NRT 2016-2017: Transdisciplinary Report
Ocean Condition Forecasting Team

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Photo credit: Port of Brookings-Harbor

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Introduction

The Oregon Coast is located in the Pacific Northwest of the United States along the eastern boundary of the Pacific Ocean, where diverse marine resources support productive fisheries. Commercial fishing is culturally and economically important to coastal communities in Oregon, contributing more than $500 million annually in personal income (ODFW 2017).

Crab boats in Newport, OR loaded with gear awaiting the start of the season, an important time for the fishery. Photo: Ken Gange

However, commercial fishermen regularly risk personal safety, property, and economic loss due to the hazards that arise from navigating the marine environment in the Pacific Northwest. Ocean conditions can become hazardous due to dynamic weather patterns and large storms that travel across the Pacific Ocean. This is particularly dangerous in the winter months when fishermen are most likely to be at sea harvesting Dungeness crab, the most valuable fishery in Oregon (ODFW 2017). The act of entering and leaving port, or "crossing the bar," is especially hazardous in the Pacific Northwest due to the way coastal rivers meet the ocean. This complex interaction of the natural and human systems along the Oregon coast creates risks and uncertainties around the safety and economics of the commercial fishing fleet, as well as the ability to forecasters predict the conditions of the ocean.

To cope with these risks, commercial fishermen regularly seek out sources of ocean condition information about temperatures, currents, waves, and wind to inform their decisions. In recent years, on a national level, researchers have brought forth integrated coastal observing and modeling systems that have substantially advanced the quality of coastal forecasts with the recognized need to transform them into products that meet the data needs of the ocean use community (Kourafalou 2015). To address these needs in Oregon, a research project was undertaken in the Marine Resource Management (MRM) graduate program at Oregon State University (OSU) to engage with members of the commercial fishing fleet in Newport, OR. The goal of this project was to make an effort to document and understand how fishermen make strategic decisions about ocean use (Duncan 2014). Findings revealed that the fishermen used a wide variety of data sources for multiple reasons, and lacked a single trusted source of information. This led to a collaborative effort that created seacast.org (Seacast 2017), a web interface that presents ocean forecast data provided by marine scientists at OSU in a simple and intuitive format driven by the needs of the fishermen (Figure 1). Today, Seacast (2017) continues to be used and improved based on feedback from local fishermen.

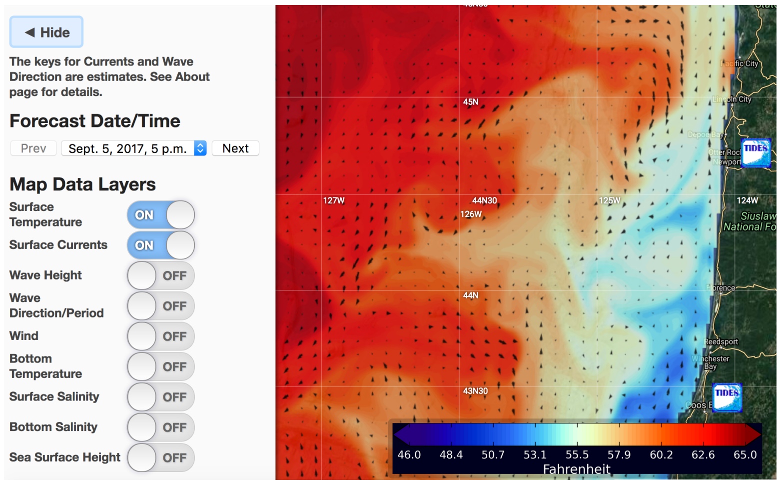


Figure 1: Screenshot of seacast.org interface with SST and surface currents displayed.

Forecasting tools and the models that inform them (such as Seacast (2017)) are subject to error due to the chaotic character of the atmosphere and the inevitable inadequacies in observations and computer models (NRC 2006). Uncertainty, while a fundamental characteristic of any forecast, is rarely reported or visualized in ocean condition forecasts. In many cases, this is due to the nature of the ocean forecasting models being used, which differ from those used for weather forecasting. In typical weather forecasting methods, uncertainty is defined as a range of values wherein the "true" value exists. To derive this range of values, weather prediction often uses ensemble forecasting. This methodology produces a set of forecasts from slightly different initial conditions to result in a range of possible outcomes (NOAA 2017). Ocean condition forecasts utilized by Seacast (2017), on the other hand, use only one model forecast to produce one result for a given time and space, which is referred to as deterministic modeling. The OSU modeling groups involved in providing data for Seacast do not run ensembles due to limitations in their computational resources. In this type of modeling, there is no range of possible outcomes available for statistical analysis, and thus no readily available measure of uncertainty as it is defined in weather forecasting (for example, when predicting the probability of precipitation). However, if uncertainty metrics were made available, the ocean condition forecasting model output could potentially become more useful to data users during their decision making process.

The different language and perceptions surrounding the definition of uncertainty complicate the communication of uncertainty between scientists and fishermen, which can lead to confusion and a lack of trust between the two parties. One way to overcome these differences in communication and strengthen relationships, is to work toward understanding the underlying perceptions of risk and uncertainty towards the ocean and ocean forecasting for both communities (Duncan 2014). Web interfaces that deliver ocean condition forecast information, like Seacast (2017), serve as boundary objects that bring together different groups of people and bridge perceptual and practical differences in understanding (Huvila 2014, Karsten et al. 2001, Star 2010, Star and Griesemer 1989). Implementing this understanding can bridge the gap in communication through the creation of uncertainty metrics that serve as boundary objects for both parties. For scientists, this would mean the creation of metrics that are mathematically rigorous, and for data users, this would translate into uncertainty metrics that are consistent with their intuition and experience. These uncertainty metrics would therefore be comfortable for both parties. For the purposes of this report, the term 'uncertainty metrics' refers to model accuracy measurements which will be further described in the 'Methods and Results' section. Communicating these metrics could ultimately serve to empower strategic decision-making based on each fisherman's unique situation and provide more objective and transparent forecasts with respect to the perceptions of each party.

In this report, we build off of the knowledge and relationships created from the Seacast tool (2017) to explore the perceptions of uncertainty for both data providers and users. We then use the knowledge of these perceptions to derive metrics that address uncertainty which are acceptable to both parties. These metrics are then visualized using cartographic techniques related to visualization methods that fishermen are already familiar with. We developed the following research question in order to guide our work on this topic: 'How can ocean forecasts and their uncertainty be quantified and communicated to commercial fishermen?' To address this question and achieve these goals, the Ocean Condition Forecast (OCF) Team was formed in September of 2016 as part of the National Science Foundation Research Trainee (NRT) Fellowship in Risk and Uncertainty Quantification and Communication in Marine Science at OSU. It is composed of four graduate students that represent different facets of the ocean condition forecast process. This process includes the generation of forecasted data and associated uncertainty metrics, integration of uncertainty metrics into map-based visualizations, and assimilation of divergent user and data provider perspectives into the entire process. The team members who are the respective counterparts to this process include two ocean modelers, one cartographer, and one social scientist. A transdisciplinary approach was used to generate the uncertainty metrics and communication design, and will be explained further in the following section.

Approach

Transdisciplinarity

A transdisciplinary approach was used to guide OCF team members to inform and expand their disciplinary limitations and definitions of technical concepts, which ultimately resulted in a product that no one student could have achieved on their own. The societally-driven questions of how to create useful ocean condition forecasts and how to account for and represent the uncertainty of forecasts do not reside in a single disciplinary home, as the meaning of uncertainty transcends disciplinary boundaries, professions, and problem domains (Smithson 2008). Transdisciplinary research is well suited to this problem because it goes beyond disciplinary boundaries and brings together researchers with varied expertise to address a problem they define under a joint conceptual framework (Ciannelli 2014). This approach involved creating a clear framework for communication between the team members and cultivating strong relationships between them. Establishing this groundwork allowed team members to collaborate more effectively (Cheruvelil et al. 2014, Klein 2013).

Defining Uncertainty

The team's approach to defining uncertainty involved developing a quantification of ocean condition model uncertainty that was meaningful to both scientists and fishermen given the constraints of ocean condition forecasting. Uncertainty may be broadly defined as a situation in which a given event may result in more than one expected outcome. People make decisions in an effort to manage this uncertainty (Pielke 2007). Uncertainty associated with the creation, dissemination, and use of ocean condition forecasts has a strong influence on the decision-making process of fishermen, yet it is rarely expressed or reported as part of forecast products (AMS Council 2008, NRC 2003, NRC 2006). The difficulty in expressing uncertainty in forecasts is due to the nature of uncertainty, which is such that there is no one universal definition. Some ways it can be expressed include: something that is known or known imprecisely, more than one possible outcome in a situation, or simply – doubt (BIPM et al. 2008, NRC 2006, Pielke 2007). Deriving one definition of uncertainty that satisfies data providers as well as data users poses challenges, in that each group defines uncertainty differently. This has resulted in a lack of current standards for representing the uncertainty contained within ocean condition model output.

Ocean condition forecast providers think of uncertainty as a quantifiable number, such as a bias or a measure of variance (Pielke 2007). They derive this number from the uncertainty associated with deterministic ocean models. These uncertainties may consist of structural uncertainty, which refers to the underlying physics which govern model behavior, or parametric uncertainty, which refers to numerical model inputs (Charles 1998). This typically results in a metric of uncertainty that is quantified as a statistical distribution, or a range of values which can encompass the true value. In contrast, fishermen have a more tangible experience with uncertainty. For fishermen, uncertainty in the context of ocean conditions is strongly related to personal and financial risk. From their perspective, uncertainty is related to doubt. Doubt is associated with the accuracy of forecasts and weighing costs and benefits which, in turn, can complicate decision making. For fishermen, forecasts are predictions that they assign relative confidence to based on their intuition, which is derived from their experience with the ocean and using a variety of forecast tools.

Communicating Uncertainty in Ocean Forecasts

The team's approach to communicating uncertainty related to ocean condition forecasts aims to use map-based visualization techniques that are closely related to those that fishermen are already familiar with. These techniques include contour lines, arrows, wind barbs, and color ramps (for example, a gradient from red to blue). The quantification of model uncertainty metrics must be paired with the communication of those metrics in a way that is clear and readily understood. Challenges arise when techniques for quantifying uncertainty are incompatible with the types of visualizations that fishermen are accustomed to. For example, offshore buoys are effective for validating wave models at a coarse spatial resolution at specific locations, but it could be more useful to fishermen if the model could be validated at a finer resolution over the entire area in which they work, or at a minimum, over the model grid. Ocean condition forecasts already serve as a platform for conveying information, and should be used for integrating new uncertainty metrics. While perfecting the form of this communication is outside the scope of this project, preliminary visualizations of the resulting uncertainty metrics were produced and these are described in the 'Methods and Results' section.

Transdisciplinary Process

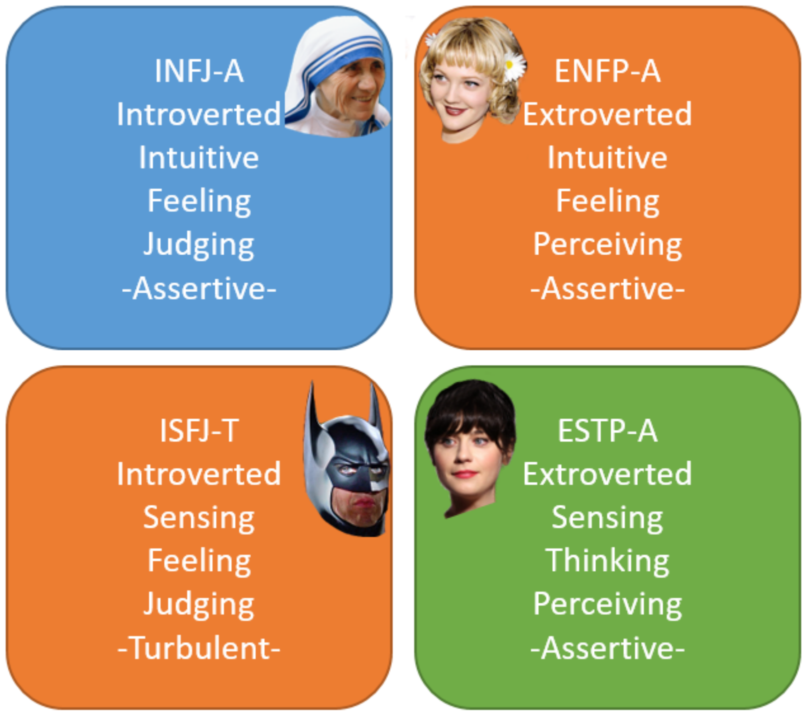
To achieve the goals of this transdisciplinary research, the OCF team had to collaborate on many tasks, ranging from problem formulation and hypothesis development to data analysis, interpretation, and reporting. Natural challenges arise when people from different disciplines approach a problem due to differences in tacit knowledge, research methods, research processes, and philosophical approach (Eigenbrode et al. 2007). Therefore, in order to undertake transdisciplinary work, the OCF team needed to ensure clear communication between team members. The OCF team implemented various methods to enhance communication and an understanding of each other's research and interests that ultimately led to a shared conceptual framework (Figure 2). These methods included scheduling structured and unstructured time together, identifying interdependencies, and incorporating advice from advisors and suggestions from the literature on collaborative research related to these activities.

