DEVELOPING MARINE HABITAT SUITABILITY MODELS IN THE ARCTIC FROM REMOTELY-SENSED DATA AND TRADITIONAL ECOLOGICAL KNOWLEDGE

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Authorization to Submit Thesis

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Abstract

There is a lack of information regarding critical habitat for many marine species, including the bearded seal, an important subsistence species for the indigenous residents of Bering Strait. An objective approach to modeling marine mammal habitat in polar regions using Traditional Ecological Knowledge (TEK) of Alaskan Native hunters is developed to address this gap. The approach substitutes lifetime and cross-generational knowledge of subsistence hunters and their harvest data for observational knowledge gained from formal scientific field surveys of marine mammal sightings. TEK information for summer and fall seasons was transformed to seal presence/absence and used to train Classification Tree Analyses (CTA) of environmental predictor variables to predict suitable habitat for bearded seal in Bering Strait. A Kappa of 0.883 was achieved for habitat classifications. The TEK information used is spatially restricted, but provides a viable, replicable alternative when Western scientific observational data is limited or non-existent.

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Chapter 1: Project Background

Humans have been active participants in the changing Arctic environment for thousands of years. During the long months of winter, ice often caps the seascapes of this vast region. When the sun returns to Arctic skies, it brings gradual warming which is accompanied by annual thinning and disappearance of sea ice. The sun eventually dips below the horizon as another winter approaches, chilling the environment back to its familiar frozen state. Throughout these annual changes, human hunters venture out onto the pack ice and fragmented ice floes, carrying with them skills and knowledge passed down from time immemorial. Knowing when and where to hunt marine mammals is not for sport or trophies, but instead for subsistence and survival. Relying on marine mammals for subsistence may be jeopardized as the Arctic experiences fundamental shifts in temperature regimes that in turn may result in shifting patterns of habitat. For over a decade, MODIS Aqua has stood sentinel over the changing Arctic seas, recording the growth and diminishment of the sea ice and other characteristics of the marine environment and producing a collection of digital imagery of changing conditions. The temporal and spatial information recorded from space may be combined with information obtained by hunters who have accumulated a lifetime of experiences observing and pursuing marine mammals across Arctic marine environments; this pairing of information sources may be a step toward better understanding Arctic marine mammal habitat characteristics.

Global climate model projections call for a warming Arctic and declining sea ice throughout the 21st Century (Maslowski et al. 2012). Arctic sea ice is a dynamic polar phenomenon, covering approximately 15 million km^2 at its March maximum each year, and shrinking to approximately 7 million km^2 by September (Kwok and Untersteiner 2011). The

September minimum sea ice extent decreased by an average linear rate of 79,000 km^2/yr between 1979-2009, and the March maximum extent is projected to be 25% less by 2050 and 60% less by 2100, with the ice-free period that currently consists of 5.5 months on average projected to increase to a median of 8.5 months (Douglas 2010). Arctic temperatures up to 2.9 degrees C warmer when comparing the 2001-09 mean to the 1951-2000 mean (Walsh et al. 2011) accompany an overall loss of 1.59m of September sea ice thickness when comparing 2003-07 to 1958-1976 (Kwok and Rothrock 2009). The majority of sea ice loss occurred on the Pacific side of the Arctic (Wang et al. 2012), and one Arctic sub-region, the Bering Strait, is of particular concern for a number of interested parties.

Commercial interests identify the Bering Strait as an important route for trade and exploration for natural resources (Brigham and Smith 2008; Council 2009; Kitagawa 2008; Stephenson et al. 2013); the value of oil reserves of the Outer Continental Shelf in the Beaufort and Chukchi Seas is estimated at $193-312 billion, and the Bering Strait is the passageway to markets in Asia, North America, and Europe (Conley and Pumphrey 2013). The United States Coast Guard has estimated that the number of ships traversing the Bering Strait increased from 245 in 2008 to more than 400 in 2011 (Conley and Pumphrey 2013). This significant increase in ship traffic and general utilization of Bering Strait has considerable ramifications, and the economic interests of outsiders may conflict with the subsistence economy of the indigenous residents who live and hunt there. This subsistence economy revolves around a complex marine mammal population that inhabits the Bering Strait (Ackerman 1988; Ahmasuk et al. 2008; Huntington and Sookiayak 2000; Wolfe and Walker 1987).

To help guide complex, multinational policy discussions that will shape the future of the Bering Strait, a need exists for enhanced knowledge and characterization of marine mammal habitat in order to help plan for the conservation of these animals as climate- and human-induced changes occur across the area. Marine spatial planning efforts incorporate physical information about habitats within the marine environment, characteristics of marine species found within those habitats, and humans who interact with the marine environment and its resources (Kaplan et al. 2010; Katsanevakis et al. 2011). Geospatial analysis and mapping techniques have been used for various threatened and endangered marine species such as mussels (Wilson et al. 2011), turtles (Schofield et al. 2013), and monk seals (Schmelzer 2000) to aid in understanding environmental conditions within habitats and to help guide policy decisions for managing environmental and human pressures upon habitats.

The increasing availability of remotely-sensed and other environmental data has allowed ecologists to develop spatially-explicit maps of habitat suitability and species distributions using only a limited number of field observations by modeling relationships between species observations and predictor variables (Azzellino et al. 2012; Boyd and Foody 2011; Dobrowski et al. 2008; Elith and Leathwick 2009; Guisan and Thuiller 2005; Miller 2010). Terrestrial habitat classification at a variety of spatial scales using multiple sources of spatial data is a common application of remote sensing analysis (Janssen et al. 1990; Lu and Weng 2007; Piwowar and LeDrew 1990; Rautiainen et al. 2010; Treitz and Howarth 2000; Vogelmann et al. 1998). While satellite data products have been used to study marine environmental phenomena such as sea surface temperature (SST), photosynthetically active radiation, suspended particulate matter, chlorophyll/plankton concentrations, and sea ice extent (Talley et al. 2011), marine habitat classification using remotely-sensed data lags somewhat behind terrestrial applications. This is due in part to a smaller number of dedicated sensors and fewer observations over time; the number of images and data products has been increasing since the late 1990s with the introduction of sensors designed for marine environmental applications (McClain 2009). One challenge in developing these models for non-stationary, migratory species in remote regions (like the Arctic) is the lack of training and validation data derived from field observations of animal numbers, locations, and movement patterns.

The bearded seal (*Erignathus barbatus*) is a marine mammal inhabiting the Bering Strait that is highly-dependent on pack and sea ice and is a favored subsistence resource for Alaskan Native hunters (Kawerak 2013a; Kawerak 2013b) with a wide range of traditional uses (Burns 1981). The bearded seal is a protected species under the Marine Mammal Protection Act and has recently been listed as 'threatened' under the Endangered Species Act (NMFS 2012). Bearded seals are found throughout the Arctic region and prefer to remain in close proximity to broken sea ice, preferentially hauling-out on ice rather than shore, and they tend to avoid massive shorefast ice packs (Burns 1981). Adult bearded seals are primarily benthic feeders, subsisting on fish, invertebrates, and other bottom-dwelling prey items found at depths of up to 500m or less, but more typically at depths or 200m or less (Cameron et al. 2010; Quakenbush et al. 2011). Adults associated with the Bering Strait tend to migrate north and south as the pack ice shrinks northward in warmer months and expands southward in colder months, moving with the active ice edge that produces fractures, areas of thin ice, and other features that provide haul-out surfaces and protection from predators (Cameron et al. 2010). Maps of bearded seal range or habitat typically encompass the majority of the Bering and Chukchi Seas, and the entirety of the Bering Strait

(Burns 1981; Cameron et al. 2010; NMFS 2009). Bearded seals live in remote areas with environmental conditions that make obtaining observations difficult, and these areas also span international boundaries between nations that do not always cooperate well in scientific ventures (Cameron et al. 2010). Certain areas within the Bering Strait region were historically favored by bearded seal hunters, such as locations near Shishmaref, the Solomon River, and Port Clarence on land, and Sledge and King Islands offshore (Ray 1984, 1992), but anthropological records are not clear about why those locations were favored by the bearded seals. Likewise, the archaeological record does not explain why bearded seal remains were found in any given location, since they may have been hunted some distance away from an excavation site (Oswalt 1967).

