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Climate Change Considerations for the North Pacific Albacore Stock Assessment[1]

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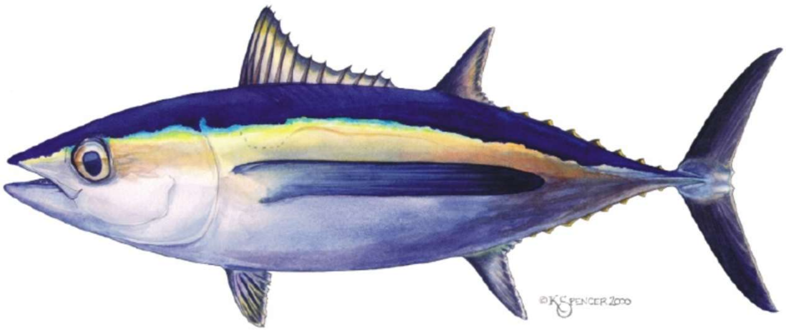

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ABSTRACT

Environmental variability influences the distribution, migration, and productivity of highly migratory pelagic species, such as North Pacific albacore (NPALB; *Thunnus alalunga*). NPALB inhabit temperate transition-zone habitats structured by oceanographic conditions including sea surface temperature, productivity gradients, and ocean fronts (Xu et al. 2013; Phillips et al. 2014; Xu et al. 2017). These environmental conditions vary across seasonal, interannual, and decadal time scales. Ocean warming, ecosystem shifts, and increased environmental variability may affect migration patterns, recruitment dynamics, and fishery availability. Recent analyses conducted within the International Scientific Committee for Tuna and Tuna-like Species in the North Pacific Ocean (ISC) Albacore Working Group (ALBWG) have explored relationships between environmental variability and albacore catch rates, suggesting that oceanographic conditions may influence the spatial overlap between fishing fleets and albacore habitat (Xu et al. 2013; Xu et al. 2017). In addition, long-term climate change may alter habitat suitability and migration pathways (Christian and Holmes 2016), as well as NPALB recruitment (Kiyofuji 2013). These changes may also influence the interpretation of abundance indices and biological parameters used in stock assessments. This working paper summarizes recent research relevant to climate-related changes in NPALB ecology and fisheries and synthesizes climate indicators and research priorities identified to guide future ALBWG work.

INTRODUCTION

Climate variability and long-term ocean change are increasingly recognized as important sources of uncertainty in fisheries stock assessment and management (Punt et al. 2014). For highly migratory pelagic species such as, North Pacific albacore (NPALB; *Thunnus alalunga*), environmental conditions play a fundamental role in shaping habitat suitability, migration patterns, and population dynamics. Variability in ocean temperature, productivity, and circulation occurs across seasonal, interannual, and decadal time scales, and can influence both the distribution of fish and their availability to fisheries.

NPALB stock assessments are conducted cooperatively by member countries of the International Scientific Committee for Tuna and Tuna-like Species in the North Pacific Ocean (ISC) and rely primarily on fishery-dependent data, including catch-per-unit-effort (CPUE) indices, to infer stock status and inform management decisions by the tuna regional fisheries management organizations in the Pacific, including the Western and Central Pacific Fisheries Commission (WCPFC) and the Inter-American Tropical Tuna Commission (IATTC). However, environmental variability can affect CPUE independently of abundance by altering spatial distribution, aggregation behavior, and the degree of overlap between fish and fishing fleets (Xu et al. 2013; Phillips et al. 2014; Xu et al. 2017). As a result, the ALBWG recognizes that changes in CPUE could potentially reflect environmentally driven shifts in habitat and catchability rather than true changes in stock size.

Recent research conducted by the ALBWG has highlighted the need to better understand and account for these processes when interpreting stock assessment outputs. In particular, there is increasing recognition that environmental indicators can provide important context for evaluating trends in fishery data and identifying potential climate-driven changes in NPALB ecology.

This working paper synthesizes our current understanding of the environmental drivers affecting NPALB ecology and identifies climate related considerations relevant to stock assessment results interpretations and evaluating model assumptions. The objective of this summary is to provide a framework for evaluating the potential influence of environmental variability on assessment outputs under changing ocean conditions.