Ocean Condition Forecast Team

OCF Team Composition: Personalities, Education, and Disciplinary Differences

The OCF team is composed of four very different members. While disciplinary differences inform variations within terminology and contextual knowledge, diversity in upbringing and culture also contribute to ambiguity in language and ideas. Each member of the OCF team comes from different parts of the United States; Oregon, Virginia, Colorado, and New York are each represented. Team members were raised in rural, suburban, and urban environments. Three of the team members are the eldest siblings in their families, while one is a middle sibling. The educational backgrounds and professional work experience of each team member also differ. The undergraduate disciplines represented are engineering, geology, and mathematics. The graduate disciplines branch further apart, including physical oceanography, civil engineering, paleontology, cartography, and marine resource management.

The team also took an online personality type test (NERIS Analytics Limited 2011) based on the Myers-Briggs personality test (Myers 1962, Young 2001) in order to assess their differences and use the results as a learning tool to aid in communicating more effectively as a team. According to Young (2001), understanding the preferences of team members and making an effort to communicate in a way that suits them can improve team communication and relationships. The test results showed that the four personalities represented are ENFP-A, INFJ-A, ESTP-A, and ISFJ-T (Myers 1962, NERIS Analytics Limited 2011). The differences in these personalities led to differences in strengths between each of the members— some were good at coming up with original ideas, others were skilled at refining these ideas, and yet others excelled at implementing these ideas. The team collaborated well in that they were able to recognize these differences and leverage them as strengths throughout the collaborative process.



The OCF team is composed of members with a variety of personality traits.

Weekly Meetings

Weekly team meetings were the most consistent way that the team interacted, beginning soon after the Intensive Field Camp (IFC) in September and continuing throughout the project. Meetings were usually scheduled for two hours. The meetings were most often held in the MRM office in Strand Agricultural Hall, in Wilkinson Hall, or in Dawes House on the OSU campus. The structure of the meetings varied throughout the year depending on the stage of the research process or if a team member had information to present to the group. During the Fall term, meetings focused on presenting and discussing each team member's research and the formulation of the team research question. In the winter, the focus shifted to creating an outline for the research project. The team met less during Spring term so that each member could focus on their individual contributions to the project, and during the Summer, the team started meeting weekly again to write the transdisciplinary report.

Each meeting had an agenda that was created and agreed upon at the end of the previous meeting. There was a designated note-taker for each meeting to capture the content, which naturally rotated between two team members who were more inclined to take notes. During the early stages of the project, the team considered rotating the note-taker so that everyone would fill the role equally, but the equity of note taking was not an issue. The team used a collaborative folder on Google Drive to share information and all meeting notes were kept in Google Docs so that anyone could access or add to them at any time. The team did not come up with an agreed upon file structure for the group Google Drive, which led to some confusion about the location and status of documents throughout the project.

Cluster Meetings

The OCF cluster included the OCF team, each team member's advisor, and some additional Seacast project staff that served in advisory roles. Monthly cluster meetings provided an opportunity to keep advisors up to date and allowed everyone present to ask questions and provide feedback. The structure of these meetings also varied throughout the year depending on the stage of the research. Similar to the team meetings, each cluster meeting had an agenda that was created and agreed upon by the OCF team. The responsibility of leading the cluster meetings fell to the OCF team and not to the advisors. Various communication strategies were enacted in order to ensure that the team, and not their advisors, would maintain control of the flow of these meetings. For example, ground rules had to be set to limit how often interruptions could occur when a team member was presenting. Members of the OCF team rotated as cluster meeting facilitator. One member of the OCF team was responsible for all e-mail communications with the cluster, and created a "contacts group" in Gmail for consistency. The dates of the monthly cluster meetings for each term were established at the first cluster meeting of the term when all members were present. Occasionally a cluster meeting would have to be scheduled or rescheduled using a Doodle Poll (www.doodle.com). There was a designated note-taker for each meeting.

Socializing

Establishing personal relationships outside of school and research-related activities was essential to building good working relationships and trust between the OCF team members. Activities most often included going out to drinks after a team meeting, going out to dinner, and barbecuing. Personal rapport proved to be important as the year progressed, in that the members felt that they could speak candidly about their frustrations. This helped to ensure that no member felt personally offended if disagreements did arise, because each member trusted the other's intentions. This trust developed as a result of these casual meetings where each team member could open up about their background and personal life.

Identifying Interdependencies

Each member of the OCF team was at a different point in their research at the beginning of the year, ranging from the early literature review stage to finishing up data analysis. Because of this, team members had to be up front about their timelines and what they could accomplish during the eleven months of collaborative research. It was important to identify when one member was waiting on data from another member and to hold each other accountable for meeting deadlines set within the group.

Early expectations about the project changed throughout the course of the year. At the onset, some team members had expectations about what tasks would be involved, but those deliverables changed as the year progressed. While this initially caused some frustration, the team learned to recalibrate as necessary in order to ensure that each team member's individual degree needs were met along with the requirements of the NRT program.

Results of the Transdisciplinary Process: What We Learned

Barriers to Communication: Unpacking the Black Box

A common metaphor that conveys the challenges in collaborating across disciplinary boundaries is that of a 'black box'. Literally, a black box is a process where only inputs and outputs are visible and the internal processes are not. Metaphorically, a social black box is the process by which verbal and physical communication is apparent, but the underlying thinking process is not. This thought process is influenced by a person's unique social conditioning, formal training, and projections of reality (Stone 2014). From the start, one of the most significant barriers to communication between team members was an insufficient understanding of the underlying processes within each other's black boxes. Specifically, this includes the influence of tacit, disciplinary knowledge and the ambiguity in language within team conversations. At times, the omission of crucial subject specific information led to misunderstandings, frustration, and some stagnation. Eventually, all members of the group made a conscious effort to request the clarification of ideas and terminology as needed when communicating with one another. A big part of this involved slowing down and explaining things in different ways, often with the aid of boundary objects, such as diagrams or metaphors, or discussing when a word had different meanings for different people. While ensuring that everyone understood the issue at hand took more time in the short term, it saved time in the long term because small misunderstandings did not develop into larger problems. The OCF team developed the following exercises to facilitate the unpacking of the black box.

Exercise: Getting in Each Other's Heads

During a particularly difficult meeting when the team was developing an outline, one team member suggested an exercise where each person stated what they thought another team member, with their implicit disciplinary knowledge, would write for each section in the outline. This exercise made explicit some of the assumptions team members were making, and led to productive discussions that revealed parts of each member's tacit knowledge that were not apparent before.

Exercise: System Diagrams

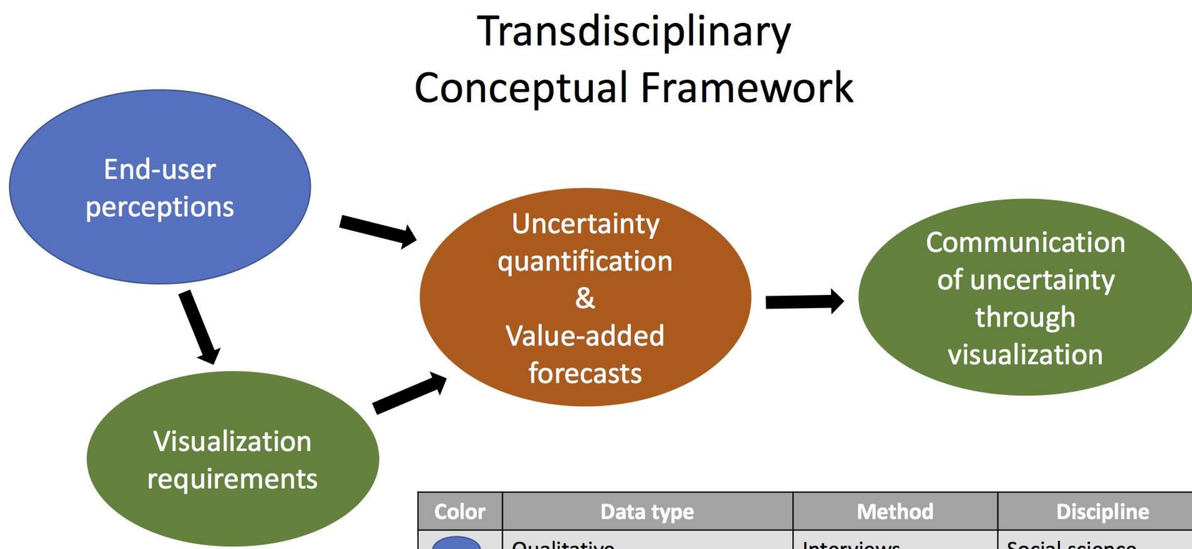
Another exercise the team conducted included creating a team-developed diagram of the coupled natural-human system within which the project was framed. This exercise required that each person in the group draw or write out, in detail, how they understood the system they were working on within the framework of their research. The system could include human and natural components, risks and uncertainties, etc. While this exercise did not contribute to a deliverable, it created a space to expand each team member's understanding of each other's point of view of the project and the system as a whole.

Recommendations

1) **Slow down to improve communication**. Do not be afraid to ask a team-member to explain or define something multiple times. The admission of ignorance may be difficult or intimidating, but it will have big payoffs down the road. It is likely that the team as a whole will benefit from the thorough clarification of concepts and terminology. Metaphors and diagrams are useful tools for this. Revealing misunderstandings creates awareness within the group of each other's knowledge base (or lack thereof). This can also generate empathy and strengthen personal relationships.
2) **Be aware of the timeline.** A year seems like a long time initially, but in terms of transdisciplinary research with a newly formed team, it is extremely short. Bear in mind that there are only 11 months between the start of the program and the due date of the final report. Do not be a hero. You are not Bilbo Baggins. Stay in the Shire.
3) **Get comfortable with discomfort**. Even though the OCF team members are supposed to be "experts," in their individual disciplines, transdisciplinary research asks one to be willing to *not* be the expert, and allow somebody else to take that role. This is not easy and it takes time. It is okay to feel completely confused and at a loss about what the other person is saying.
4) **The importance of being deliberate**. Take time to discuss and agree upon seemingly mundane things, like meeting locations, room reservations, workflows, timelines, and the file structure in shared drives.
5) **Socialize early and often**. Transdisciplinary research is just as much interpersonal as it is intellectual. Socialization will lead to improved trust between teammates, and when discomfort or misunderstandings arise, you will be able to trust that your team member is well-intentioned.
6) **Keep an open-mind**. Allow mental space for the project to change as needed as the team dynamics evolve and logistical constraints arise.

Conceptual Framework

Clear communication skills were a prerequisite to collaborating on a transdisciplinary project. The transdisciplinary component of the project required that the technical knowledge of each teammate would be connected in such a way to create a cohesive product. The perspectives of the commercial fishermen served as this connection between each team member's unique technical knowledge. This guaranteed that the product would leverage the skills and perspective of each team member and ultimately be transdisciplinary in nature. In order to meet these ends, methods included the analysis of interview data, quantification of forecast accuracy through calculation of error metrics and the use of data mining techniques, and map-making. The joint conceptual framework which describes these methods is described in Figure 2 . The implementation of these methods resulted in the derivation of uncertainty metrics and visualizations thereof which were informed by the needs of end users.



Color	Data type	Method	Discipline
	Qualitative	Interviews	Social science
	Quantitative: ROMS model	RMSE	Oceanography
	Quantitative: WW3 model	Machine Learning	Coastal Engineering
	Visualization	Programming	Cartography

Figure 2: Uncertainty (in the form of accuracy) was quantified and communicated using different techniques for the ROMS and the WW3 models which were informed by end-user perceptions and the requirements of the visualization tools.

The remainder of this paper describes the methods and results of the transdisciplinary process, briefly outlined below:

- Fishermen were interviewed to understand their perceptions of risk and uncertainty and understand how this influences use of ocean condition forecasts.
- The accuracy of the Regional Ocean Modeling System (ROMS) model in the coastal ocean was evaluated using High-Frequency (HF) radar to calculate root-mean-square error (RMSE) over a 35-day period.
- Machine learning was used to create a gridded output, and the times that were most important to fishermen were evaluated.
- The two different uncertainty quantifications from two different models (ROMS and WaveWatch III (WW3)) were used to create visualizations based on what would be familiar and useful to fishermen.

Methods and Results

Methods: Integrating Stakeholder Perceptions

This section describes the OCF team's interaction with stakeholders during a Seacast meeting and how interview data was collected, analyzed, and integrated into the transdisciplinary research.

Seacast Meeting

All members of the OCF team attended an annual meeting facilitated by an advisor from the cluster in continuation of the Seacast project. The meeting was attended by a core group of commercial fishermen involved in past Seacast meetings. The meeting was held at Englund Marine in Newport, OR in mid-November, prior to the start of Dungeness crab season, and lasted approximately two hours. There were six commercial fishermen present from various fisheries including the Dungeness crab, salmon, tuna, and black cod fisheries. The purpose of the meeting was to present updates to features on the Seacast (2017) website, to collect feedback from the fishermen on what updates they would like to see in the future, and to introduce the OCF team. The Seacast interface was presented to the fishermen and updates included the addition of tide information at key ports and the addition of a wind speed and direction forecast visualization. Requests from the fishermen for future work included the addition of a "data at the cursor" feature and the addition of a bathymetry dataset. The meeting fostered open discussion about the data needs and wants of the fishermen, provided insights about how the fishermen utilize and think about ocean condition forecasts, and introduced perceptions of risk and uncertainty in the context of ocean use. The meeting was recorded, transcribed, and shared with the OCF team and the cluster.