Attempts to observe marine mammal ranges and activities in the region are typically limited to the window of relatively good weather and ice-free conditions experienced in the summer months, and a population estimate is difficult to determine accurately (Cameron et al. 2010); recent work to estimate populations includes helicopter survey observations of hauled-out ice seals (Ver Hoef et al. 2014). An alternative to standard ecological approaches that is gaining traction and is drawn from the social sciences is the integration of Traditional Ecological Knowledge (TEK). TEK has been defined as “a cumulative body of knowledge, practice, and belief, evolving by adaptive processes and handed down through generations by cultural transmission, about the relationship of living beings (including humans) with one another and with their environment” (Berkes et al. 2000). The TEK of Alaskan Native subsistence hunters includes information from those who have observed, tracked, and harvested seals in the Bering Strait region, and who have passed down that knowledge over successive generations (Ackerman 1998; Dumond 2000; Giddings 1961).

Modern subsistence hunters have a vested interest in more completely understanding the ecology of their prey, and hunters in the Bering Strait region have been cooperating with Western scientists, sharing geospatial information about hunting traditions and locations that can potentially be integrated with Western scientific geospatial data analyses (Brodnig and Mayer-Schonberger 2000; Gadamus 2013; Huntington 2000; Moller et al. 2004; Whyte 2013).

Bering Strait has been occupied for at least 4,000 years (Ackerman 1998) by humans whose culture established traditions still practiced in the modern era, such as hunting various marine mammals for meat, oil, and other subsistence and survival materials. Nearly 2,700 pounds of marine mammals are consumed annually as food by the Inupiat, Yup'ik and St. Lawrence Island Yupik households in the Bering Strait region, and sea mammal foods have tremendous cultural importance (Ahmasuk et al. 2008; Gadamus 2013). Long-term climatic change may result in shifting or lost habitat, which could influence marine mammal population distributions as well as the communities that depend upon them (Grebmeier 2012; Moore and Huntington 2008), even though there is no documentation of climate-change related shifts in migration patterns of marine mammals in the existing scientific record (Laidre et al. 2008). Marine mammal populations in Bering Strait may experience a variety of stressors related to health impacts of climate change (Burek et al. 2008), increasing underwater resource exploration and surface vessel traffic (Sackinger and Jeffries 1988; Stafford 2013), and commercial fishing activities (Huntington 2009).

This study focuses on developing and proofing a method to utilize remotely sensed environmental data and training data derived from TEK to create habitat suitability maps for marine mammals in polar environments. Specifically, the objectives include: (1) identifying an approach for converting TEK data to training and validation points for classification processes; (2) determining which predictor variables contribute the most information to the classification process; (3) ascertaining whether time series analysis outputs improve the accuracy of the classification process; and (4) developing habitat suitability maps that can inform policy discussion in the Bering Strait.

Chapter 2: Methods

2.1. Study Area

Establishing a scene model describing the study area is important in geospatial research applications (Strahler et al. 1986; Woodcock and Strahler 1987). The area of the current study encompasses the Bering Strait region and areas to its north and south between 159-175 degrees West longitude and between 60-68.5 degrees North latitude (Figure 1). The area typically experiences the formation and growth of sea ice beginning in October, generally centered along the coast, with ice thickening and expanding as temperatures drop and prevailing winds advect sea ice southward; the sea ice expands to maximum coverage by late March and begins a process of melt and decay until the ocean is again exposed by late June (Pease et al. 1982). Three major rivers (Yukon, Kobuk, Noatak) and numerous smaller rivers and streams drain much of Interior Alaska into the Bering coastal zone. With northward ocean currents mixing Pacific Ocean-derived water with freshwater and nutrient runoff along the coast, combined with prevailing offshore winds of the Polar Easterlies, coastal upwelling processes help contribute to a bloom of plankton productivity during ice-diminished and ice-free months (Loughlin et al. 1999).

2.2. Predictor Variables

For an initial, exploratory study, spatial data were obtained for a collection of environmental variables in Bering Strait. Some of the variables are known by Western science to be associated with bearded seals (e.g., bathymetry, sea ice), others are recommended by indigenous hunters (e.g., distances from shore or anadramous fish streams (Kawerak 2013b)), while others are assumed to be of relative importance (e.g., bathymetric slope, distances from shore or anadramous fish streams, sea surface temperature, chlorophyll concentration, etc.) for characterizing the habitat of bearded seals (Pittman and Costa 2010). Environmental predictor variables used in this study are listed in Table 1.

2.2.1. MODIS Aqua

Given such a large study area, and the maritime environmental focus, selecting a sensor that provides the best compromise between temporal and spatial resolution and variety of data products is critical (Phinn 1998; Phinn et al. 2003). The Moderate Resolution Imaging Spectroradiometer (MODIS) instrument on board the NASA Aqua satellite platform provides near-daily global imaging data at resolutions ranging from 250 m to 1 km, using 36 spectral bands, resulting in many different raster products output by four major NASA research groups (NASA 2013). The data products selected from NASA research groups were 8-day composites produced natively at, or resampled to, a spatial resolution of 4 km where each grid cell value represents the maximum value observed for the cell over each 8-day time period, for the mid-June through October study period from 2003-2012. The mid-year window corresponds to the generally ice-free (or broken ice floes) period from Julian Day 137 to Julian Day 280. From the Land Products group (https://lpdaac.usgs.gov/), surface reflectance (SRF; MOD09) data for Bands 4, 3, and 1 were acquired for tiles 9,2; 10,2; 11,2; and 12,2. Sea ice extent data for the Northern Hemisphere (SI; MOD29) was provided by the National Snow and Ice Data Center (http://nsidc.org/). The Ocean Color group (http://oceancolor.gsfc.nasa.gov) provided global scale data for chlorophyll-a concentration as a proxy for prey (CHL; MOD21), photosynthetically active and instantaneous photosynthetically active radiation (PAR, IPAR; MOD22), suspended solids as a measure of turbidity (PIC; MOD23), and sea surface temperature (SST; MOD28). Data voids in the Ocean Color products were infilled using the Ocean Color group's decadal climatology layers.

2.2.2. Other Spatial Data

The Alaska Geospatial Clearinghouse (Alaska n.d.) provided vector data for the coastline at mean sea level (MSL) and hydrography for major rivers and river mouth locations. Distance grids with 4 km cell sizes were generated using Euclidean distances from the coastline vectors. A digital elevation model (DEM) containing terrestrial elevations above MSL and bathymetry below MSL was obtained from the SRTM 30 Plus repository (Becker et al. 2009); slope degrees was generated from the DEM.

2.3. Response Variables

Although presence/absence data are preferred for species distribution and habitat suitability modeling, presence-only data has been successfully utilized (Brotons et al. 2004; Hirzel et al. 2006; Sequeira et al. 2012). TEK data was acquired from expert hunters and elders living in Bering Strait villages and includes geospatial information about the density of bearded seals across space and important hunting and search areas, including static and dynamic environmental characteristics of those areas across each season that were considered important for hunting success (Kawerak 2013b); participants were asked to exclude locations that were no longer considered productive (excluding historical hunting sites), and to include only those locations that were considered to be productive with regard to bearded seal hunting success. TEK information was collected from indigenous hunters through interviews and focus groups, recorded in qualitative verbal responses and as locations marked on nautical charts, topographic maps, and other map products. TEK data encompassing the summer and fall seasons were extracted as both Presence and Absence data based on the assumption that the experiences and traditional knowledge of these hunters would function as proxies (Figure 2). TEK polygons that indicated both high concentrations and a high probability of successful hunting were categorized as Good Habitat or Presence. The TEK data was presence-only data, but areas outside of those marked by hunters as good hunting or habitat area were categorized and treated as a type of pseudoabsence data for the purpose of this study.

Pseudoabsence data can be used in ecological studies when there is no data for true absences within a study area (Sequeira et al. 2012; Wisz and Guisan 2009). Including absence (or pseudoabsence) data has been found to increase the accuracy of species' predictions compared to presence-only data (Brotons et al. 2004). Given that the entire study area is within the diving range of bearded seal and potentially habitat, a simple random point selection process was used within the TEK polygons that were categorized as Absence (Stokland et al. 2011). This differs somewhat from applications in terrestrial environments where habitat edges or ecotones are more well-known and can be more readily defined; for bearded seal, known edges are drop-offs such as the continental shelf where depths exceed their diving range, and such depths do not exist within Bering Strait.