ENVIRONMENTAL DRIVERS OF NORTH PACIFIC ALBACORE TUNA ECOLOGY AND IMPLICATIONS FOR STOCK ASSESSMENT

Several climate indicators relevant to the NPALB are summarized in Table 1 and reflect the current understanding that NPALB ecology is strongly structured by a combination of thermal habitat, ocean productivity, circulation dynamics, and mesoscale oceanographic features. These environmental drivers influence NPALB distribution, migration patterns, foraging behavior, and population processes, and therefore have direct implications for the interpretation of fishery-dependent data and the assumptions underlying stock assessment models.

Thermal Habitat and Distribution

Sea surface temperature (SST) is widely recognized as a primary determinant of NPALB habitat suitability and spatial distribution. Albacore are associated with specific thermal ranges characteristic of temperate transition-zone waters, and their seasonal migrations reflect movements that track these preferred conditions (Laurs and Lynn 1991; Childers et al. 2011; Christian and Holmes 2016). Habitat modeling and tagging studies further demonstrate that both horizontal distribution and vertical habitat use are closely linked to ocean thermal structure (Kitagawa et al. 2004; Xu et al. 2013). Variability in SST, including marine heatwaves and long-term warming trends, can shift the spatial distribution of suitable habitat, often resulting in poleward displacement (Christian and Holmes 2016). These changes are directly reflected in Table 1 through SST trends and anomalies, as well as fishery-based indicators such as CPUE centroid latitude. These shifts can alter the spatial overlap between NPALB and fishing fleets, affecting catchability and the representativeness of CPUE indices. As a result, the assumption that CPUE is proportional to abundance may not hold if changes in catch rates reflect environmentally driven redistribution rather than population size.

Ocean Productivity and Foraging Habitat

Ocean productivity plays an important role in structuring NPALB foraging habitat. Chlorophyll-a concentration (Table 1) is a key environmental indicator that serves as a proxy for primary productivity and is strongly associated with prey availability. NPALB are frequently observed in productive frontal regions, where enhanced trophic transfer supports high prey densities (Polovina et al. 2001; Bograd et al. 2004; Nieto et al. 2017). The Transition Zone Chlorophyll Front (TZCF) is also a particularly important indicator, acting as a dynamic boundary between oligotrophic subtropical waters and nutrient-rich subarctic waters. Seasonal and interannual variability in the position of the TZCF influences the distribution of productive feeding habitats and has been shown to correspond closely with NPALB catch locations (Bograd et al. 2004; Polovina et al. 2017; Santora et al. 2017).

Changes in productivity patterns, whether driven by climate variability or long-term ecosystem change, may influence NPALB growth, survival, and spatial aggregation. For stock assessment, these processes can affect CPUE by altering fish density and aggregation behavior, potentially introducing variability that is not directly related to stock abundance as it is often assumed to be.

Climate Variability and Ecosystem Processes

Large-scale climate variability, represented in Table 1 by indices such as the Pacific Decadal Oscillation (PDO) and the North Pacific Gyre Oscillation (NPGO), influences NPALB ecology through broad-scale changes in ocean temperature, circulation, and nutrient dynamics. The PDO has been associated with regime shifts in North Pacific ecosystems, including changes in plankton communities and forage fish abundance (Chavez et al. 2003; Kiyofuji 2013). Similarly, the NPGO reflects variability in gyre circulation and nutrient transport, influencing primary productivity and ecosystem structure (Di Lorenzo et al. 2008; Bograd et al. 2009). These climate drivers can affect NPALB through bottom-up processes, including changes in prey availability and ecosystem productivity, and may influence recruitment variability (Singh et al. 2016; Singh et al. 2018; Zhang 2018). However, empirical relationships between climate indices and NPALB recruitment remain uncertain. In stock assessment models, recruitment is often treated as a stochastic process or modeled using simplified assumptions. The potential influence of climate variability on recruitment introduces additional uncertainty and highlights the need to evaluate environmental drivers as part of model development and interpretation.