Qualitative Data Collection, Analysis, and Integration

Interviews

The social scientist on the OCF team conducted interviews with marine scientists (data providers) and commercial fishermen (data users) about their perceptions of risk and comfort with uncertainty as the subject of her thesis research project. The goal of the thesis work is to explore similarities and differences in perceptions between the two communities, how these similarities and differences impact forecast availability, and how availability impacts the ability of both communities to cope with the risks and uncertainties they face. For the scope of this OCF transdisciplinary research report the focus was mostly limited to perceptions of the commercial fishermen. While the original interview protocol was not designed to specifically answer the OCF team research question, valuable information on the perceptions, beliefs, and values of the commercial fishermen informed the uncertainty quantification and visualization methods developed by the OCF team.

Recruitment of members from the commercial fishing community started with key contacts and contributors already engaged in the Seacast project, while additional contacts were obtained at the suggestion of current participants. Commercial fishermen were mostly based out of Newport, the second-largest port for commercial fishing landings located along the central Oregon coast, while two participants were based out of Charleston-Coos Bay, a smaller port in southern Oregon. Participants represented the typical Oregon fisheries (ODFW 2017) and a range of gear types, boat sizes, and ages.

For this research, mental model interviews were conducted with individual participants following a protocol developed by Morgan et al. (2002) that provides a systematic and repeatable interview procedure to elicit an individual's mental model about risk. Mental models are a way to represent the manner in which individuals organize their thoughts and beliefs about how something works or how something is, and influence the way that new information is interpreted (Cone and Winters 2011). There are several procedures to elicit and interpret an individual's mental model based on research ranging from cognitive psychology to natural resource management. The Morgan et al. (2002) line of inquiry begins with open-ended questions that allow participants to freely express their views about a risk followed by more specific, semi-structured questions that target the typical risk assessment topics of exposure, effect, and mitigation of risk. (Cone and Winters 2011, Morgan et al. 2002). Interviews for each community were conducted either in-person at a location chosen by the participant, or over the phone until saturation was reached. A total of 11 commercial fishermen were interviewed and all interviews were recorded.

Data Analysis

All recorded interviews were transcribed and coded using a grounded theory approach and MAXQDA software. Initial open coding developed categories and then expanded to themes that connected back to the research questions in a stepwise process (Aurbach and Silverstein 2003). Repeating themes and key quotes were derived from the transcripts using a mostly deductive approach.

Communicating stakeholder perceptions to OCF Team

Interviews were conducted primarily during the Spring 2017 term. The social science researcher had to develop a method that provided access to interview content for the rest of the OCF team prior to data analysis. As an exploratory measure, the researcher set up an individual "read through" session with each of the three members of the OCF team. The purpose of the "read through" was to provide insight to the team about the kind of information gained during the interviews, while simultaneously informing the social science researcher about what kind of information might be interesting and useful to the OCF team. The OCF team members were particularly interested when the commercial fishermen described scenarios at sea, specified threshold conditions, and referenced trust in the forecasts. The "read through" took place at a location selected by each team member that was casual and convenient. One location was at the home of a team member, one was at a coffee shop, and one session was split up over lunch and at a bar. The social scientist brought a printed transcript from an interview with one commercial fisherman and had the other members read through it, and discuss verbally when something grabbed their attention. The social science researcher took notes about what was discussed.

It was not appropriate for the entire OCF team to read the interview transcripts in their entirety, so the social scientist made one-page summaries of the transcribed interviews based off of the initial "read through" exercise. These summaries were stored on the team Google Drive and presented at the weekly team meetings. Over time, as the social science researcher conducted more interviews with the commercial fishermen as part of her thesis data collection, she was able to naturally integrate the stakeholder perspective into team discussions through informal means.

Results: Integrating Stakeholder Perceptions

There is a link between the perceptions of risk and uncertainty as they relate to ocean use and ocean condition forecasting and the risks associated with running a small business. Mitigating financial loss and preserving the safety of crewmembers must be balanced with maximizing returns. Ocean condition forecasts are one important tool in the decision-making process of commercial fishermen where profit, boat size, gear type, time of year, time of day, and fishery are important factors in framing the context of any decision. Commercial fishermen also rely on constant observation and evaluation of their environment to manage the risks and uncertainties they face. Understanding these drivers yields insights to how ocean condition forecast uncertainty can be quantified and visualized.

Risk and Uncertainty: Hazards and Impacts

Major risks cited by participants included navigation-related hazards (marine debris and traffic), equipment failure, stress due to lack of sleep and long hours, and the natural hazards associated with atmospheric and ocean conditions, hereby referred to as hazardous ocean conditions. Hazardous ocean conditions include the interaction of wind, waves, and current. For waves, it is important to distinguish between swell and wind waves. The most often cited impact to a fishing operation from these conditions is lost fishing time leading to a decrease in productivity and profitability. Smaller vessels (less than 60 ft) are impacted more than larger vessels (greater than 60 ft) that can “muscle through” all but the most extreme conditions. While maximum threshold conditions vary for each individual commanding a vessel, 20-25 knot winds and 15-16 foot seas were cited by participants as a typical threshold between safe and unsafe working conditions that would impact productivity for a smaller vessel. Due to these limitations, weather and ocean condition forecasts play a particularly important role in the decision-making process of smaller vessels during marginal conditions. While wind and waves are mostly linked to hazards associated with crossing the bar, currents were cited as hazards when they run in opposition to wind and waves creating “chaotic” conditions, and when they affect the ability to deploy and retrieve gear. For example, current direction impacts how crabbers lay their pots and strong currents impact whether crabbers can retrieve them. Further reducing the window of opportunity to cross the bar on a daily basis is the timing of the tide, where flood stage during slack high-water is the most optimal time to cross.

Factors that influence when ocean conditions become hazardous to commercial fishermen, beyond vessel size and gear type, include time of year and fishery. For example, wintertime is characterized by large storms and large swells that coincide with the start of the profitable Dungeness crab fishery in mid- to late- December and early January. High wind speeds and wave heights impact the productivity of vessels by preventing them from leaving or entering port due to dangerous bar conditions. For larger vessels that remain at sea during storms, productivity is limited due to breaking waves that create hazardous conditions on deck. The timing of these hazardous conditions is important because Dungeness crab is a derby fishery, where the goal is to fish as much as possible at the beginning of the season. It is a time when fishermen are most willing to take risks to support their business, with lost days translating to lost dollars that typically cannot be recovered.

The 52 ft Coast Guard Motor Lifeboat "Victory" crossing the Yaquina Bay bar on a winter day. Photo: William Powell

Even beyond lost fishing time, hazardous ocean conditions impact the fleet from gear and equipment loss, injury, and death. Loss of gear is a major financial cost that typically occurs during crab season when big storms can move nearshore pots into deeper water or onshore. Hazardous bar crossings can result in blown out windows, loss of electronics and steering, and even a Coast Guard rescue in the most severe cases. Most participants cited extreme cases that resulted in a vessel overturning and loss of life, and several participants had experienced this first-hand.

Risk and Uncertainty: Mitigation

Since ocean conditions play a crucial role in determining the success of a fishing operation, commercial fishermen are adept at seeking out and interpreting weather and ocean condition forecasts and they have evolved alongside the technology in recent years. Despite reliance on these forecasts, their perceptions of the accuracy of the forecasts was dependent on how far in advance they were looking. Overall, participants expressed confidence in forecasts extending 12 to 24 hours into the future, but were more skeptical of anything beyond that. This confidence in predicting conditions in the near term has strengthened through the years.

The most often used and trusted source is the National Weather Service Marine Forecast (NWS 2017), which provides wind and waves forecasts, but not currents. Checking the weather was part of the daily routine for fishermen, with smaller vessels constantly monitoring every update. Any other sources of forecast information served as supplemental information to the Marine Forecasts and these are used more when conditions are marginal and during high-stakes times of year (for example, the winter months). Some examples of additional sources include the websites Seacast (2017), Stormsurf (www.stormsurf.com), and Windy (www.windy.com). Participants associated weather and ocean conditions with atmospheric fronts, whose approach they could track over time, often citing wind as the driving force behind all weather and ocean conditions. Trust in forecasted information was based on experience and how well the forecasts correlated with personal and buoy observations, as articulated in the following quotes:

“Well, I’ve used the NOAA forecast center for so long, and you compare it to what you’re actually seeing, so in using it for so long I’ve built a lot of confidence in it.”

“I’ll look at it tonight, and I’ll look at it tomorrow morning, and I’ll look at it tomorrow night and then I’ll look at the buoys, like I was saying - see how everything lines up. How accurate everything is, just kind of go from there.”

Though participants do not have as much confidence in longer-range forecasts beyond 24 hours, they still find them useful for planning and operate under the assumption that the forecast will change. Interpreting weather and ocean conditions is a constant mental calculation that also incorporates physical observation. When deciding whether to cross the bar, participants described going down to the vessel at the dock, monitoring barometric pressure, listening to the Coast Guard bar report, timing the wave series, communicating with other vessels, and even observing cloud formations and animal behavior. When navigating at sea, changes in current are detected through subtle changes in the way gear buoys lie in the water, or changes to the electronics or the speed of the boat when going through a tidal rip confluence. Commercial fishermen are constantly observing their surroundings and trust in their ability to make decisions based on those observations.

“We’re responsible for our own observations. And it’s even good - in this age of abundant information but imperfect forecasting - there’s a place for our own intuitive interpretation for what’s going on around us. And so, we’ve got to keep using our senses. Regardless of how good modeling is. They’re not that good.”

Commercial fishermen cited several other ways to manage the risks and uncertainties they face as a result of operating a business in a hazardous environment. Without an ability to control or predict the weather, commercial fishermen focus on what they can control. There is an emphasis on keeping vessels in the best possible condition with backup plans, redundancies, and de-watering systems while also understanding and respecting the limitations of each vessel. Though it is a competitive business, there is a great deal of communication and cooperation between vessel operators when it comes to bar crossings and hazardous conditions. Experience, composure, and the ability to be flexible and adapt were often cited as characteristics that are effective in coping with the risks and uncertainties of commercial fishing.

Linking Perceptions to Uncertainty Quantification and Visualization

Commercial fishermen are advanced navigators of the marine environment who, in part, rely on forecasts to mitigate risk. An exploration of the risks and uncertainties they face has revealed important considerations that can influence the way uncertainty in forecasts is quantified and communicated, as summarized below:

- Forecasts are not useful unless they are accurate. Framing model uncertainty in terms of forecast accuracy would be useful to them, with accuracy referring to how well the forecasted conditions agree with buoy and personal observations.
- There are certain times and locations where the accuracy of forecasts is more important for managing risk, outlined below:
    - Mid-December through January because it coincides with the most hazardous ocean conditions as well as the Dungeness crab fishery, where there is more pressure to fish.
    - During "marginal" conditions, when small vessels are close to their upper threshold of safety: 20-25 knot winds and 15-16 foot wave height.
- In addition to the National Oceanic and Atmospheric Administration (NOAA) Marine Forecasts, fishermen use various sites like Seacast (2017), Stormsurf, and Windy to visualize forecasted conditions. These interfaces can be referenced when creating uncertainty visualizations.

Methods: Wave Modeling

This section describes the wave model that was used to make the wave height forecasts, the method used to determine the metrics of accuracy throughout the model grid, and the validation of that method. Two case studies are presented to validate the utility of this method. These case studies use the method to predict the error associated with the original forecasts during specific wave events. These events represent the types of conditions that are most hazardous for fishermen.

In the context of this project, measures of wave model accuracy can be used by fishermen to determine the level of skepticism they should place on forecast information. The wave model is used in part to determine whether or not it is safe enough to leave or return to port. This determination is made after considering whether the wave height is large enough to pose a hazard to their gear and crew on board the ship. The hazard itself is caused by large waves breaking across the 'bar', an area where the fishermen cross into and out of the harbor. Wave model accuracy is especially important during threshold conditions (as mentioned previously, 15-16 foot seas and 20-25 knot winds) where fishermen may or may not go out to sea, depending on the conditions forecasted. During these times, small differences in wave height or wind speed will factor into the physical and financial risk the fishermen take on.

In the Seacast (2017) forecasts, wave height predictions are available on the model grid. However, observations of wave height are only available at offshore buoys. Therefore, validation of wave height on the entire grid is not possible for the wave model. Corrections that are made at only one point (such as a buoy) might not be sufficient to relay information about the accuracy of conditions in the other parts of the ocean traveled by fishermen. The method presented here remedies this problem by predicting wave height error throughout the grid using historical information at the places where data is available.

Although the wave observations lack spatial resolution, they have an abundance of temporal resolution. Observations are available for several years on the National Data Buoy Center (NDBC) website (NDBC 2017). Given this trade-off in temporal and spatial resolution, a methodology was devised using NDBC observations to train a machine learning algorithm. This algorithm predicts wave height error throughout the model domain (Figure 3).