Training and validation points were randomly-generated within the Presence and Absence polygons at a minimum distance of 4 km from each other to match the predictor variable cell size. One of the challenges of random point generation methods is identifying the optimal number of training and validation points and the minimum distance between points. To find the optimal number, we conducted multiple classifications using increasingly dense networks of points in order to examine the sensitivity of classification processes to the TEK data. The lowest-density trial data set generated included 30 training and 30 validation points (60 points total at the first level), and each subsequent trial data set progressed in size at 60-point increments for each new classification until reaching the final trial at 450 points for both training and validation (900 points total at the final level). Each trial evenly split the training and validation points between the two classes; e.g., at the 60-point level, 15 random training points were contributed by the Presence set with 15 random training points from the Absence set, and likewise with the validation points to reach a total of 60 points. The sampling universe was 1,222 potential cells for Presence and 16,287 for Absence.

2.4 Data Extent and Pre-Processing

The greatest number of variables sharing a common projection, datum, and coarsest resolution came from the Ocean Color group; the Plate Caree (Fenna 2007; Snyder 1993) became the target projection for all other geospatial data. Data layers not already in the Plate Caree (an equidistant rectangular or geographic projection) were reprojected to that coordinate system, and all finer-scaled data were resampled to 4.1666667 km cell size. All data layers were subset to the study area's latitude and longitude window.

Seasonal trend analyses (STA) were conducted on the time series MODIS products using Theil-Sen's Estimator, a non-parametric approach that fits lines between all possible pairs of geographically coincident points in a time series for any given variable, and indicates whether the variable is increasing or decreasing in value and strength over time. Theil-Sen's Estimator is a robust analysis technique, able to withstand up to 29% missing data and still produce reliable outputs (Eastman et al. 2009; Eastman et al. 2013; Fernandes and Leblanc 2005; Neeti and Eastman 2011). Among its outputs are the mean of the data array, the median of all the slopes between pairwise coincident points throughout the time series, and the median for all of the intercepts in each time series. Prior to conducting Theil-Sen, the time series data were inspected, and although missing data were detected in the non-SST data across the study area, only in smaller, nearshore locations did it approach the 29% threshold. In order to be consistent with the SST data which has no data voids (Campbell et al. 1995), missing values in other time series data were infilled using Ocean Color decadal climatologies. Theil-Sen slope and intercept values for each time series predictor variable were calculated and used as input layers during the classification process; these are dynamic indicators of environmental processes that increase predictive and explanatory power of habitat modeling (Austin 2002).

The time series predictor data was selected to match the TEK data seasonality of summer and fall. The imagery and products represented a time span from May to October (Julian Day 137-280) with 8-day composite images and products. The dates of the time series data were modified in the analysis software to simulate a year rather than a seasonal portion of a year; for most variables, JD 144 images were recoded as JD 23, JD 152 became JD 46, and so forth until JD 172 became JD 355. SST data were recoded such that JD 144 became JD 14, and JD 180 became JD 364. Anomalies in several OC data sets resulted in removing JD 180 data layers from STA analyses.

2.5 Analysis

To develop a habitat suitability map, Classification Tree Analysis (CTA) was conducted (De'Ath and Fabribius 2000; Loh 2011; Miller and Franklin 2002) using GINI splitting rules with 10 percent pruning (Zambon et al. 2006). The major benefit of employing CTA, besides being non-parametric, is its transparent, “open box” approach that explicitly identifies which input layers (predictor variables) contribute to any particular classification output, and to which degree each input layer influenced the classification output (Lawrence and Wright 2001). In an exploratory study, it is important that the contributing variables are identified and known, as opposed to “black box” approaches that enshroud contributing variables (such as “hidden layers” in artificial neural networks) and only reveal the classification output (Qiu and Jensen 2004). Two major groupings of predictor variables were processed with CTA analyses and are presented in Table 2; the Theil-Sen (TS) group included the distance, bathymetry, OC climatologies and STA input layers, while the Non-Theil-Sen (NTS) omitted the STA input layers. Kappa statistics (Congalton 2001) were calculated for each CTA classification.

Chapter 3: Results

Test classifications indicated that the distance layers were a major driver of the classification results, constricting the output layer’s data within the zones covered by TEK polygons. This was due to the TEK data being concentrated near coastal areas and mouths of rivers joining the waters of the Bering Strait and in areas closer to the settlements where hunters engage in subsistence hunting activities. This constriction was addressed by establishing a second CTA batch for each group that removed the distance layers (*sans distance;* -SD). The secondary batch indicated that bathymetry was the next important environmental factor. A third CTA batch (-SD-SB) removed the bathymetry layers and only used satellite-derived data products. Output layers from each individual CTA run classified bearded seal habitat as 1 and non-habitat as 0; each batch's output layers were additively combined to construct model agreement map visualizations.

3.1 What is the optimal number of training and validation points to use in a classification?

Kappa values for each classification run are presented in Figure 4. The CTA kappas from TS and NTS series converge at the 480-point level (240 training & 240 validation), which may indicate the optimal point selection set for this study area and pixel size. The highest kappa value for both TS and NTS (0.883) was achieved for the runs that included all of the predictor variables for each series.

3.2 Which predictor variables provide the most useful information for classification?

The frequency of input layer selection was summed from CTA output trees for each of the classification runs at the 480-point level, and is presented in Figure 5. For the Theil-Sen series of predictors, the TS Slope of MODIS B01 was selected five times, Bathymetric Slope was selected three times, Chlorophyll OC Climatology was selected three times, and 11 predictors from the array were each selected once (Sea Ice TS Intercept and Sea Ice TS Slope were among the predictors selected once each). For the Non-Theil-Sen predictors, IPAR OC Climatology was selected six times, Bathymetric Slope and SST OC Climatology were selected four times each, and Distance from Stream Outlets and Suspended Solids were each selected once. A covariance diagram depicting the relationships between predictor variables is shown in Figure 3 (predictor band numbers and names are listed in Table 2).

3.3 Does the Theil-Sen time series data improve the accuracy of the classification?

The frequency count data alone would seem to indicate that the Theil-Sen time series predictors are quite useful, perhaps to the point of excluding the non-Theil-Sen predictors. However, upon examining the output rasters for the two main CTA series, it appears that the NTS series produces similar results in areas that are nearer to the TEK presence training polygons. Figure 6 shows the individual habitat cell selections for each of the predictor variable sets, while Figure 7 shows composites of the TS and NTS series. Figure 8 is a composite of both TS and NTS series; all of these figures draw from the 480-point CTA analyses.

At the 480-point level where Kappa converges for both experimental series, there is variation in the number of predictor variables (bands) selected, the number of cells selected as suitable habitat, and the Kappa values for each CTA run. Table 3 shows that the TS series selects more cells as suitable habitat than NTS, and both TS and NTS series have maximum Kappa values of 0.883 when using the full set of environmental predictors assigned to each series. The –SD run for each series results in the greatest area selected as habitat combined with the highest number of bands selected during CTA analysis, but for the TS-SD run, it is also the lowest Kappa value. The –SD-SB run for each series selects less area as suitable habitat than –SD, and the TS series has a higher Kappa value than the

NTS series. Overall, using the TS series of environmental predictors appears to improve classification accuracy and the TS predictors also result in larger areas selected as suitable habitat.

Chapter 4: Discussion

4.1 Does TEK function as a reasonable proxy for observational scientific data?

Western scientific observation is limited in remote areas such as Bering Strait, especially when observations are also constrained by short seasonal opportunities to establish research posts and collect information. Existing maps of bearded seal habitat (Burns 1981; Cameron et al. 2010; NMFS 2009) essentially describe the spatial extent of depths within the bearded seal's documented diving capacity, which includes the entirety of the Bering Strait and adjacent areas within the Bering and Chukchi Seas.

