frequency and magnitude of similar conditions, or conditions outside the historical range, will also inform how often these events can be expected in the future. Both the ensemble mean of the forecasts and the expected frequency of events can provide a baseline to anchor risk analysis given climate change. For example, in addition to showing a time series with respect to its historical mean, it can also be shown with respect to the forecasted ensemble mean. We expect this project to provide a first attempt at incorporating risk analysis of environmental conditions fundamental to assess ecosystem status that incorporates vulnerability to climate change.

Deliverables: The project will result in four main products: 1) paper on ‘Using high resolution models to improve ecosystem indicators and estimate uncertainty; I2) final report to FATE, 3) presentation at scientific conferences (FATE and PICES/ICES); 4) inclusion of indicators and uncertainty estimates to the Ecosystem Considerations chapter and Alaska Integrated Ecosystem Assessment.

The paper will be submitted for publication in a peer-reviewed publication (e.g. Marine Ecology Progress Series). Time series and results will be incorporated into the environmental assessment contained in the Ecosystem Considerations chapter produced annually by the AFSC for the NPFMC. Suggested complementary information to the ecosystem indicators will be presented to the eastern Bering Sea ecosystem team, as well as the Council's Bering Sea/Aleutian Islands Plan Team and Scientific and Statistical Committee, for their consideration and final decision on changes adopted. Model outputs will be available by request.

References

Aydin, K., N. Bond, E.N. Curchitser, M.G.A. Gibson, K. Hedstrom, A.J. Hermann, E.Moffitt, J. Murphy, I. Ortiz, A. Punt, and M. Wang. Integrating data, fieldwork, and models into an ecosystem-level forecasting synthesis: the Forage-Euphausiid Abundance in Space and Time (FEAST) model of the Bering Sea Integrated Research Program. ICES CM 2010/L21 downloaded 07/02/2012 http://www.ices.dk/products/CMdocs/CM-2010/L/L2110.pdf

Coyle, K.O., B. Konara, A. Blanchard, R.C. Highsmith, J. Carroll, M. Carroll, S.G. Denisenko, and B.I. Sirenko. 2007. Potential effects of temperature on the benthic infaunal community on the southeastern Bering Sea shelf: Possible impacts of climate change. Deep Sea Research II 54: 2885-2905.

Curchitser, E. N., D. B. Haidvogel, A. J. Hermann, E. L. Dobbins, T. M. Powell, and A. Kaplan.2005. Multi-scale modeling of the North Pacific Ocean: Assessment and analysis of simulated basin-scale variability (1996–2003), Journal of Geophysical Research. , 110, C11021, doi:10.1029/2005JC002902.

Danielson, S., E. Curchitser, K. Hedstrom, T. Weingartner, and P. Stabeno. 2011. On ocean and sea ice modes of variability in the Bering Sea. Journal of Geophysical Research, 116 , C12034, doi:10.1029/2011JC007389.

Fulton, E.A., Smith, A.D.M. and A.E. Punt. 2004. Which ecological indicators can robustly detect effects of fishing? ICES Journal of Marine Science, 62: 540-551

Gibson, G.A. and Y.H. Spitz. 2011. Impacts of biological parameterization, initial conditions, and environmental forcing on parameter sensitivity and uncertainty in a marine ecosystem model for the Bering Sea. Journal of Marine Systems 88: 214-231.

Haynie, A.C. and L. Pfeiffer. 2012. Why economics matters for understanding the effects of climate change on fisheries. ICES Journal of Marine Science. doi: 10.1093/icesjms/fss021

Heintz, R.A., Siddon, E.C., Farley, E.V., Napp, J.M. 2013. Correlation between recruitment and fall condition of age-0 pollock (Theragra chalcogramma) from the eastern Bering Sea under varying climate conditions. Deep Sea Research II 94: 150-156.

Hermann, A. J., G.A. Gibson, N.A. Bond, E.N. Curchitser, K. Hedstrom, W. Cheng, M. Wang, P.J. Stabeno, L. Eisner, K.D. Cieciel. 2013. A multivariate analysis of observed and modeled biophysical variability on the Bering Sea shelf: multidecadal hindcasts (1970-2009) and forecasts (2010-2040). Deep Sea Research II, doi:10.1016/j.dsr2.2013.04.007

Hollowed, A.B., K.Y. Aydin, T.E. Essington, J.N. Ianelli, B.A. Megrey, and A.E. Punt. 2011. Experience with quantitative ecosystem assessment tools in the northeast Pacific. Fish and Fisheries, 12:189-208.