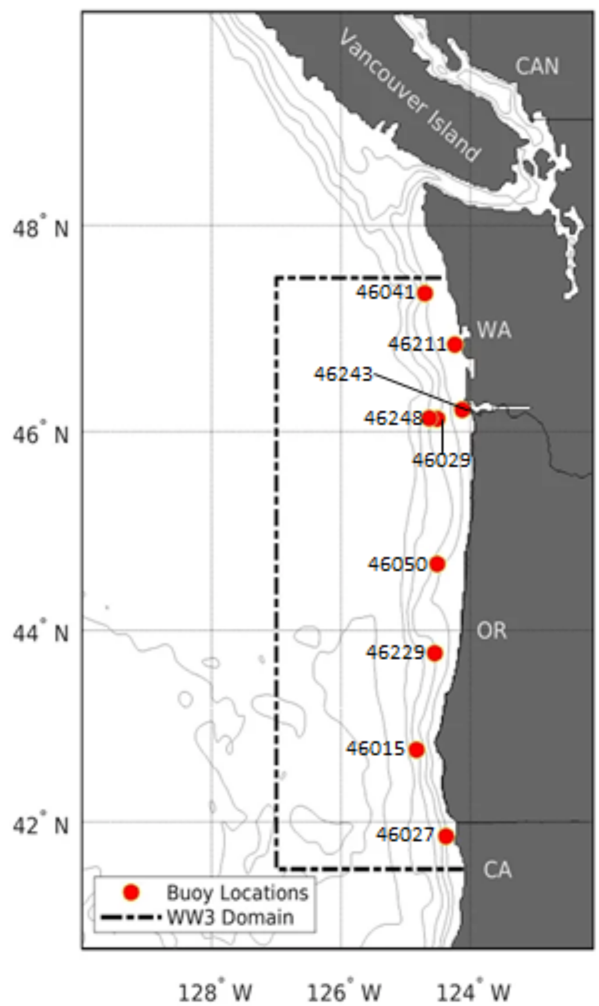


Figure 3: Regional Ocean Modeling System Domain including the WaveWatch III (WW3) domain (black dashed line), NDBC buoy locations (red dots), and the 100, 200, 500, 1000, 3000, and 5000 m isobath contours (gray). Buoy locations are all roughly inshore of the 500 m isobath.

Physical Models

The physical wave forecasting model is WaveWatch III (WW3) (Garcia-Medina 2013). The first grid spans the entire Pacific Ocean at a 30 arc-minute resolution, the second grid spans the Eastern North Pacific at a 7.5 arc-minute resolution, and the third grid spans the continental shelf (40.3° to 49.5°N and 233° to 236.25°W) at a 90 second resolution (Figure 3). The wind model used as input is the National Center for Environmental Prediction's (NCEP) Global

Forecast System (GFS) (NOAA 2017). This product is available every 3 hours at a spatial resolution of 0.5°.

Machine Learning Model

Generally, machine learning algorithms have the ability to find patterns within large amounts of data (Alpaydin 2014). In this case, the machine learning algorithm is used to find the pattern connecting the predicted environmental conditions and the observed error at the different buoys (Figure 3). The machine learning algorithm implemented in this case is a Bagged Decision Tree (BDT).

The input data (feature data) used in the BDT are ocean conditions and location information (latitude, longitude, and depth at each buoy, WW3 predicted wave height, mean period, mean wave direction, and GFS predicted wind speed and wind direction). The output from the BDT (or the target) is the error between historical NDBC observations and the historical forecast predictions of wave height. The specific type of input data were chosen to distinguish the buoys from one another in order to apply the machine learning algorithm to a grid. The output from the BDT was chosen in order to determine the predicted error associated with the forecast for the uncertainty metrics.

The data used to train the BDT is comprised of a time series of each input variable for 300 days prior to the event. These time series are pulled for nine different buoy locations, resulting in a combined total of 64,800 hours of data points. The BDT is trained on 70% of this training data. The remaining 30% is used for BDT validation and parameter optimization. Predictions are then made on the gridded forecast of two case studies, which are described in the following section.

Wave Height Event Time Series Descriptions

In order to determine the events which best represent threshold conditions for the fishermen, two wave height events were chosen by the wave modeler and the social scientist. The time series for each wave height event is shown below (Figures 4 and 6). The buoy observations are plotted in black and the original model predictions are shown in blue. In the first event, the largest wave height is widely variable across the shelf, while in the second event, the wave heights are more similar between the buoys.

The first event is characterized by two wave height peaks, with the first reaching a much higher maximum wave height (15 ft) than the second (~10 ft). The first peak is represented by a gradual onset, while the second peak arrives quickly (Figure 4). The duration of this event is one day longer than the second event, and all of the buoys record large wave heights. The dominant wave direction is from the W/NW, and the wave period decreases throughout the event from approximately 17 seconds to 9 seconds. The wind speed ranges from 0-12 knots, and the wind flows initially from the North and then shifts to the East, South, West, and ultimately back to the North.

The second event is characterized by a rapid growth in wave height (Figure 6). Wave heights reach 15 feet for the majority of the buoys, the dominant wave direction is from the W/NW, and the wave period is approximately 12 seconds. The wind speed ranges from 0-10 knots for the majority of the event. During the first half of the event, the wind primarily flows from the North, and shifts to the East during the second half of the event.

Results: Wave Modeling

In order to assess the performance of the BDT on the forecasts over a grid, the predictions are validated at buoy locations within the grid for the two events. To do so, the predictions of the BDT (the error) are added to the original model output error to derive a BDT wave height. The performance difference between WW3 wave height and the BDT post-processed wave height is compared through the calculation of error metrics: root-mean-square-error (RMSE), percent error (PE), scatter index (SI), and bias.

Overall, the post-processed wave height time series yields larger error metric values than WW3 (see scatter plot of wave height and error values in text in Figures 5 and 7). However, when the performance of the BDT is evaluated at each buoy, the error metric values are less for the BDT than for WW3 for some buoys. For both events, the BDT increases predicted wave heights as compared to WW3, resulting in an increase in bias. In the first event, the BDT shows an overall increase in wave height that results in inaccurate values compared to the buoy observations. For the second event, this results in greater accuracy in predicting peak wave heights (Figure 4, buoys 46248 and 46029). Generally, the BDT can reproduce sudden jumps in wave height more effectively than WW3. At times, reproducing these sudden jumps can result in better estimations, such as in the final hours of the first event or the peak wave height in the second event. At other times, this results in overestimations as seen in the first part of the wave height time series for the second event (Figure 6).

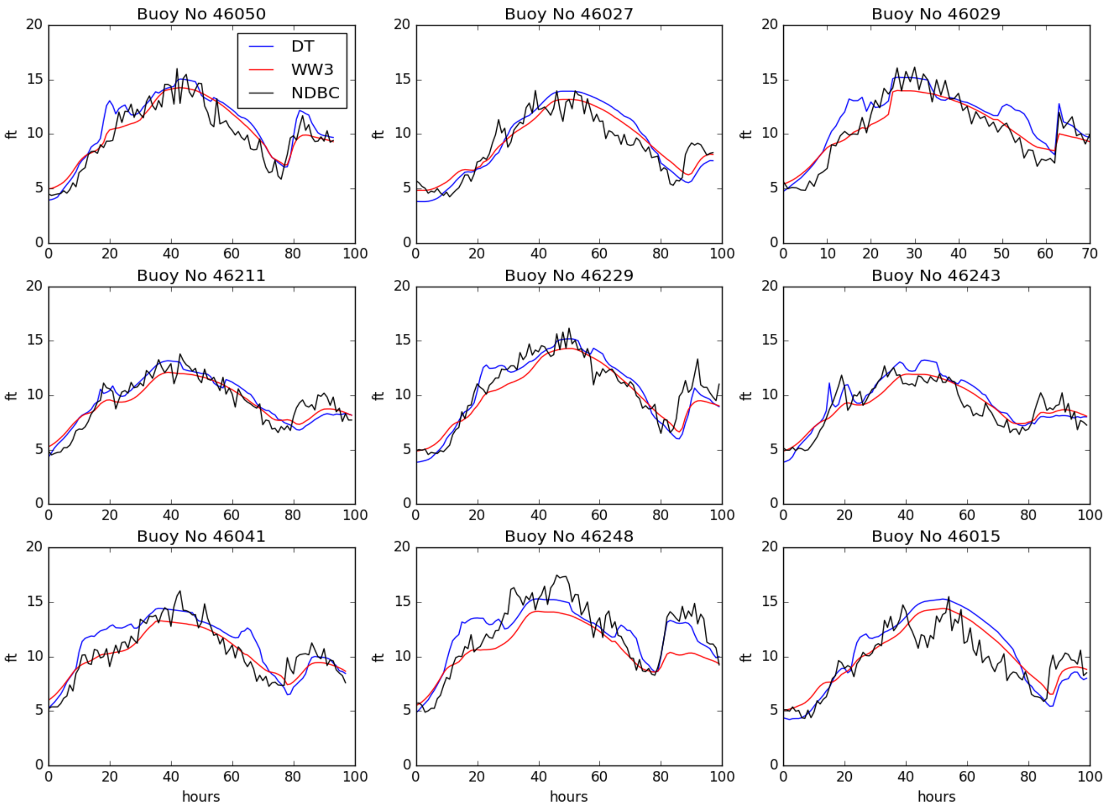


Figure 4: Time series of significant wave height (Hs) for Event 1 at the nine different buoys (NDBC, black), as predicted by WaveWatch III (WW3, red) and the BDT post-processing method (DT, blue). The average peak wave height is similar for each buoy. The post-processing done by the decision tree results in overestimations at some points throughout the time series.

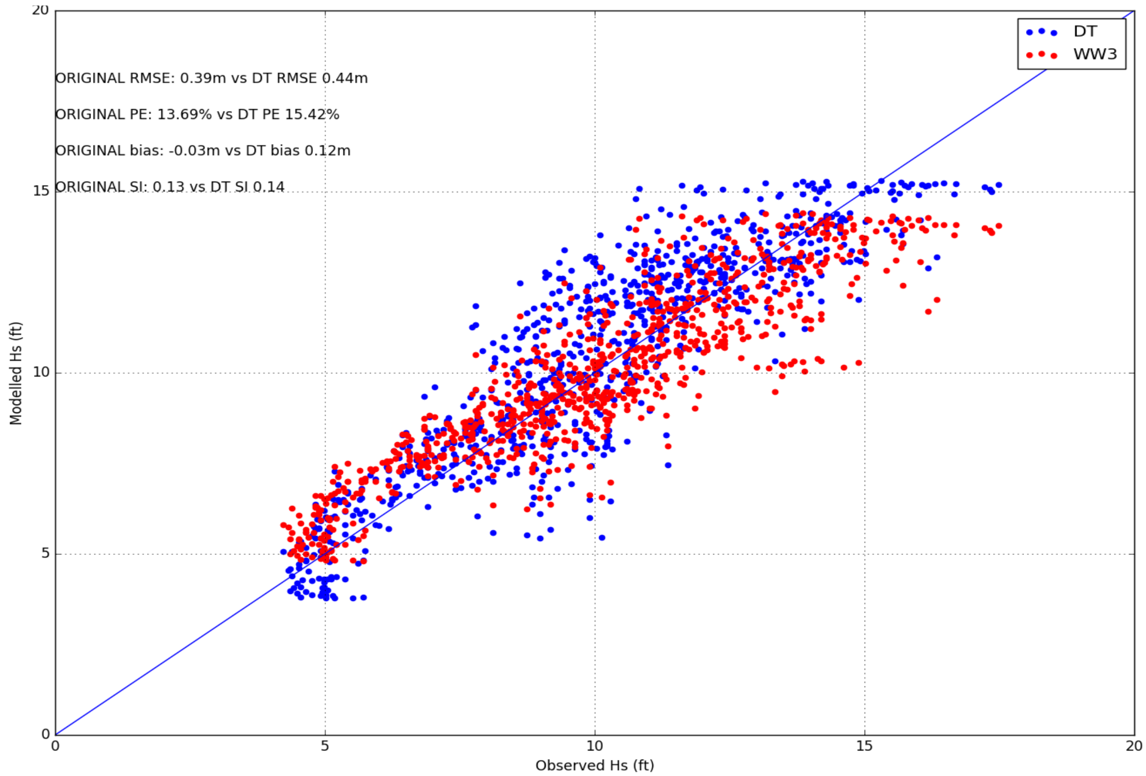


Figure 5: Event 1 wave height scatter plot. WaveWatch III (WW3) is shown in red, and the BDT post-processed wave height time series (DT) is shown in blue. The error metrics (RMSE, PE, SI and bias) are also included.

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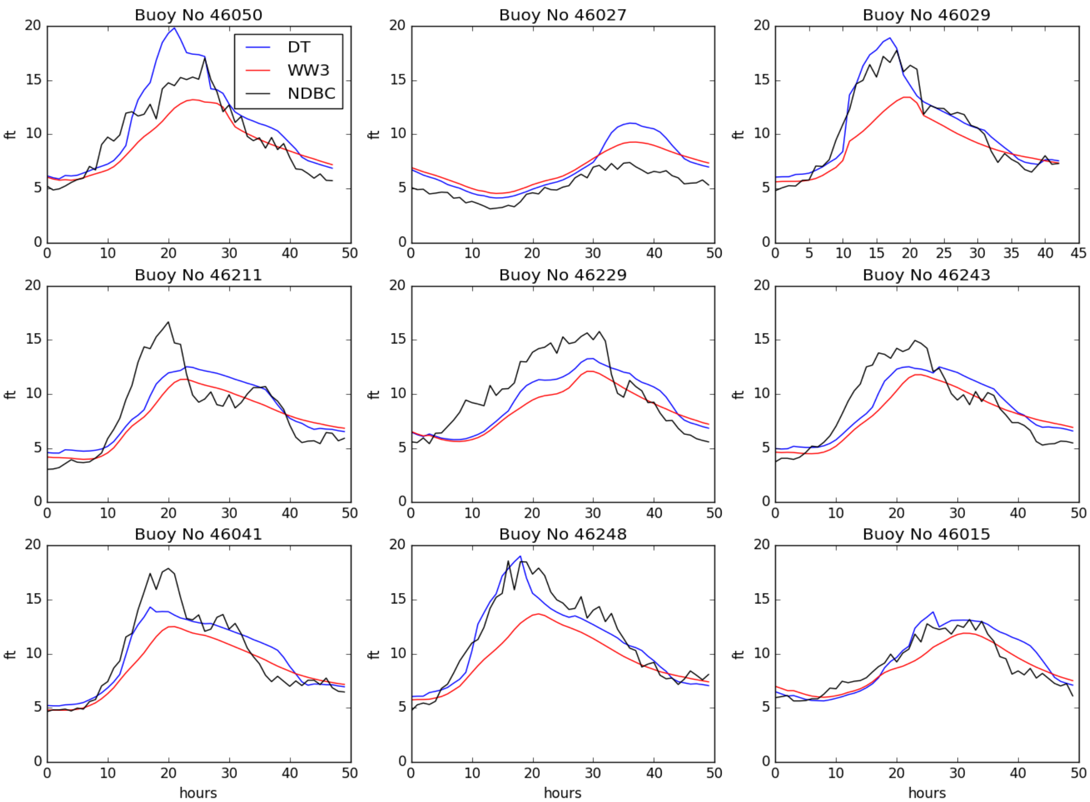

Figure 6: Time series of significant wave height (Hs) for Event 2 at the nine different buoys (NDBC, black), as predicted by WaveWatch III (WW3, red) and the BDT post-processing method (DT, blue). The maximum wave height reached is different for each buoy. The decision tree accurately reproduces the peak wave height for buoys 46029, 46248, and 46015, but it overestimates the peak wave height for buoys 46050 and 46027.