This study applies terrestrial habitat classification techniques to marine environments, building on the foundation of TEK data provided by Native hunters. The analyses selected subsets of the study area which are in turn subsets of established habitat maps for bearded seal in Bering Strait; these subset areas have similar characteristics to locations where bearded seal are known to have been harvested in subsistence hunts or locations where they were physically sighted (if not actually pursued by hunters). Using a more expansive selection of environmental predictor variables has provided a glimpse at portions of the Bering Sea that might be more important or critical habitat zones for bearded seal populations within the more general habitat characteristic of maximum diving depth.

4.2 What is the optimal number of training and validation points to use in a classification?

The sensitivity analysis conducted in parallel with the CTA analysis showed a convergence occurred at 480-points, split into 240 for training and 240 for validation. For the area encompassed by the study, and the pixel resolution used for the input predictor variables, 480 points appears to be an optimal number for classification. The areal extent of the classifications also expanded at all sensitivity levels when the restrictive distance environmental variables were removed from the input set.

A potentially confounding factor with this study is that the training (1,222) and validation (16,287) cell sets account for nearly half of the marine study area (45,694) prior to sampling. The Kappa statistic naturally improves and approaches 1.0 as the number of training and validation points increases at each experimental CTA level as shown in Figure 4. Directly related to this factor is that the 4km pixel size aggregates and smooths environmental information in each data layer for both temporal and non-temporal geospatial data. Predictor variables at finer spatial resolutions, such as 250m pixels, could provide more insight into the importance of the various predictors within the complex environment of Bering Strait.

The TEK information is also somewhat limited in its spatial extent (see Figure 2). Although the TEK polygons used to generate training and validation points for presence cover 19,552 km^2 of area in the Bering Strait, those locations are still relatively close to the shorelines of the mainland and larger islands. The TEK information itself acts as a constraint on the habitat mapping since the nearshore environmental conditions are overrepresented compared to offshore environmental conditions as a function of where hunters preferentially seek their prey.

As noted earlier, there aren't clear demarcations for what constitutes habitat vs. non-habitat for bearded seal in Bering Strait within the standing literature, except that the seals will not wander very far inland on dry land and have a maximum diving depth. The TEK observations of Presence during the summer and fall seasons are very likely not capturing all the locations within Bering Strait where bearded seals exist and forage; failure to detect the presence of a species within a cell does not mean that it is truly absent from that cell (Brotons et al. 2004). These errors of omission (Congalton and Green 2009), or false negatives, within the TEK data and subsequent habitat classification analyses result in conservative predictions of bearded seal habitat in this study.

4.3 Which predictor variables provide the most information for classification?

Using the entire array of predictor variables for CTA analyses resulted in the Theil-Sen slope and intercept variables dominating when producing habitat maps. Removing those variables and using only the NASA-produced Ocean Color climatologies produced habitat maps that were very similar to the Theil-Sen-based maps within the core of the study area (i.e., the region encompassing Norton Sound and St. Lawrence Island); both the TS and NTS environmental predictor series produced maps that matched the TEK data within the study area core. If an analyst has access to software that can produce the Theil-Sen predictor layers, the prediction results cover a broader geographic range; if the Theil-Sen layers are not producible, however, the reduced set of predictor layers appears to give comparable results near the core of the study area. Distance from shore and anadramous fish streams severely restricted the analyses, while bathymetric depth and slope contributed to the results. Although identified in the ecological and ethnographic literature as one of the “ice seals”, the analysis did not indicate that the TS Sea Ice environmental layers were important predictors. Bearded seal are most highly associated with sea ice during the winter and spring seasons. Adults tend to migrate northward through Bering Strait in late spring and early summer (May-June) during breakup and tend to return southward during late summer and early fall (September-October); adults are found in higher numbers in the area around the narrowest portion of Bering Strait during these months. Young bearded seal tend to be found near shore during the summer (June-August). The band counts for TS and NTS series are shown in Figure 5; the band numbers refer to the list of predictor variables shown in Table 2.

4.4 Is the Time Series data useful for the classification analysis?

The TS predictor set provides greater predicted habitat than the NTS predictor set at each of the three levels of analysis; the TS base level results in 3.4% more predicted habitat, the SD level results in 41.8% more, and the SD-SB level results in 37.2% more. The increased predicted habitat tends to occur further from the study area core, where the TEK presence polygons are located; the TS series appears to select more pixels in locations farther north in the Chukchi Sea and farther south in the Bering Sea. The NTS approach provides habitat selections similar to the TS selections in areas with closer proximity to the TEK polygons. Theil-Sen may be indicating areas of interest that could be more fully investigated at a later date with expanded predictor variable sets. A tradeoff may exist in terms of resources required for TS and NTS data; preparing NTS data may take a few days and select smaller areas as habitat, whereas a lengthy time resolution for TS data may take several weeks or months to pre-process prior to conducting analysis and select larger areas as habitat.

4.5 Why isn't sea ice selected as a primary predictor?

Analysis revealed a conundrum, in that the bearded seal (one of the "ice seal" species) did not appear to be associated with the sea ice predictor layers. Bearded seals are known to prefer ice floes as platforms for diving and hauling-out, and will preferentially select sea ice over other types of solid coastal features (rock outcrops, beaches, etc.). Adult bearded seals tend to migrate northward through the study area during late spring (May-June) and tend to migrate southward through the study area during late summer and early fall (September-October), while young bearded seals tend to remain closer to shore. With ice floe surfaces diminishing during the summer, bearded seals will haul-out on islands and coastal land surfaces.

The environmental predictor selected most often in the TS array was derived from MODIS Aqua Band 01, which is sensitive to the red portion of the electromagnetic spectrum. This may be due to associations of red algal communities that exist in snow and ice structures (Takeuchi 2013; Takeuchi et al. 2006), along marine shallows that get scraped by sea ice masses (Heine 1989), and perhaps in the upper pelagic layers as sea ice decomposes. In the NTS array, the predictor most often selected was derived from MODIS Aqua IPAR product, which could also be detecting red reflectance in areas rich in snow, ice, and decomposing ice due to red algal blooms. Although sea ice itself did not appear to be important as an environmental habitat predictor, perhaps the algal features of the ice influenced the selection of predictors sensitive to 645 nm. It would be interesting to determine if these predictors were still selected if the spatial resolution of the input layers was increased from 4km to 1km or higher.

Chapter 5: Conclusion

This study applied analysis techniques derived for use in terrestrial environments and has discovered that they are potentially quite useful in marine environments. This synthesis of indigenous knowledge and Western science demonstrates that the Traditional Ecological Knowledge of Native hunters can be transformed into digital training and validation information and effectively used in geospatial modeling of marine mammal habitat. In vast areas traversed by few scientists, the lifetime and generational knowledge of expert hunters and foragers can be substituted for, and used instead of, traditional scientific areal and site survey information; the TEK of indigenous hunter and gatherers provides an often untapped and rich resource of environmental information.

If this approach is explored in the future, there are several other sources of data that might improve and refine the results of habitat modeling. Ocean current direction and velocity information throughout the Bering Strait could be very useful, both at the surface and at depth. Prey species data layers could be very beneficial, especially if the data included not only spatial location but also variation in time in order to establish relationships to the satellite time series data. Acquiring Level 2 MODIS imagery and custom processing it to produce Level 3 data may provide better control over filling data gaps that occur in the MODIS-based Theil-Sen analyses. Another data source would be TEK information from the Chukchi, inhabitants of the Western coast of the Bering Strait. Overall, however, this effort demonstrates an objective, replicable methodological approach that can be applied in the absence of Western science, particularly when time and resources are limited and policy decisions rely on the best available science.