Ocean Structure and Vertical Habitat Use

Ocean structure, including mixed layer depth and thermocline characteristics, influences the vertical distribution of both NPALB and their prey. Mixed layer depth (Table 1) affects light availability, temperature gradients, and prey aggregation, all of which contribute to foraging efficiency and habitat use (Lehodey et al. 2008; Williams et al. 2015). Changes in vertical habitat structure may alter the availability of NPALB to surface fishing gears, thereby affecting catchability. For example, deeper mixed layers or changes in thermal stratification may result in fish occupying depths that reduce their vulnerability to surface fisheries. These processes challenge the assumption of constant catchability used in stock assessment models and suggest that vertical habitat dynamics should be considered when interpreting CPUE indices.

CLIMATE-RELATED RESEARCH PRIORITIES

The climate-related research priorities outlined in Table 2 build directly on the environmental indicators identified in Table 1 and reflect current understanding of how climate variability influences NPALB ecology, fishery interactions, and stock assessment processes. Collectively, these priorities are focused on improving the interpretation of fishery-dependent data, evaluating key model assumptions, and advancing the integration of environmental variability into stock assessment frameworks.

Environmental Influences on CPUE and Catchability

One of the most immediate and actionable research priorities is the incorporation of environmental variability into the CPUE standardization. Indicators in Table 1 such as SST, chl-a, mixed layer depth, and mesoscale features (e.g., eddy kinetic energy) are known to influence NPALB aggregation, distribution, and habitat accessibility (Lehodey et al. 2008; Williams et al. 2015; Xu et al. 2017). These processes can affect catchability independently of abundance, potentially biasing CPUE indices that are used as key inputs into stock assessment models (Phillips et al. 2014). Research should focus on quantifying these relationships using spatially resolved CPUE data and environmental covariates. Candidate approaches for this research include generalized linear and additive models (GLM/GAM), as well as spatiotemporal frameworks, which allow for the explicit incorporation of environmental drivers (Xu et al. 2013; Phillips et al. 2014). Improving CPUE standardization using these methods would reduce uncertainty in abundance indices and improve consistency with underlying ecological processes.

Climate-Driven Shifts in Spatial Distribution

Indicators such as SST, the TZCF, and CPUE centroid latitude (Table 1) provide strong evidence that NPALB distribution is dynamic and responsive to environmental variability (Polovina et al. 2001; Bograd et al. 2004; Xu et al. 2013). There is a need to quantify these spatial shifts and evaluate their implications for stock assessment (Table 2). Changes in NPALB distribution can alter the spatial overlap between fish and fishing fleets, leading to changes in catch rates that are not directly related to stock size (Phillips et al. 2014; Xu et al. 2017). Analyses of CPUE centroid shifts, habitat suitability modeling, and spatial mapping are therefore essential for diagnosing potential biases in CPUE and for informing spatial components of assessment models. This research priority is particularly important in the context of long-term ocean warming, which may drive poleward shifts in habitat (Christian & Holmes 2016).

Fishery Behavior and Effort Redistribution

In addition to changes in fish distribution, fishing effort itself may respond dynamically to environmental conditions. Indicators in Table 1, including SST, chlorophyll-a, and frontal features such as the TZCF, are known to influence fishing strategies and targeting behavior (Zainuddin et al. 2006; Nieto et al. 2017). The effects of fish distribution need to be disentangle from fleet behavior on CPUE (Table 2). Analyses of effort distribution, vessel movement, and environmental conditions can help separate changes in fishing strategy from changes in stock abundance (Phillips et al. 2014). This work is particularly valuable because it relies largely on existing fishery-dependent datasets and can provide important insights into the mechanisms driving observed CPUE patterns.

Recruitment Variability and Climate Linkages

Large-scale climate indices such as the PDO and NPGO (Table 1), may influence NPALB recruitment through bottom-up ecosystem processes (Chavez et al. 2003; Di Lorenzo et al. 2008). However, these relationships remain poorly understood and represent a key source of uncertainty in stock assessment.

It is important to evaluate potential linkages between climate variability and recruitment using time series analyses, including lagged correlations and regime shift detection (Kiyofuji 2013; Singh et al. 2016; Singh et al. 2018; Zhang 2018). Incorporating environmental covariates into stock–recruitment relationships may improve model performance and provide a more mechanistic understanding of recruitment variability. Given the central role of recruitment in determining stock dynamics, advancing this research area is important for improving both assessment accuracy and projections.