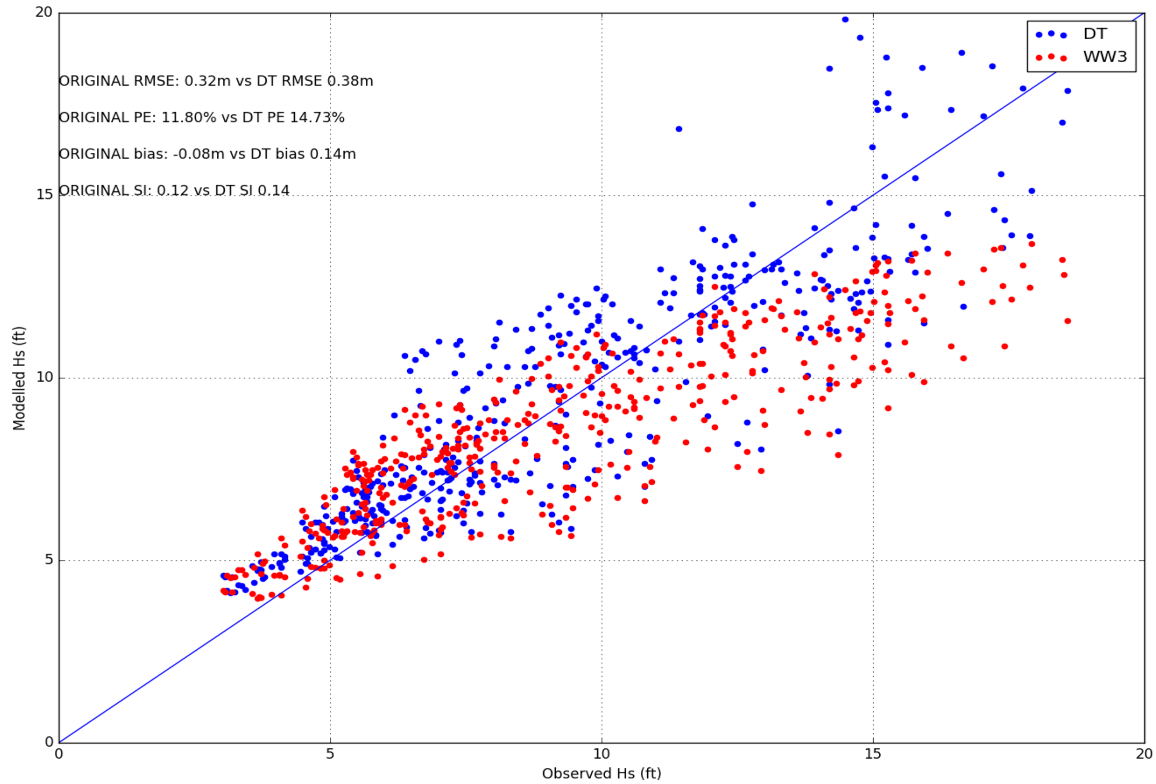

Figure 7: Event 2 wave height scatter plot. WaveWatch III (WW3) is shown in red, and the BDT post-processed wave height time series (DT) is shown in blue. The error metrics (RMSE, PE, SI and bias) are also included. Overall, the BDT results in worse performance as measured by error metrics, but better performance for the largest wave heights.

Methods: Regional Ocean Modeling System (ROMS)

This section describes the OCF team's process of developing a thermocline depth forecast and uncertainty metrics for forecasts of the surface currents.

Considering the stakeholder perspective on risk and uncertainty helped shape the efforts in quantifying the uncertainty in the surface current forecast. Accurate forecasts are valued by commercial fishermen, so quantifying a measure of accuracy would be most useful for this stakeholder group. Additionally, interactions with the stakeholders have revealed that commercial fishermen define model accuracy as how well the models represent observations. These revelations guided the OCF team to use root-mean-square-error (RMSE) as a method of accuracy quantification. The interests of the commercial fishermen also led the team to use the ocean model to calculate and forecast the depth of the thermocline.

This model is based on the Regional Ocean Modeling System (ROMS, www.myroms.org) which is a hydrostatic, three-dimensional, non-linear, Boussinesq, free surface ocean model. It uses terrain following vertical coordinates and advanced numerics (Shchepetkin and McWilliams 2005, 2003). Vertical, subgrid turbulence is parameterized using the Mellor-Yamada scheme (Mellor and Yamada, 1982).

The model domain spans 40˚ N to 50˚ N (the middle of Vancouver Island) and 130˚ W to the U.S. West Coast (Figure 3). The model grid is a regular latitude-longitude grid with a horizontal resolution of about 2 km and 40 vertical, terrain following layers. The vertical resolution is better near the surface and bottom of the ocean.

A bulk flux formulation is used to force the model (Fairall et al. 1996) which requires the following atmospheric fields: near surface wind speed and directions, air pressure, incoming shortwave, relative humidity, air temperature and cloud cover. These fields are obtained from the NOAA North American Mesoscale Model (NAM, www.emc.ncep.noaa.gov) which has a 12-km horizontal resolution and a 3-hour temporal resolution. Freshwater discharges from the Columbia and Fraser Rivers, along with 15 small rivers that enter the Puget Sound and the Juan de Fuca Strait are included.

This model produces three-day forecasts of ocean currents, temperature, and salinity which are constrained by open boundary conditions formulated from the 1/12˚ degree resolution, U.S. Navy global data assimilation Hybrid Coordinate Ocean Model (HYCOM, www.hycom.org) (Chassignet et al. 2007). HYCOM provides instantaneous fields once a day. To avoid aliasing inertial motion and day-to-day noise, a five-day half amplitude filter is applied to these fields. At open boundaries, tides are added using the tidal sea level and the barotropic velocity amplitudes and phases for the eight most dominant tidal constituents (M_2, S_2, N_2, K_2, O_1, K_1, P_1, and Q_1) (Egbert and Erofeeva 2002).

The OSU forecast system delivers daily updates of three-day forecasts of ocean currents, temperature, and salinity. Once every three days, data assimilation is run to correct the recent ocean state estimate to bring it closer to the available observations of surface currents from a network of high frequency (HF) radars, sea surface temperature from the Geostationary Operational Environmental Satellite (GOES), and sea surface height from multiple different satellite altimetry missions. The data assimilation is done using the 4DVAR variational method in three-day time windows using tangent linear and adjoint codes developed at OSU (Kurapov et al. 2009, 2011, Yu et al. 2012).

Results: ROMS

Thermocline Depth Forecast

Providing a forecast of the thermocline depth for commercial fishermen required some inquiry into their definition of the thermocline. One way to define the thermocline is to use the buoyancy frequency squared, given by $N^2 = \frac{g}{\rho_o}\frac{\delta\rho}{\delta z}$. Correspondence with the commercial fishermen at the initial Seacast meeting revealed that they commonly define the thermocline as the depth in which the temperature is 2˚ F less than the surface temperature. Both of these methods were used to calculate and forecast the depth of the thermocline. In this calculation, daily averaged temperature and salinity were used in an effort to smooth potential inversions and remove false shallow depths.

Due to the changing vertical resolution of the model with bathymetry, using the buoyancy frequency definition in this calculation can produce rapid changes in thermocline depth in the horizontal (Figure 8). The commercial fishermen’s definition creates a smoother forecasted field, but in well-mixed waters it does not produce a number, i.e. the temperature does not change by more than 2˚ F (Figure 9). Both of these methods produce relatively similar results with the difference in depth rarely exceeding 10 m.

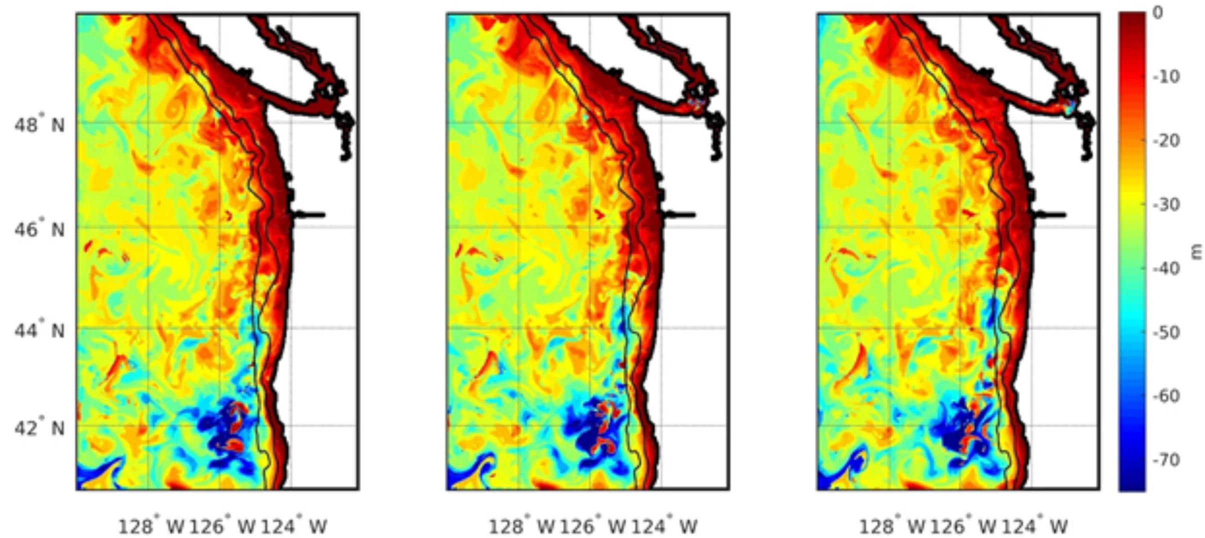

Figure 8: Depth of the thermocline calculated using N^2 with the 200 and 1000 m isobaths contoured (black) for forecast horizons of 1 day (left), 2 days (middle), and 3 days (right).

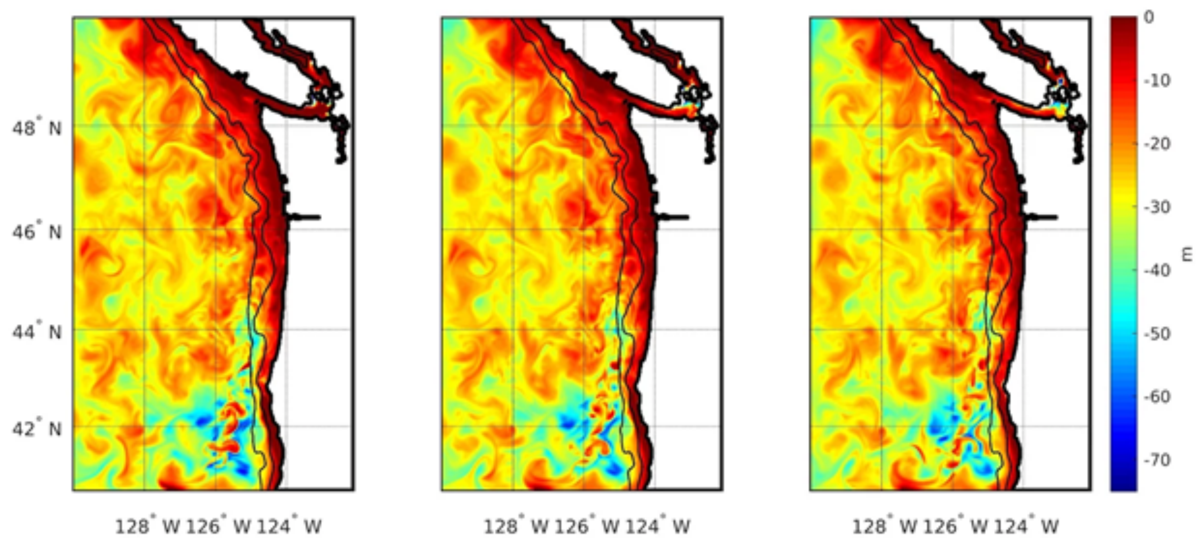

Figure 9: Depth of the layer 2˚ F difference from the surface with the 200 and 1000 m isobaths contoured (black) for forecast horizons of 1 day (left), 2 days (middle), and 3 days (right).