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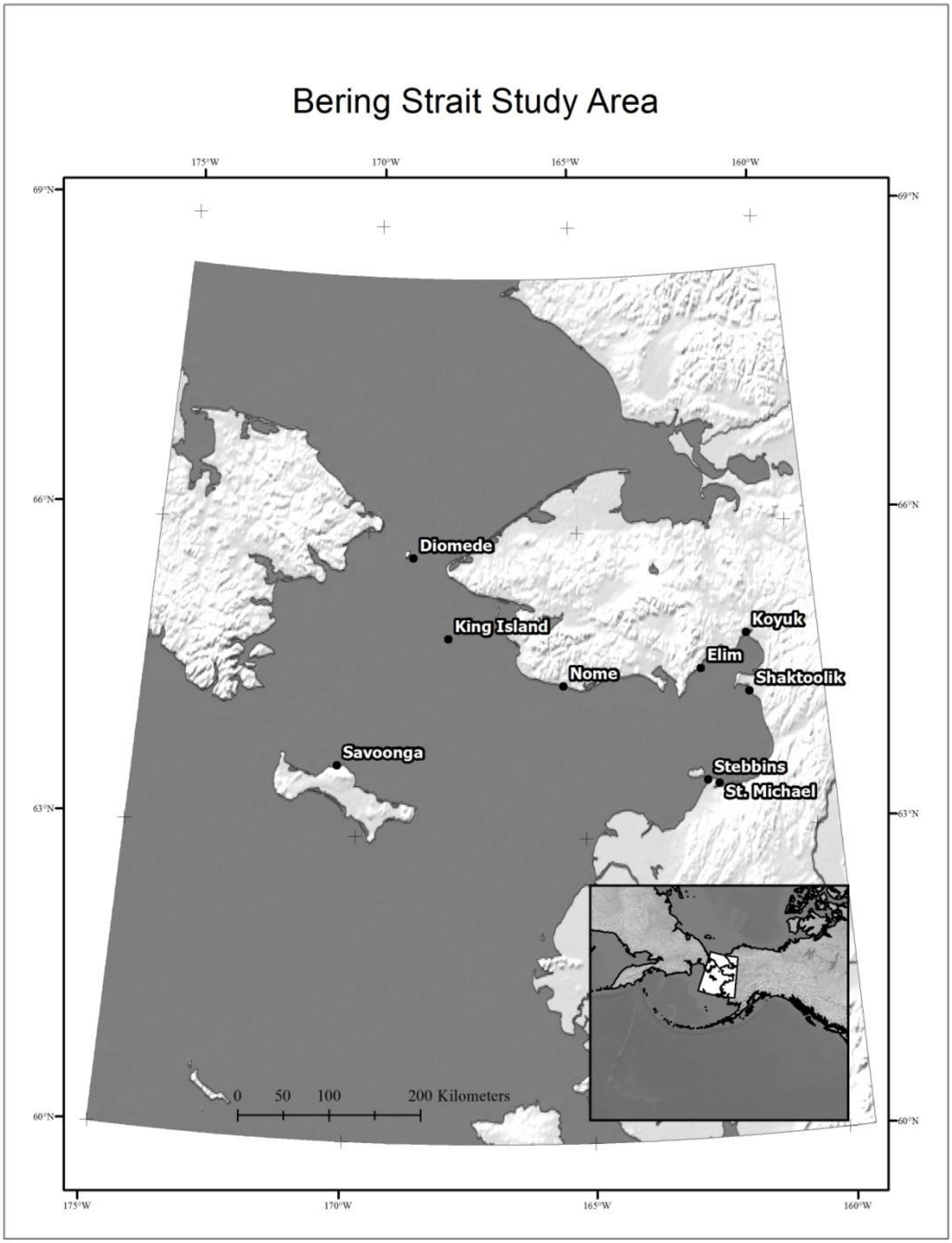


Figure 1. Map of Bering Strait study area.

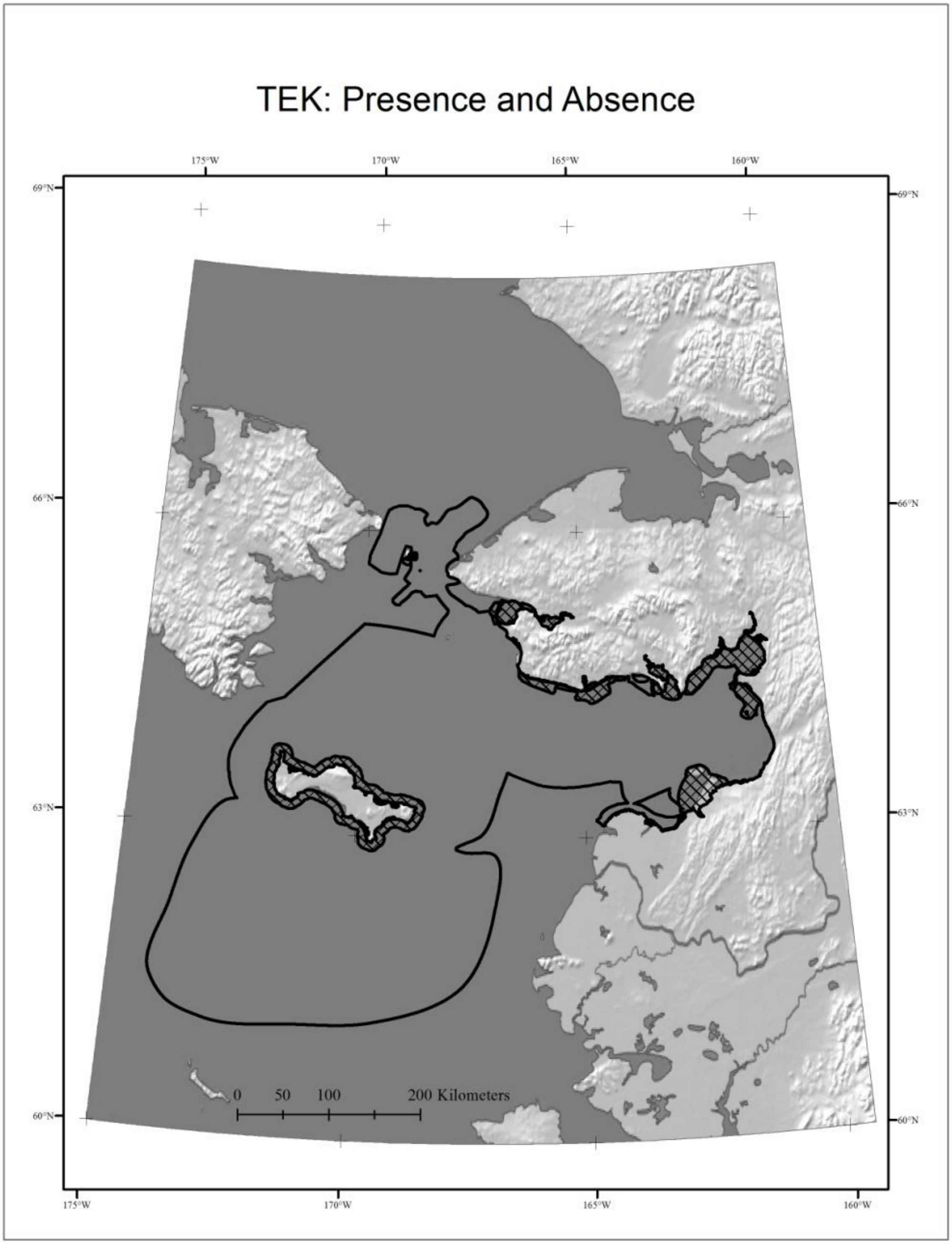


Figure 2. TEK Presence and Absence. Presence data is indicated by hatching, including some land surfaces where seals were present in rivers. Absence data is indicated by the open polygon extending throughout Norton Sound and Bering Strait.