Impacts of Marine Heatwaves and Extreme Events

Marine heatwaves, represented through SST anomalies, are increasingly recognized as important drivers of short-term ecological change. These events can rapidly alter thermal habitat, stratification, and productivity, leading to shifts in NPALB distribution and changes in fishery performance (Christian & Holmes 2016; Cavole et al. 2016). Targeted analyses of these events, including comparisons of conditions before, during, and after heatwaves are important to help quantify the magnitude and duration of climate impacts and provide context for interpreting anomalous CPUE observations (Table 2). Understanding the effects of these extreme events is particularly important as their frequency and intensity are expected to increase under climate change.

Ocean Structure and Vertical Habitat Dynamics

Ocean structure indicators, including mixed layer depth and thermocline characteristics (Table 1), influence the vertical distribution of NPALB and their prey (Kitagawa et al. 2004; Lehodey et al. 2008). These processes affect the accessibility of fish to surface fishing gears and therefore have direct implications for catchability. Evaluating vertical habitat dynamics using oceanographic data and, where available, tagging observations to inform analytical approaches such as habitat envelope models and depth-use analyses can help quantify these relationships (Williams et al. 2015). Incorporating vertical habitat considerations into CPUE interpretation may improve understanding of variability in catch rates and reduce bias associated with unobserved changes in fish behavior.

Habitat Modeling and Climate Change Projections

Habitat suitability modeling represents a key tool for linking NPALB distribution to environmental drivers, including SST, chlorophyll-a, and mesoscale features (Zainuddin et al. 2006; Xu et al. 2013; Nieto et al. 2017). Habitat models can support spatial analyses and improve interpretation of CPUE patterns. Over longer time scales, they can be coupled with climate projections to evaluate potential changes in NPALB habitat under future ocean conditions (Lehodey et al. 2008; Christian & Holmes 2016). It is difficult to incorporate climate projection work directly into stock assessment models, however they provide important context for long-term management and trade-off and risk evaluations.

Ecosystem Productivity and Trophic Linkages

Indicators of ocean productivity, such as chl-a and frontal systems (Table 1), reflect the base of the food web supporting NPALB (Polovina et al. 2001; Bograd et al. 2004). However, the pathways linking climate variability to prey availability and NPALB growth and survival are not fully understood. Ecosystem and trophic research are longer-term priorities and approaches such as diet studies, prey field analyses, and ecosystem modeling can help clarify these relationships (Nieto et al. 2017). Although these processes are more difficult to quantify and incorporate into stock assessment models, they are important for understanding variability in stock productivity and resilience of the NPALB stock overall.

Migration Timing and Phenology

Climate variability may influence not only where NPALB are distributed, but also when they occupy different regions. Indicators such as SST and seasonal productivity (Table 1) can affect migration timing and seasonal availability to fisheries (Childers et al. 2011; Xu et al. 2017). Phenological shifts can be evaluated using seasonal CPUE data and environmental time series (Table 2). Changes in timing may affect seasonal CPUE patterns and should be considered in both data standardization and interpretation of stock assessment results.

RECOMMENDATIONS

Incorporating climate change considerations into the NPALB stock assessment should first focus on improving the interpretation of existing assessment outputs while laying the groundwork for long term integration of environmental processes in the future. A first step is to include a climate change considerations paragraph that summarizes recent trends in key environmental indicator (e.g., SST, chl-a, and large-scale climate indices) and link these to observed patterns in CPUE, spatial distribution, and recruitment variability. This paragraph should clearly identify implications of key stock assessment assumptions, including the relationship between CPUE and abundance and the assumption of catchability.

The ALBWG should prioritize using environmental information to contextualize assessment results rather than modify the assessment model structure. This includes evaluating whether recent changes in CPUE trends, spatial distribution, or fishery performance may be driven by shifts in thermal habitat or productivity. For example, poleward shifts in habitat or changes in mixed layer depth can alter the spatial overlap between NPALB and fishing fleets, resulting in changes in catch rates that are not related to stock size. Acknowledging these mechanisms in the assessment report will improve interpretation of model outputs. The next step would be for the ALBWG to begin incorporating environmental covariates into supporting analyses. Approaches such as GAMs, spatiotemporal models, and habitat suitability analyses can be used to quantify relationships between environmental variability and catchability. These analyses can initially be presented as sensitivity analyses, with potential for further integration into index development.