Uncertainty Quantification

As mentioned previously, the social scientist on the OCF team conducted interviews with commercial fishermen and set up an individual “read through” session with each of the three members of the OCF team. In one such session it was revealed that commercial fishermen often think about model uncertainty in terms of how accurately the model represents in-situ conditions or their own observations. In an effort to recreate this thought process, root-mean-square-error (RMSE) was chosen as the uncertainty metric to evaluate surface currents provided by the ocean model. Due to availability of the model data and preferences of the commercial fishermen, this calculation was performed for the past 30 days of each forecast. The forecasts used in this study spanned June 27 to July 31, 2017. It should be noted that the commercial fishermen would prefer this evaluation to be performed over the past 7 days (or less) because they relate ocean conditions to rapidly changing atmospheric conditions, but RMSE on such a short time scale may not make sense from a mathematical perspective.

RMSE is calculated by comparing model surface currents to high frequency (HF) radar observations available throughout the study time period. The HF radar data used here is available as hourly fields with two velocity components: u (meridional) and v (zonal) on a regular 6 km grid. The area encompassed by this data varies from day to day due to changing environmental conditions. Model surface currents, provided every 2 hours, are sampled at times and locations when the HF radar data is available for 1, 2, and 3-day forecasts. Area averaged u and v velocity components for each forecast horizon (Figure 10, 11, and 12) qualitatively reproduce the data well, with the overall error increasing with forecast length. The ocean model appears to do better at the beginning of July for all forecasts, and there is less error in the cross-shore (u) velocity than along-shore (v).

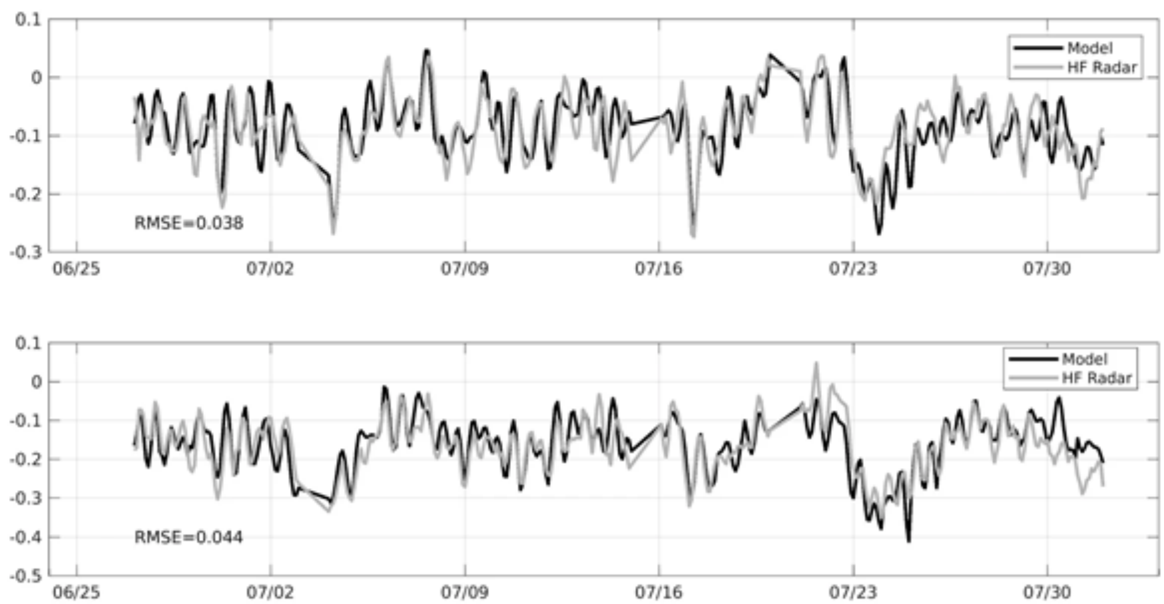

Figure 10: 1-day forecasts of area averaged instantaneous velocity for u (top) and v (bottom) velocity components for both the model (black) and HF Radar (gray).

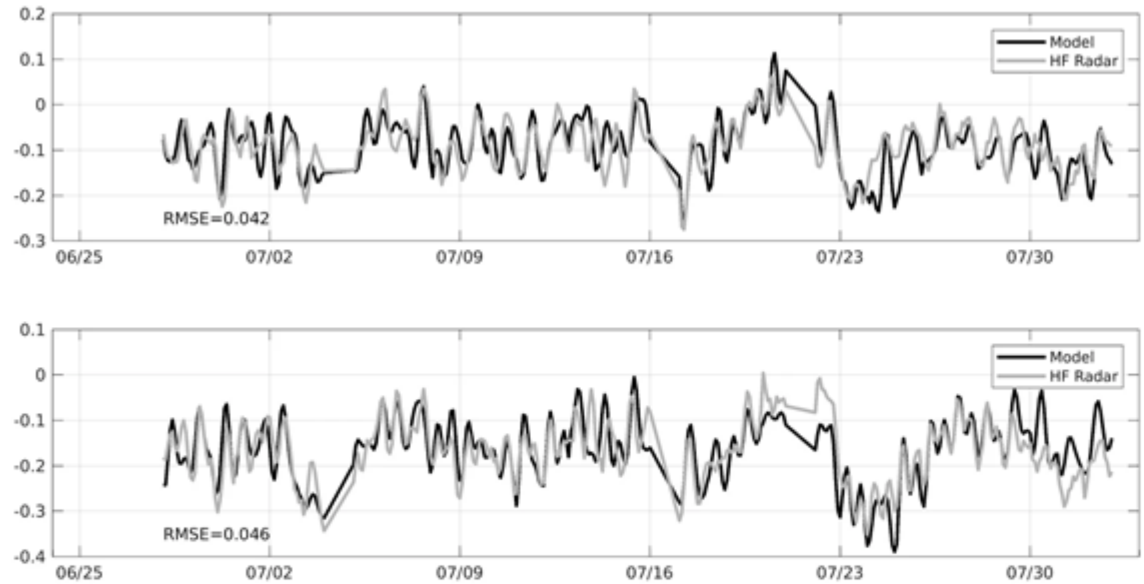

Figure 11: 2-day forecasts of area averaged instantaneous velocity for u (top) and v (bottom) velocity components for both the model (black) and HF Radar (gray).

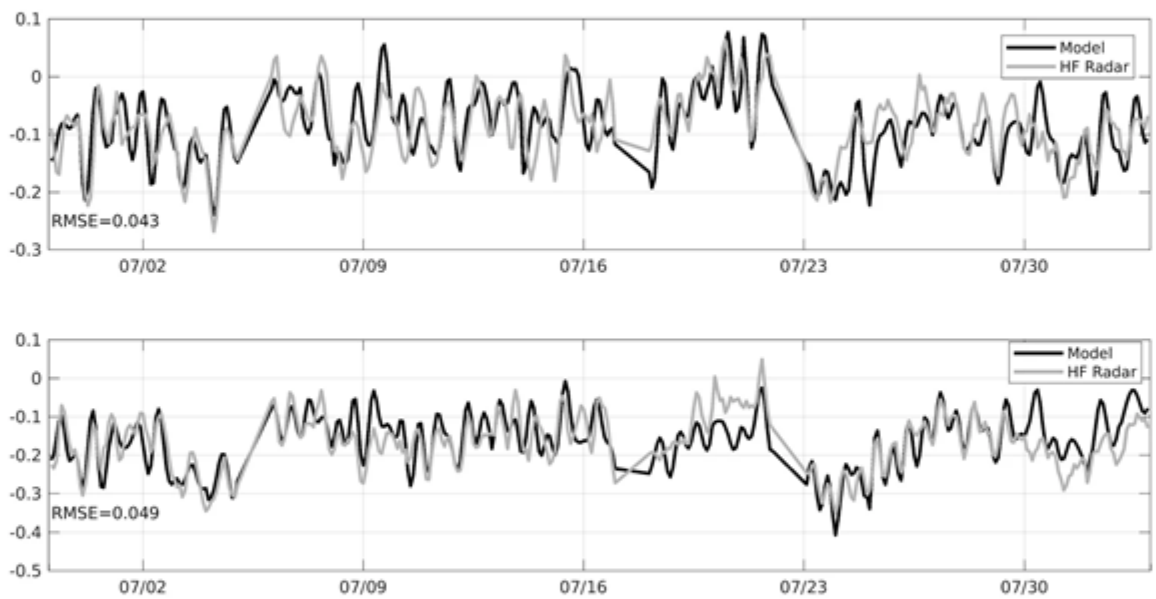

Figure 12: 3-day forecasts of area averaged instantaneous velocity for u (top) and v (bottom) velocity components for both the model (black) and HF Radar (gray).

To spatially evaluate sources of greater error, RMSE was calculated at each model point where HF radar data was available for each forecast. Each forecast shows a similar spatial error structure. The model does better north of about 43.5˚ N, where ensemble-based model predictability is generally better (Kim et al. 2009). There is also a noticeable source of error near the Columbia River estuary (just north of 46 ˚ N). The source of this error resides in both the along-shore and cross-shore components of velocity. Note that the model does not have enough resolution to represent energetic outflows from the river mouth on the ebb tides. At the same time, HF radar current estimates are in error when the current speed is close to the wave speed (which would be close to 2 m/s in the river mouth). South of about 43.5˚ N, the model does relatively worse than the rest of the domain, particularly south of 42˚ N. This error is the result of roughly equal contribution from the along-shore and cross-shore velocity components, and is associated with nonlinearities in the flow, such as coastal jet separation at Cape Blanco and eddy formation in the coastal transition zone (Koch et al. 2010). In general, the error is larger with longer forecasts.

It is important to note the lack of spatial coverage of the HF radar as a limiting factor for evaluating surface currents west of 126˚ W and north of 46˚ N. While there is adequate data for a meaningful nearshore calculation on the Oregon Coast, there is a noticeable lack of data for the northern half of Washington. The encouraging news is that the Northwest Association of Networked Ocean Observing Systems (NANOOS, www.nanoos.org) is providing funding this year to extend the HF radar network into Washington.

Methods: Visualization

This section covers the methods used to create maps from the model uncertainty metrics described in the previous sections. Multiple example maps are provided for each metric.

The OCF team decided to use maps (Figures 13-19) as the primary method of communicating the ROMS and WW3 model accuracy metrics. Fishermen are very familiar with map-based displays of ocean condition forecast information, and maps of model accuracy can be integrated into the web-map interfaces they already use, such as Seacast (2017).

Map Elements: Basemap, Labels, and Legends

The elements chosen for inclusion on the maps (Figures 13-19) were selected based on standard cartographic techniques for displaying oceanographic data, as well as their familiarity to fishermen. The basemap selected shows bathymetric characteristics, with labels for spot depths and major features of the ocean floor. It also shows the coastline and land masses. The colors used to depict the land and sea are light and suitable for a background map—they do not clash with the thematic information displayed on top. Additionally, this style of basemap is similar to those used in other web map interfaces, such as Seacast (2017), which uses basemap imagery provided by the Google Maps API (Application Programming Interface).

The latitude/longitude graticule and labels, coastal city labels and point symbols, state boundaries (where applicable), and land masses are included over the basemap to give context to the location. Although the models and their associated accuracy metrics are restricted to the ocean, the coastline and administrative labeling on land remain important elements that aid the map-reader in quickly orienting themselves on the map (Phipps and Rowe 2010).

The legends on each map (Figures 13-19) are shown in the lower-right corner. They are placed on land, to avoid covering or obscuring the model accuracy information. The legends are intentionally kept simple—fishermen are already familiar with many of the elements on these maps. Each legend contains only information about the model output shown on the map, and a scale bar is included nearby. Oceanographic data display conventions indicate that the metric system should be used for all map units. However, the preferences of fishermen differ from these conventions, and were used to inform what units should be included in the legend information. The scale bar distances are given in nautical miles (Figures 13-19), wave height differences are shown in feet (Figures 13-15), and surface current speeds are given in knots (Figures 16-19).

Map Elements: Representing Model Accuracy Metrics and Output

Conversion of Data Formats

NetCDF (Network Common Data Form) is the data format used for output from the WW3 and ROMS models, as well as their related accuracy metrics. This file format can hold multiple arrays of data (subdatasets), including latitude/longitude values, times, and model variables. NetCDFs are a standard file type used for oceanographic data, but they are not commonly used in web-mapping applications. One of the more commonly used file formats for the creation of web maps is the GeoTIFF (Geographic Tagged Image File Format). GeoTIFFs contain georeferencing information (such as coordinate systems and map projections), in addition to raster image values (such as those contained in a single NetCDF subdataset). They are also commonly used in GIS (Geographic Information Systems) software.

In order to create maps of the model accuracy metrics in a GIS environment, as well as georeferenced imagery that can be used in a wide variety of web map interfaces, it was necessary to convert the NetCDF files into the GeoTIFF file format. This was done using the Geospatial Data Abstraction Library (GDAL, www.gdal.org), which is a software library used to read, write, and translate geospatial raster and vector data.

Wave Model

The model accuracy metrics generated and mapped for the wave model represent the difference between the original wave model (WW3) and the BDT model predictions of wave height. The oceanographic convention of using a rainbow color ramp for wave height information is used on some of the maps (Figures 13 and 14), as fishermen are used to this method of display. Normally, the red end of the spectrum is associated with greater wave heights, and the blue end is associated with lesser ones. In the case of the wave model accuracy information shown in Figures 13 and 14, red still indicates the highest numbers, and blue the lowest ones, however, colors in the yellow to red range of the spectrum denote positive values, or *underprediction* of wave height by the WW3 model as compared to the BDT model (i.e. wave heights may be higher than indicated by the WW3 forecast). Conversely, colors in the yellow to blue range of the spectrum indicate negative values, or *overprediction* of wave height by the WW3 model as compared to the BDT model (i.e. wave heights may be lower than indicated by the WW3 forecast). Yellow indicates areas where the two models agree—the WW3 wave height prediction is relatively accurate.