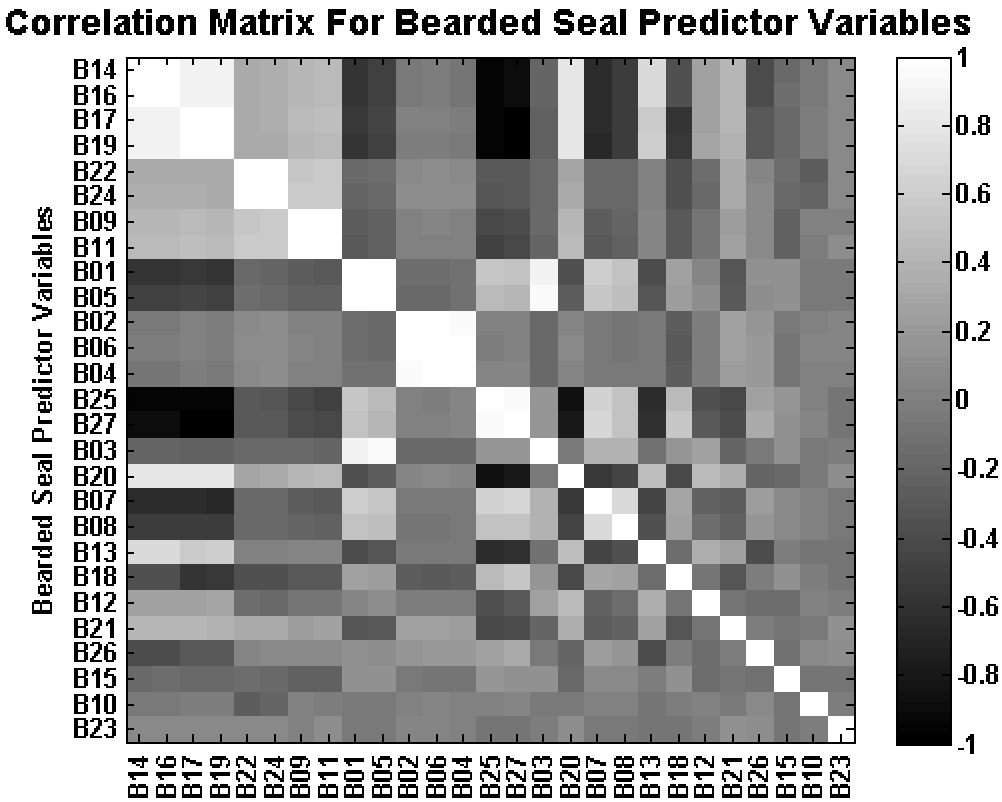
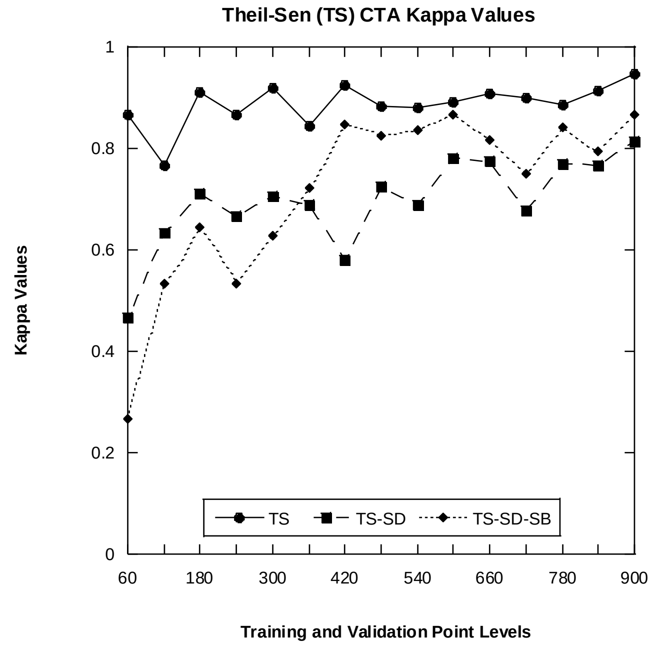


Figure 3. Pearson's correlation for predictor variable covariance. A list of predictor variable name and number identifiers is provided in Table 2.



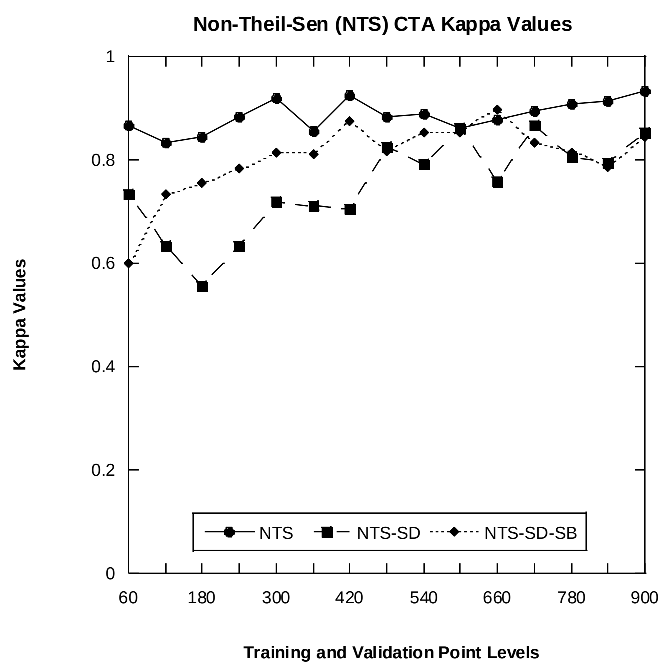
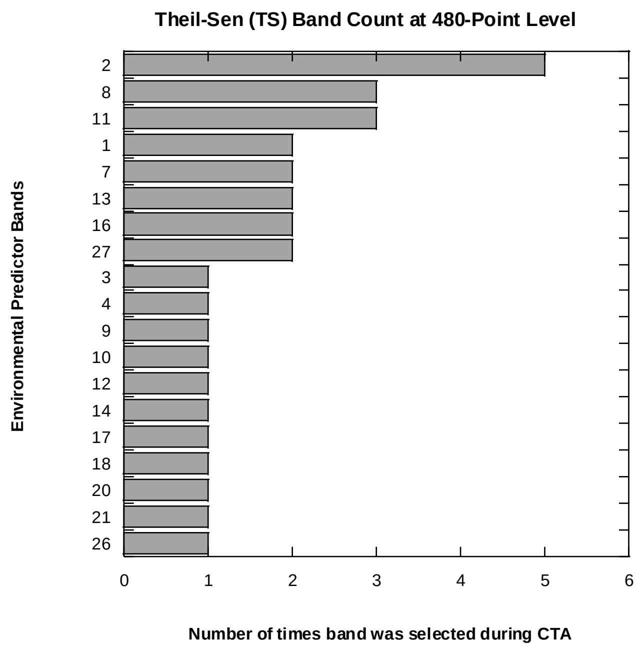


Figure 4. CTA Kappa values for TS and NTS analyses. Kappa statistic values are plotted on the Y-axis, and the number of training and validation points for each trial are plotted on the X-axis by increments of 60.



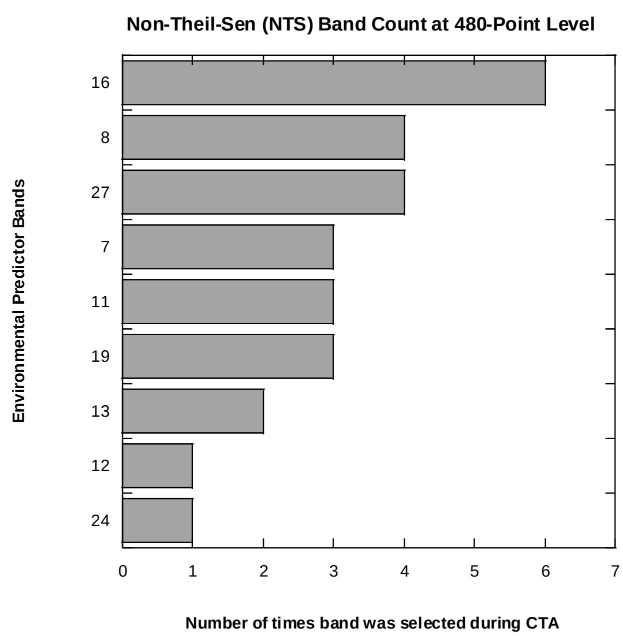


Figure 5. Band count histogram at 480-point level. The count indicates how many times a particular band was selected within each of the six CTA batches conducted with 240 Training and 240 Validation points.