The assessment should also distinguish between near-term applications and longer-term climate change projections. While the direct integration of climate projections into stock assessment models remains limited, outputs from habitat models and ecosystem models can provide valuable context for evaluating future risks and uncertainties. The ALBWG should continue research on recruitment, environment linkages and fishery behavior so these processes can be formally incorporated into the assessment frameworks.

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TABLES

Table 1. Climate Indicators Relevant to North Pacific Albacore (NPALB) Stock Assessment.

Indicator	Ecological Relevance	Link to Stock Assessment	References
Sea Surface Temperature (SST) trends and anomalies	SST is a key driver of NPALB thermal habitat, influences migration routes and seasonal distribution in temperate transition-zone waters. SST anomalies reflect basin-scale warming and marine heatwave conditions that may shift suitable NPALB habitat poleward.	Changes in SST may change spatial distribution of NPALB relative to fishing fleets, potentially affecting catch per unit effort (CPUE) indices and catchability assumptions. Persistent warming trends may alter distribution patterns for NPALB, affecting interpretation of historical CPUE time series.	Childers et al. 2011; Xu et al. 2013; Christian & Holmes 2016
Chlorophyll-a (Chl-a) Concentration	Chl-a is a proxy for ocean productivity and prey availability in pelagic ecosystems. NPALB frequently forage in productive frontal regions.	Variability in productivity may influence growth, survival, and spatial distribution of NPALB, potentially affecting catch rates.	Polovina et al. 2001; Bograd et al. 2004; Zainuddina et al. 2006; Nieto et al. 2017
Transition Zone Chlorophyll Front (TZCF) Latitude	The TZCF is a major pelagic ecosystem boundary separating oligotrophic subtropical waters from productive subarctic waters; important foraging habitat for NPALB.	Shifts in TZCF position may alter the spatial distribution of NPALB and fishing effort, affecting spatial patterns in CPUE indices.	Polovina et al. 2001; Bograd et al. 2004
Pacific Decadal Oscillation (PDO)	PDO is basin-scale climate variability influencing North Pacific ocean temperature and ecosystem structure. Important influence on overall NPALB productivity.	PDO phase shifts may influence ecosystem productivity and potentially recruitment or growth processes affecting NPALB productivity.	Chavez et al. 2003 Singh et al. 2016; Singh et al. 2018; Zhang 2018
North Pacific Gyre Oscillation (NPGO)	NPGO reflects variability in gyre circulation and nutrient transport influencing productivity in the North Pacific. This drives the productivity at the base of the ecosystems that NPALB rely upon.	Changes in circulation may affect spatial distribution of productive habitats used by NPALB.	Di Lorenzo et al. 2008; Zhang 2018

Mixed Layer Depth	Mixed layer depth influences vertical habitat structure and prey distribution in pelagic ecosystems. This directly influences NPALB foraging efficiency, habitat use, energetic balance, and productivity.	Changes in mixed layer dynamics may affect NPALB vertical habitat use and catchability in surface fisheries.	Lehodey et al. 2008; Williams et al. 2015
Sea Surface Height / Eddy Kinetic Energy	Sea surface height and eddy kinetic energy are indicators of mesoscale oceanographic processes influencing NPALB prey aggregation and predator foraging success.	Mesoscale oceanographic features may influence spatial aggregation of NPALB and fishing success.	Zainuddina et al. 2006
CPUE Centroid Latitude	CPUE centroid latitude is a fishery-derived indicator reflecting the spatial distribution of NPALB catches.	Poleward shifts in CPUE centroid may indicate climate-driven distribution changes affecting fishery indices used in the NPALB stock assessment.	Xu et al. 2013; Phillips et al. 2014; Xu et al. 2017; Ijima et al. 2023

Table 2. Climate related research priorities for North Pacific Albacore (NPALB) stock assessments.