Use of the conventional rainbow color ramp in this manner may be confusing to fishermen, so supplemental information is offered in the map legends. Additionally, the rainbow color ramp is not suitable for the color vision impaired. Eight percent of the male population in the U.S. have some form of color vision impairment (Jenny and Kelso 2007), and the commercial fishing profession in the Pacific Northwest is predominantly male (NW News Network 2017).

In light of the potential for misinterpretation, other options for displaying the wave model accuracy metrics were explored (Figure 15). A modified version of the rainbow color ramp is shown in Figure 15 (a), which omits yellow-green and green hues, and uses a darker shade of red (Jenny and Kelso 2007, Brewer 2006). This version is distinguishable for the color vision impaired, and it may be different enough from the conventional norm to alleviate confusion. A second modification of the wave model accuracy metric is shown in Figure 15 (b), which uses absolute values instead of positive and negative values to represent differences in the accuracy of the WW3 model prediction. In this case, greater values indicate higher model error (less accurate), and lesser values indicate lower model error (more accurate). A traditional red-to-green color ramp is used, where red indicates poor model accuracy, and green indicates areas of better model accuracy. This version is less likely to be confused with wave height model prediction output, however, there are two caveats. First, it contains less information, so it may not be preferred by fishermen. Second, it is not easily discernable by the color vision impaired. A purple-to-green color ramp would be a better solution to this issue—see Figure 19 for an example.

Regional Ocean Modeling System

The model accuracy metrics generated and mapped for the ROMS model represent the accuracy of the model with respect to the speed and direction of surface ocean currents, as compared with HF radar observations using root-mean-square-error (RMSE) calculations. Speed and direction model accuracy metrics are shown separately for ease of interpretation.

Surface ocean currents are conventionally depicted using arrow vectors that are scaled to represent speed and rotated to represent direction. HF radar observations cover limited areas that extend from the coastline, and the RMSE calculations cover this same area. Conventionally, RMSE calculations are shown as a continuous field when mapped, often using a rainbow color ramp. This wide range of colors and values can make it difficult to interpret the map (Jenny and Kelso 2007). In order to combat this, a red-to-green color ramp was used to display the model accuracy (current speed, in this case), and the modeled surface currents that corresponded to the RMSE timeframe (June 27-July 31 2017) were placed on top (Figure 16). However, this map was still difficult to interpret—there were no clear boundaries between areas of changing model accuracy.

In an attempt make interpretation easier, the model accuracy information (for current speed and direction) was classified into 6 groups using Equal Interval Classification. This made for a much clearer map (Figures 17 and 18), where each color always represents the same set of accuracy values, and sharp distinctions between levels of accuracy (given as a range of most- to least- accurate). In order to address the color vision impairment issues described in the previous section, a purple-to-green (after Jenny and Kelso 2007) version of the current speed map was also created (Figure 19).

Results: Visualization

Map Utility and Display

The following maps (Figures 13-19) are presented as examples of how ocean condition forecast model accuracy metrics might be communicated to commercial fishermen. The utility of these maps to fishermen remains to be determined (see 'Limitations', below).

Although the maps in this study are presented in static format, the techniques described previously would ideally be used in a dynamic web mapping format. The overlaying accuracy metrics should only be available over appropriately related model data, and fishermen should be able to turn model accuracy visualizations on or off as desired. This would also allow for the addition of other map color options for the color vision impaired.

Map Examples

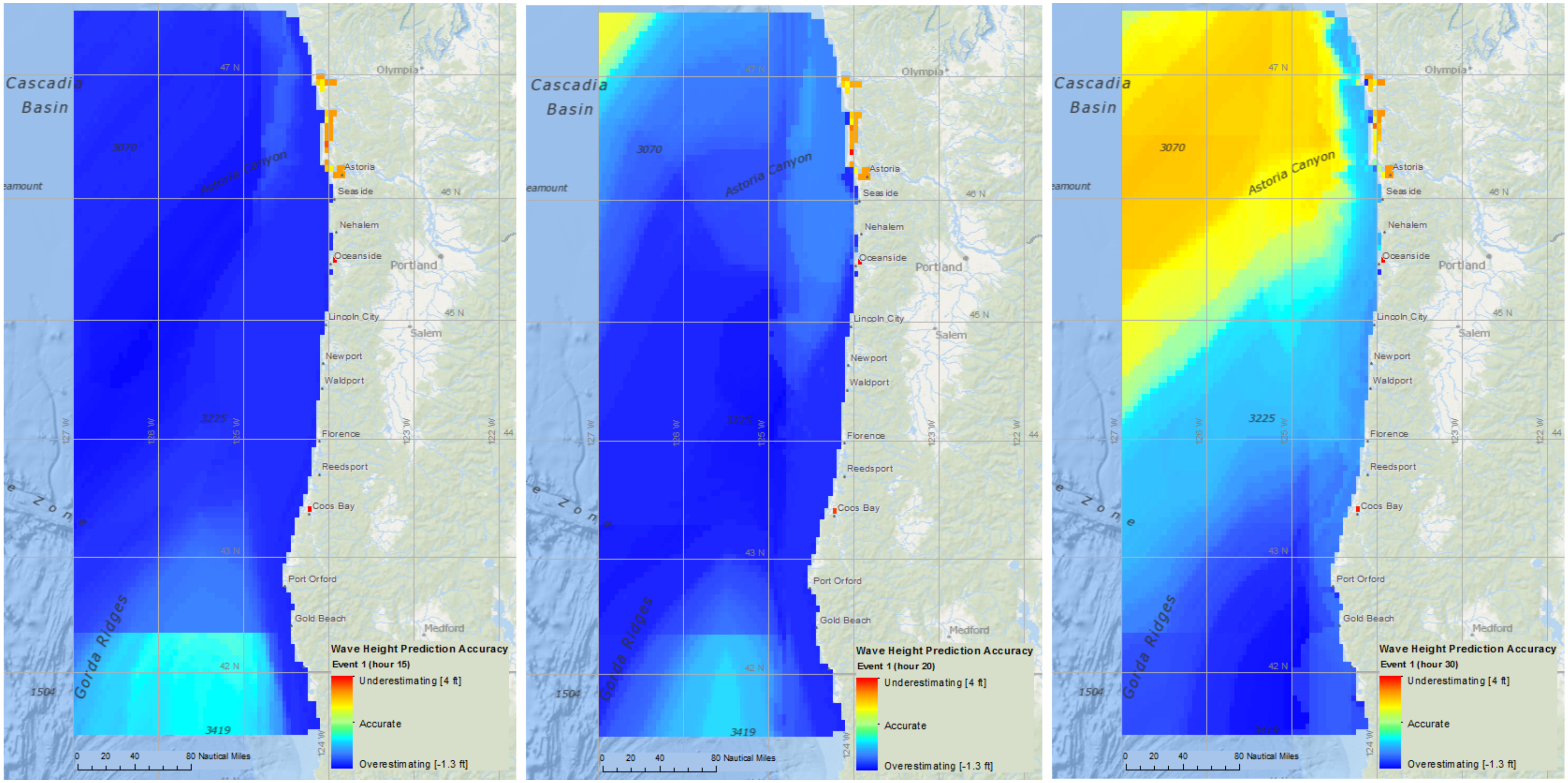

Figure 13: Time-series of 3 maps showing wave model accuracy metrics for Event 1, at hours 15, 20, and 30.

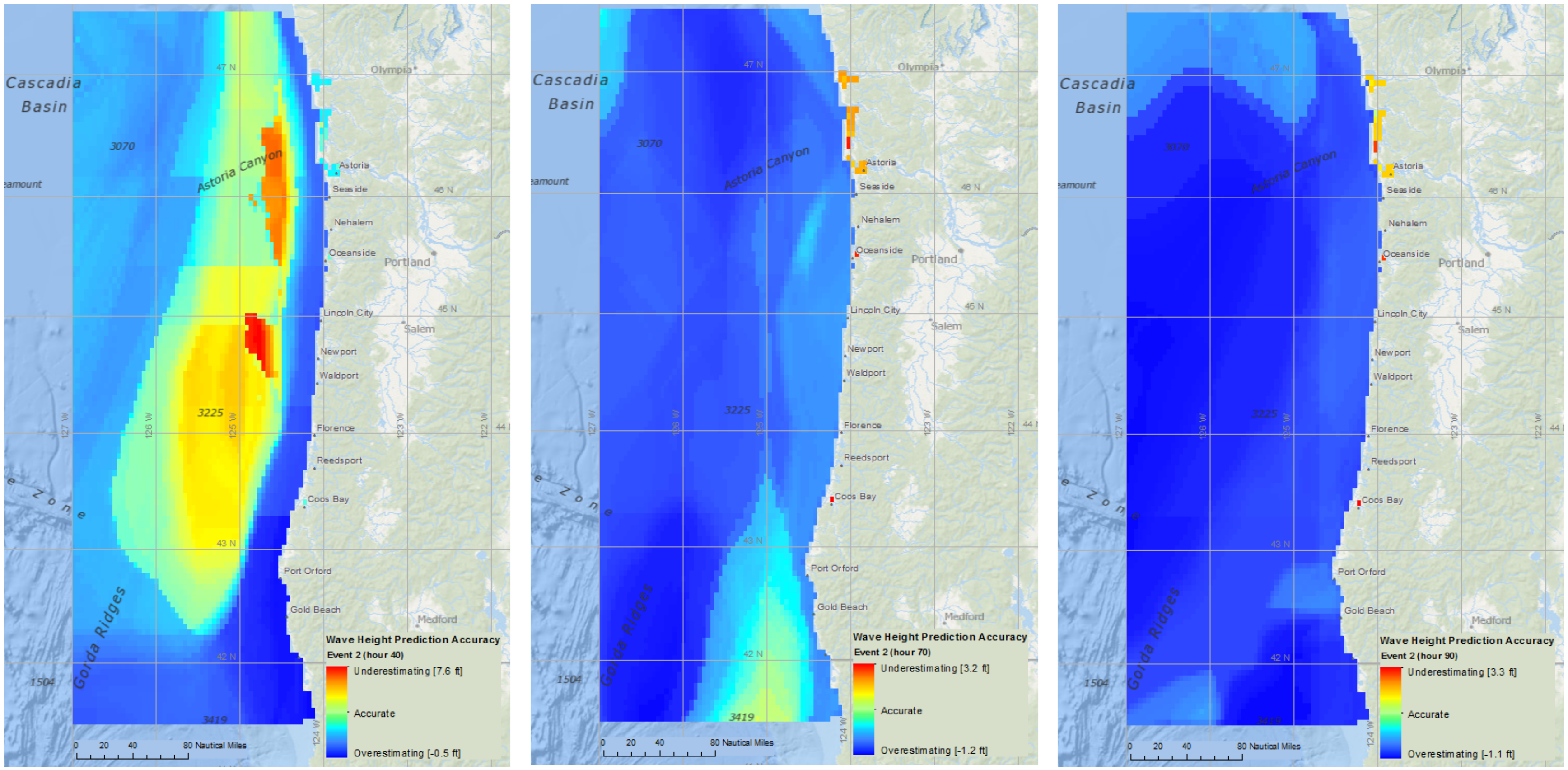

Figure 14: Time-series of 3 maps showing wave model accuracy metrics for Event 2, at hours 40, 70, and 90.

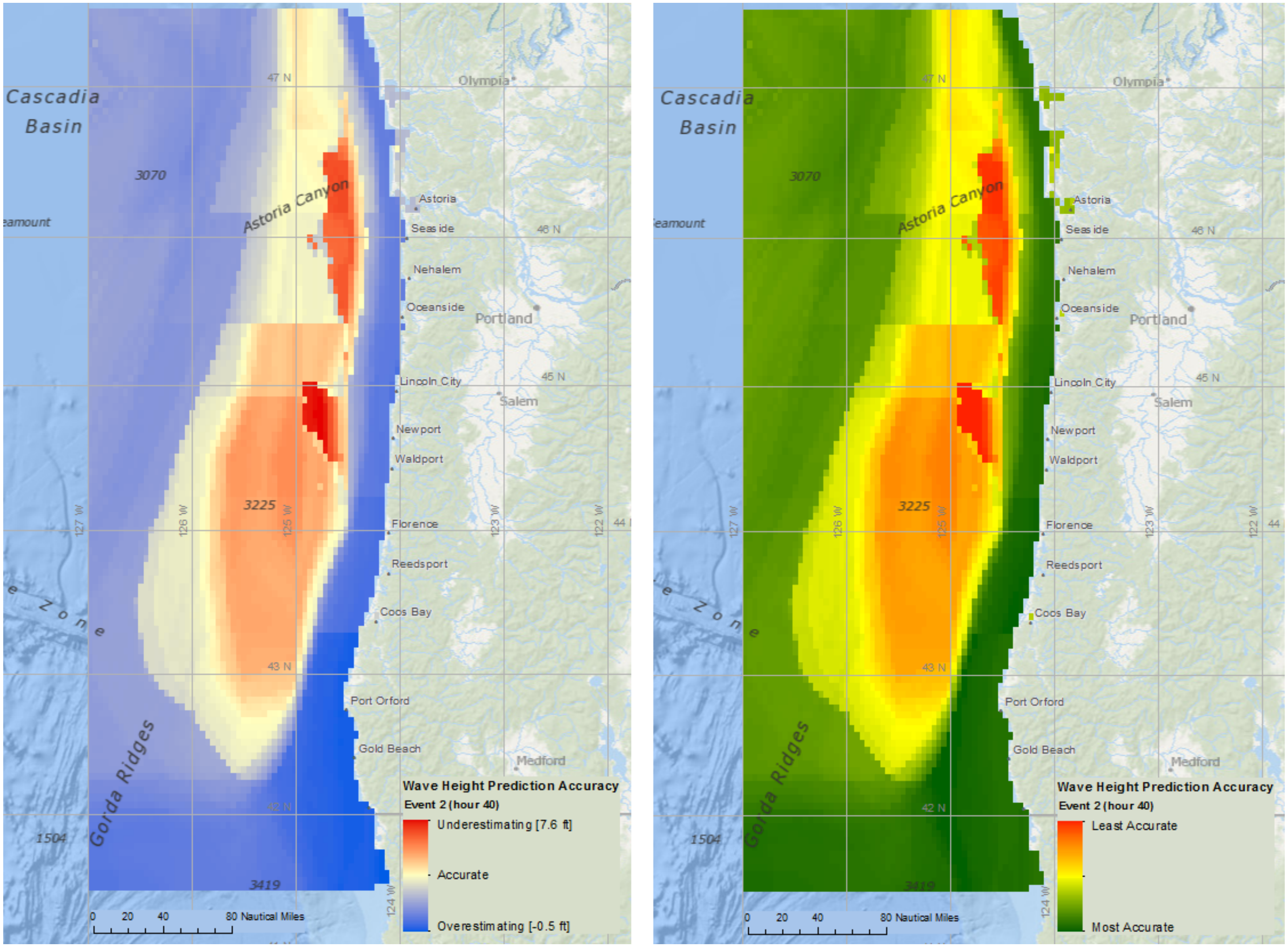

Figure 15: The map on the left (a) shows a modified version of the rainbow color ramp for Event 2, hour 40. The map on the right (b) shows the absolute value version of the wave model accuracy metric for Event 2, hour 40.