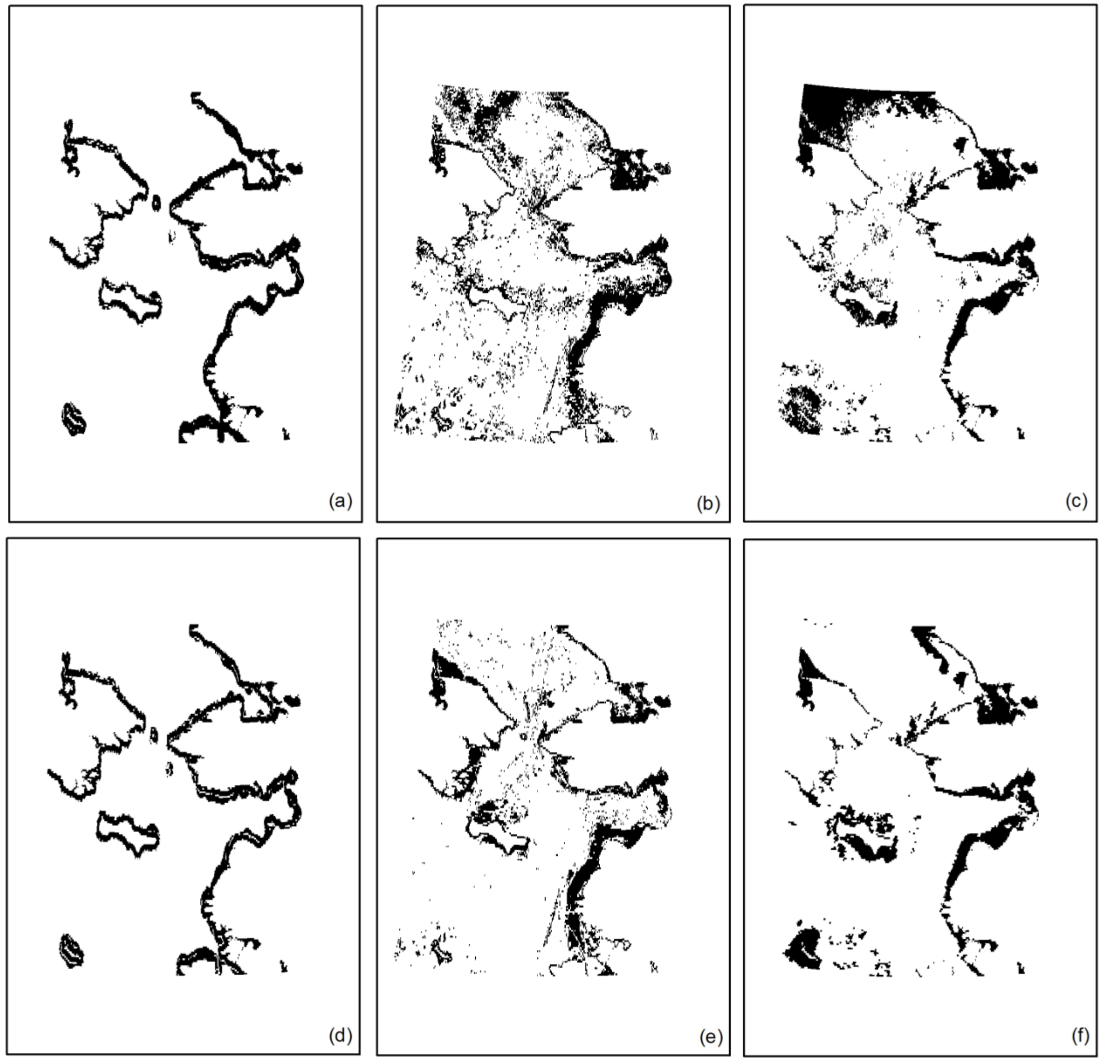


Figure 6. Initial habitat suitability maps. Theil-Sen maps: (a) all available inputs; (b) *sans distance*; (c) *sans distance, sans bathymetry*. Non-Theil-Sen maps: (d) all inputs except for Theil-Sen time series layers; (e) *sans distance*; (f) *sans distance, sans bathymetry*. All dark values are selected as bearded seal habitat for each predictor variable combination.

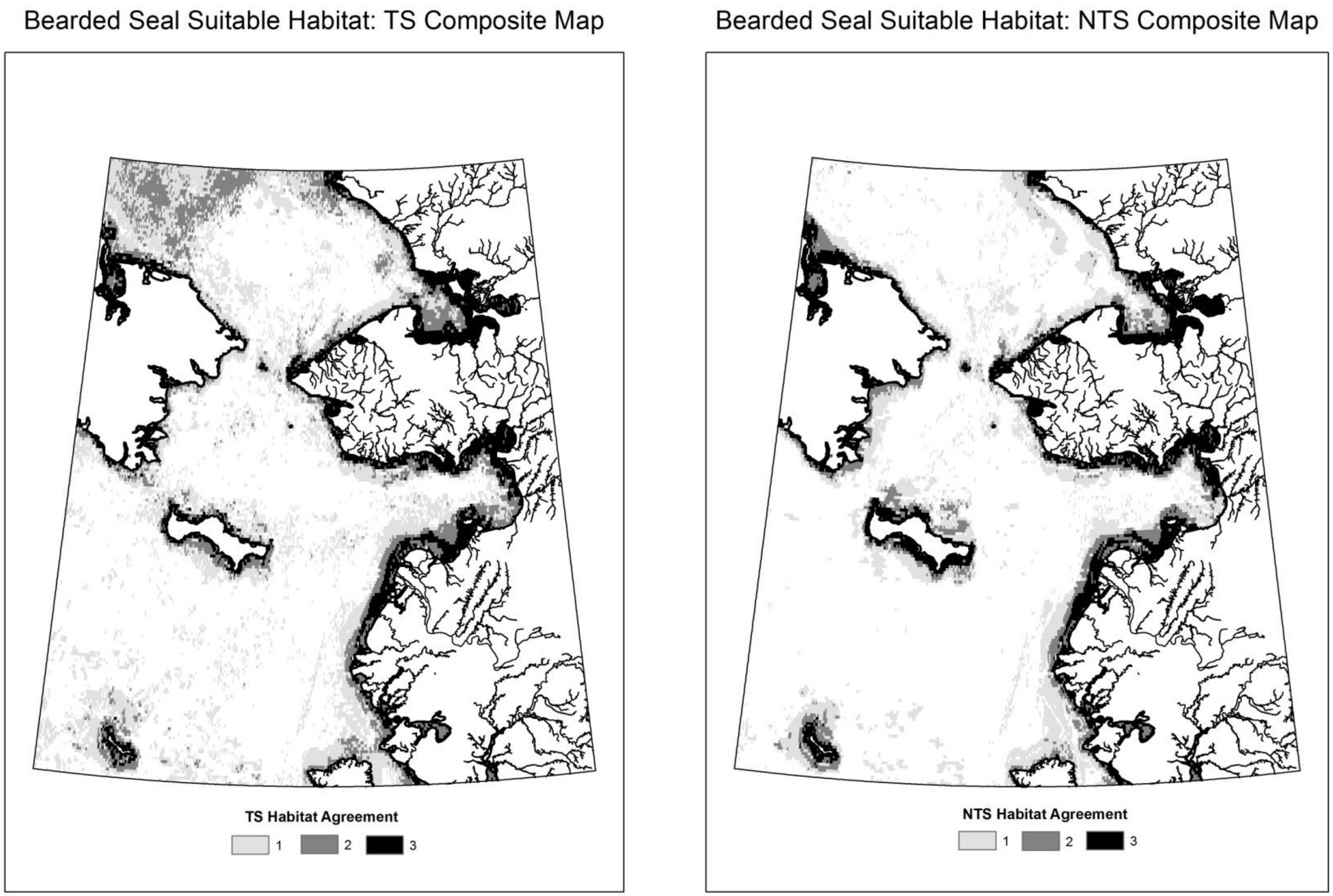


Figure 7. Habitat suitability maps for the TS and NTS analysis series. The numbers 1, 2, and 3 indicate how many models within either the TS or NTS series selected a given pixel location as suitable habitat. In areas close to the TEK training data polygons, NTS data are finding similar patterns to the TS data.