Hollowed, A.B., S. Barbeaux, E.D. Cokelet, E. Farley, S. Kotwicki, P.H. Ressler, C. Spital, and C.D. Wilson. 2012. Deep Sea Research II 65-70:230-250.

Kotwicki, S., T. W. Buckley, T. Honkalehto, and G. Walters. 2005. Variation in the distribution of walleye pollock (Theragra chalcogramma) with temperature and implications for seasonal migration. Fishery Bulletin 103:574-587

Large, W.G., Yeager, S.G., 2008. The global climatology of an interannually varying air-sea 1009 flux data set, Clim. Dyn. 33, 341-364

Levin, P.S., M.J. Fogarty, S.A. Murawski and D. Fluharty. 2009. Integrated Ecosystem Assessments: Developing the Scientific Basis for Ecosystem-Based Management of the Ocean. PLoS Biol 7(1):e1000014. doi:10.1371/journal.pbio.1000014

Link, J.S., D. Yemane, L.J. Shannon, M. Coll, Y.J. Shin, L. Hill, and M.F. Borges. 2009. Relating marine ecosystem indicators to fishing and environmental drivers: an elucidation of contrasting responses. ICES Journal of Marine Science, 67:787-795.

Mordy, C, and M. Lomas, 2012. The impact of sea-ice on bottom-up and top-down controls of crustacean zooplankton and the mediation of carbon and energy flow in the eastern Bering Sea. Report of The Bering Sea Ecosystem Study (BEST) Synthesis Workshop, convened Feb 6-9, 2012 at The Bermuda Institute of Ocean Sciences (http://www.jisao.washington.edu/data/BEST-BSIERP).

Mueter, F.J. and M.A. Litzow. 2008. Sea ice retreat alters the biogeography of the Bering Sea continental shelf. Ecological Applications, 18: 309-320.

NSF. 2011. Award 1107250: Collaborative Research: Impact of sea-ice on bottom-up and top-down controls of crustacean zooplankton and the mediation of carbon and energy flow in the eastern Bering Sea.

Overland, J.E., M. Wang, K.R.Wood, D.B. Percival, and N. Bond. 2012. Recent cold and warm events in a 95-year context. Deep Sea Research II 65-70:6-13.

Saha, S. and coauthors, 2010. The NCEP Climate Forecast System Reanalysis. Bull. Amer. Meteor. Soc. 91, 1015.1057. doi: 10.1175/2010BAMS3001.1

Spencer, P. D. 2008. Density-independent and density-dependent factors affecting temporal changes in spatial distributions of eastern Bering Sea flatfish. Fisheries Oceanography 17:396-410.

Stabeno, P.J., N. B. Kachel, S. E. Moore, J.M. Napp, M. Sigler, A. Yamaguchi, and A. Zerbini. 2012. Comparison of warm and cold years on the southeastern Bering Sea shelf and some implications for the ecosystem. Deep Sea Research II, 65-7-: 31-45.

Stabeno, P.J., J. Napp, C. Mordy, and T. Whitledge, 2010. Factors influencing physical structure and lower trophic levels of the eastern Bering Sea shelf in 2005: Sea ice, tides and winds. Progress in Oceanography, 85: 180–196.

Stabeno, P.J., N.A. Bond and S.A. Salo. 2007. On the recent warming of the southeastern Bering Sea shelf. Deep Sea Research II, 54: 2599-2618.

Stevenson, D.E. and R.R. Lauth. 2012. Latitudinal trends and temporal shifts in the catch composition of bottom trawls conducted on the eastern Bering Sea shelf. Deep Sea Research II 65-7-:251-259.

van den Dool, Huug, 2007. Empirical methods in short-term climate prediction. Oxford University Press, Inc., New York, 215 p.

Wang, M., J.E. Overland, and P. Stabeno. 2012. Future climate of the Bering and Chukchi Seas projected by global climate models. Deep Sea Research II 65-70:46-57.

Wang, M., J.E. Overland and N. A. Bond. 2010. Climate projections for selected large marine ecosystems. Journal of Marine Systems, 79: 258-266.

Wiese, F.K., W.J. Wiseman Jr. and, T.I. Van Pelt. 2012. Bering Sea Linkages. Deep Sea Research II. 65-70:2-5.

Zador, S. (Ed). 2012. Ecosystem Considerations for 2012. Appendix C. Stock Assessment and Fishery Evaluation Report for the Groundfish Resources of the erring Sea/Aleutian Islands Region. North Pacific Fishery Management Council. 254p. downloaded 08/10/2012 http://access.afsc.noaa.gov/reem/ecoweb/Eco2011.pdf