Area of Research	Research Priority	Indicators	Application to Stock Assessment	Data Requirements	Candidate Analytical Approaches	References
CPUE Standardization and Catchability	Quantify effects of environmental variability on CPUE and catchability	SST, chl-a, mixed layer depth, eddy kinetic energy	Improve abundance indices via environmental standardization	Spatial CPUE, SST, chl-a, ocean reanalysis (MLD, SSH; GLORYS12V1 (CMEMS))	GLM/GAM with environmental covariates; spatiotemporal models (e.g., VAST); model comparison diagnostics	Xu et al. 2013; Phillips et al. 2014; Xu et al. 2017
Spatial Distribution Shifts	Evaluate climate-driven changes in NPALB distribution and fishery overlap	SST, TZCF latitude, CPUE centroid latitude	Diagnose spatial bias in CPUE; inform stratification	Spatial CPUE, SST, chl-a, TZCF metrics	Time series of centroid shifts; habitat suitability models; geostatistical mapping; EOF/spatial trend analyses	Xu et al. 2013; Phillips et al. 2014; Nieto et al. 2017
Fishery Behavior and Effort Redistribution	Assess how fishing effort responds to environmental variability	SST, chlorophyll-a, TZCF, mesoscale features	Separate fleet dynamics from stock signals in CPUE	Effort data, vessel location data, environmental covariates	Effort standardization models; GAMs of effort vs environment; fleet dynamics models; spatial overlap indices	Phillips et al. 2014; Xu et al. 2017
Recruitment–Environment Linkages	Evaluate relationships between climate variability and recruitment	PDO, NPGO, SST, productivity indicators	Inform recruitment assumptions and variability	Recruitment time series, climate indices, SST/productivity	Correlation and lag analysis; regime shift detection; GAMs; state-space stock–recruit models with covariates	Chavez et al. 2003; Singh et al. 2016; Singh et al. 2018; Zhang 2018
Marine Heatwave Impacts	Quantify impacts of extreme events on distribution and CPUE	SST anomalies, marine heatwave indices	Interpret anomalous CPUE; improve diagnostics	SST anomaly datasets, heatwave indices, CPUE	Before–after/control-impact (BACI) analyses; anomaly detection; composite analysis of heatwave periods	Christian and Holmes 2016; Cavole et al. 2016

Vertical Habitat and Catchability	Assess how ocean structure affects vertical distribution and gear vulnerability	Mixed layer depth, thermocline structure	Evaluate constant catchability assumptions	Ocean reanalysis, tagging data, CPUE	Habitat envelope models; depth-use analysis from tagging; GAMs linking CPUE to vertical structure	Kitagawa et al. 2004; Williams et al. 2015; Lehodey et al. 2008
Habitat Suitability Modeling	Develop models linking NPALB distribution to environmental drivers	SST, chl-a, TZCF, mesoscale indicators	Support spatial modeling and simulation testing	CPUE or presence data, environmental covariates	Species distribution models (GAM, MaxEnt); spatiotemporal models; ensemble habitat models	Zainuddin et al. 2006; Nieto et al. 2017; Xu et al. 2013
Climate Change Projections	Project future NPALB habitat under climate scenarios	SST trends, productivity, ocean structure	Inform long-term management context	Climate model outputs, habitat models	Downscaled climate projections; habitat projections; scenario analysis using SDMs or SEAPODYM-type frameworks	Lehodey et al. 2008; Christian and Holmes 2016
Ecosystem Productivity and Prey Linkages	Understand trophic drivers of growth and survival	Chlorophyll-a, TZCF, NPGO	Inform productivity assumptions	Diet data, prey data, ecosystem outputs	Trophic modeling (e.g., Ecopath/Ecosim); correlation analyses; bioenergetics models	Polovina et al. 2001; Bograd et al. 2004; Nieto et al. 2017
Migration Timing and Phenology	Evaluate shifts in migration timing and seasonal availability	SST, productivity, CPUE timing	Improve seasonal CPUE interpretation	Seasonal CPUE, environmental time series, tagging	Time series decomposition; phenology metrics; GAMs of timing vs environment	Childers et al. 2011; Xu et al. 2017