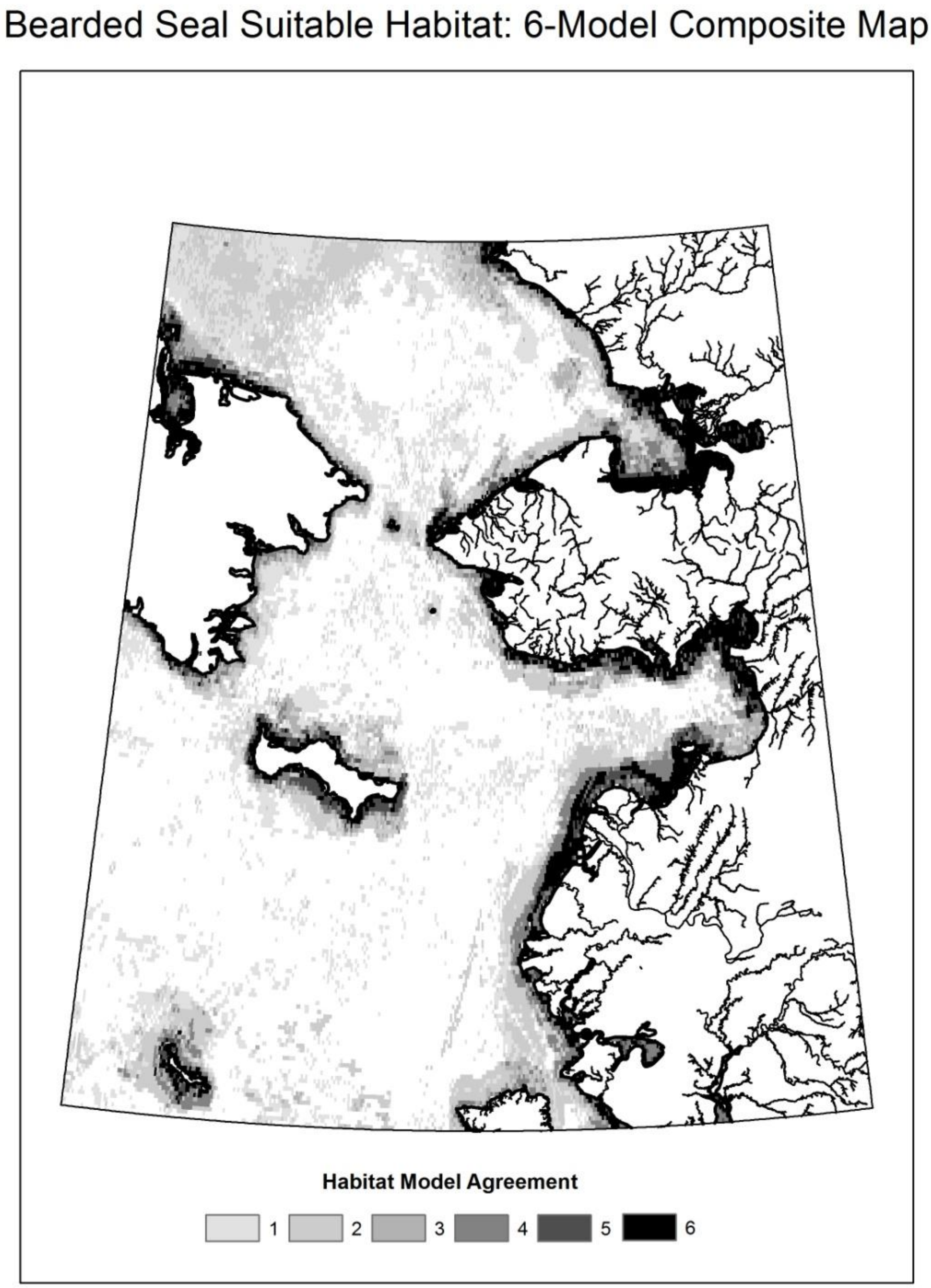


Figure 8. Composite map showing the agreement between the six habitat suitability output rasters at the 480-point modeling level.

Table 1
Environmental predictor variables for bearded seal habitat suitability modeling

Environmental data (predictor variables)	Data type	Temporal resolution	Native spatial resolution	Operational spatial resolution	Original data source
Bathymetry (m)	Raster Dataset	N/A	0.833 km	4.167 km	SRTM30_Plus
Bathymetric slope (degrees)	Raster (GIS Derivative)	N/A	4.167 km	4.167 km	SRTM30_Plus
Distance from coast (km)	Raster (GIS Derivative)	N/A	N/A	4.167 km	State of Alaska Geospatial Clearinghouse
Distance from anadromous streams (km)	Raster (GIS Derivative)	N/A	N/A	4.167 km	State of Alaska Geospatial Clearinghouse
Chlorophyll-a concentration (mg m^-3)	Raster	2003-2012	4.167 km	4.167 km	NASA Ocean Biology Processing Group
Instantaneous Photosynthetically Available Radiation (Einstein m^-2 sec)	Raster	2003-2012	4.167 km	4.167 km	NASA Ocean Biology Processing Group
Photosynthetically Available Radiation (Einstein m^-2 Day)	Raster	2003-2012	4.167 km	4.167 km	NASA Ocean Biology Processing Group
Suspended solids (mol M^-3)	Raster	2003-2012	4.167 km	4.167 km	NASA Ocean Biology Processing Group
Sea surface temperature (degrees Celsius)	Raster	2003-2012	4.167 km	4.167 km	NASA Ocean Biology Processing Group
Sea ice (presence)	Raster	2003-2012	3.607 km	4.167 km	NASA National Snow and Ice Data Center
Reflectance: Band 1 (R)	Raster	2003-2012	0.986 km	4.167 km	NASA Land Products Group
Reflectance: Band 3 (B)	Raster	2003-2012	0.986 km	4.167 km	NASA Land Products Group
Reflectance: Band 4 (G)	Raster	2003-2012	0.986 km	4.167 km	NASA Land Products Group

Table 1. Environmental predictor variables used in the study, including source location, and spatial and temporal resolution.

Table 2

Environmental predictor variables (raster layers) used in CTA Analyses

Raster Layer Name	TS	TS-SD	TS-SD-SB	NTS	NTS-SD	NTS-SD-SB	Input Band
B01 TS Intercept	+	+	+	-	-	-	1
B01 TS Slope	+	+	+	-	-	-	2
B03 TS Intercept	+	+	+	-	-	-	3
B03 TS Slope	+	+	+	-	-	-	4
B04 TS Intercept	+	+	+	-	-	-	5
B04 TS Slope	+	+	+	-	-	-	6
Chlorophyll-a TS Intercept	+	+	+	-	-	-	9
Chlorophyll-a TS Slope	+	+	+	-	-	-	10
IPAR TS Intercept	+	+	+	-	-	-	14
IPAR TS Slope	+	+	+	-	-	-	15
PAR TS Intercept	+	+	+	-	-	-	17
PAR TS Slope	+	+	+	-	-	-	18
Sea Ice TS Intercept	+	+	+	-	-	-	20
Sea Ice TS Slope	+	+	+	-	-	-	21
Suspended Solids TS Intercept	+	+	+	-	-	-	22
Suspended Solids TS Slope	+	+	+	-	-	-	23
Sea Surface Temperature TS Intercept	+	+	+	-	-	-	25
Sea Surface Temperature TS Slope	+	+	+	-	-	-	26
Bathymetry Depth	+	+	-	+	+	-	7
Bathymetry Slope	+	+	-	+	+	-	8
Distance from Stream Outlets	+	-	-	+	-	-	12
Distance from Coast	+	-	-	+	-	-	13
Chlorophyll OC Climatology	+	+	+	+	+	+	11
IPAR OC Climatology	+	+	+	+	+	+	16
PAR OC Climatology	+	+	+	+	+	+	19
Suspended Solids OC Climatology	+	+	+	+	+	+	24
Sea Surface Temperature OC Climatology	+	+	+	+	+	+	27

Table 2. Each input layer (or band) included with a particular CTA batch is marked with a + while omitted bands are marked with a – symbol. SD and SB respectively indicate sans distance and sans bathymetry.

Table 3

Classification Variances at the 480-Point Level

	TS	TS-SD	TS-SD-SB	NTS	NTS-SD	NTS-SD-SB
Band Count	7	15	10	6	12	9
Cells Selected	8,176	11,939	11,525	7,909	8,421	8,403
Kappa	0.883	0.725	0.825	0.883	0.825	0.817

Table 3. Classification variances between the Time Series (or Theil-Sen; TS) and Non-Time Series (or Non-Theil-Sen; NTS) output results.