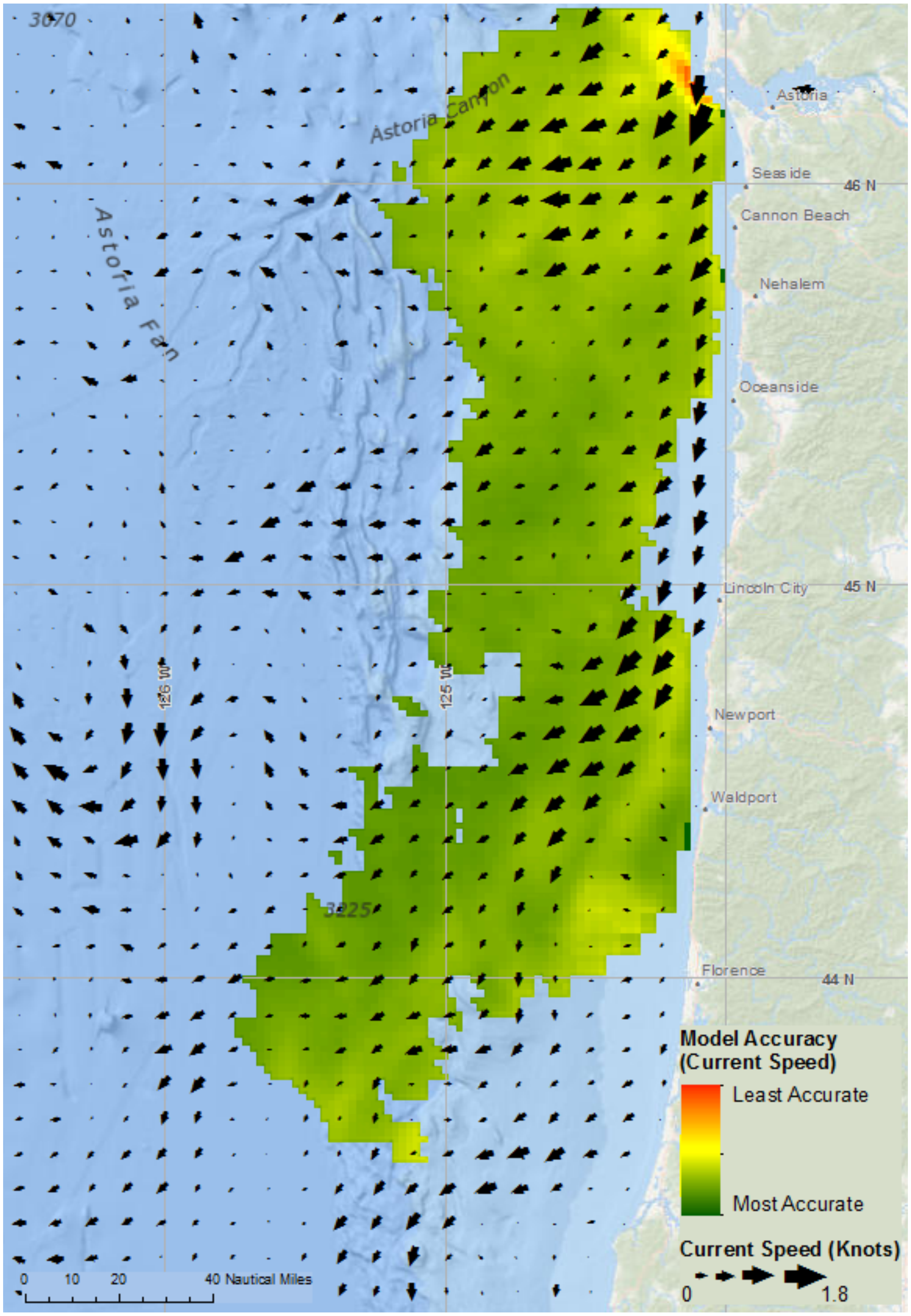

Figure 16: Map showing the ROMS model accuracy metric for current speed using a continuous, red-to-green color ramp. Surface currents are shown as black arrows.

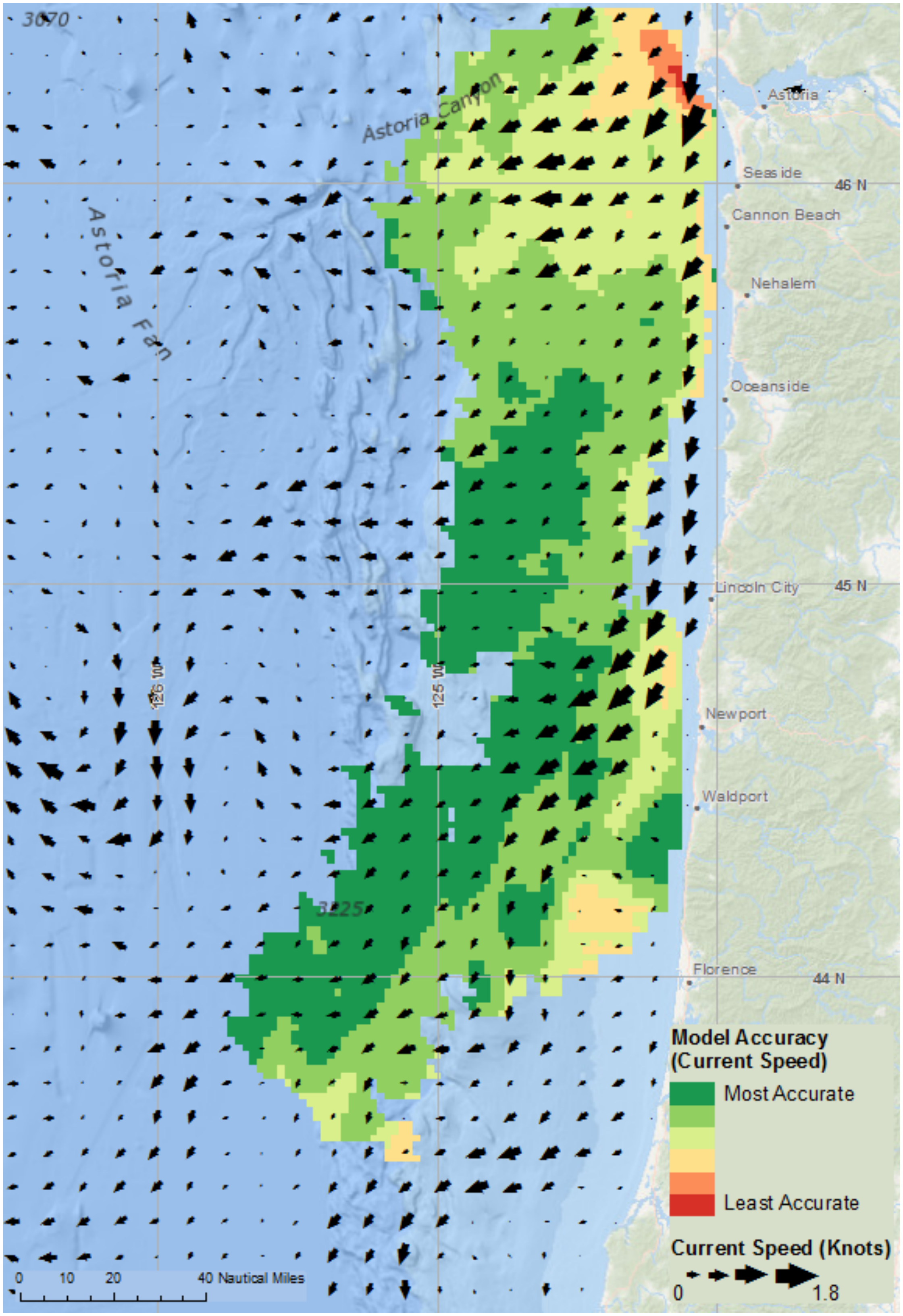

Figure 17: Map showing the ROMS model accuracy metric for current speed broken into 6 categories, using a red-to-green color ramp. Surface currents are shown as black arrows.

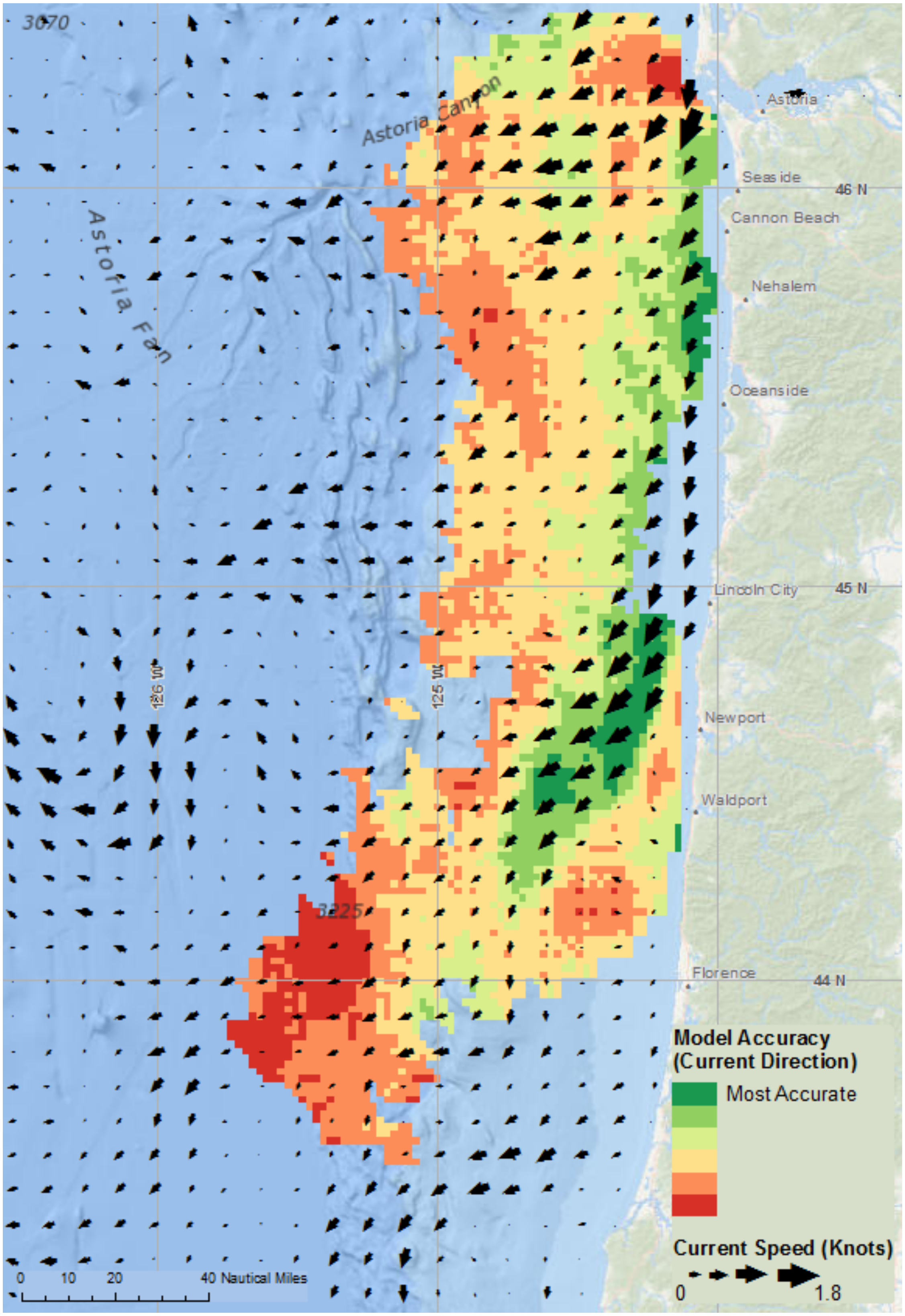

Figure 18: Map showing the ROMS model accuracy metric for current direction broken into 6 categories, using a red-to-green color ramp. Surface currents are shown as black arrows.

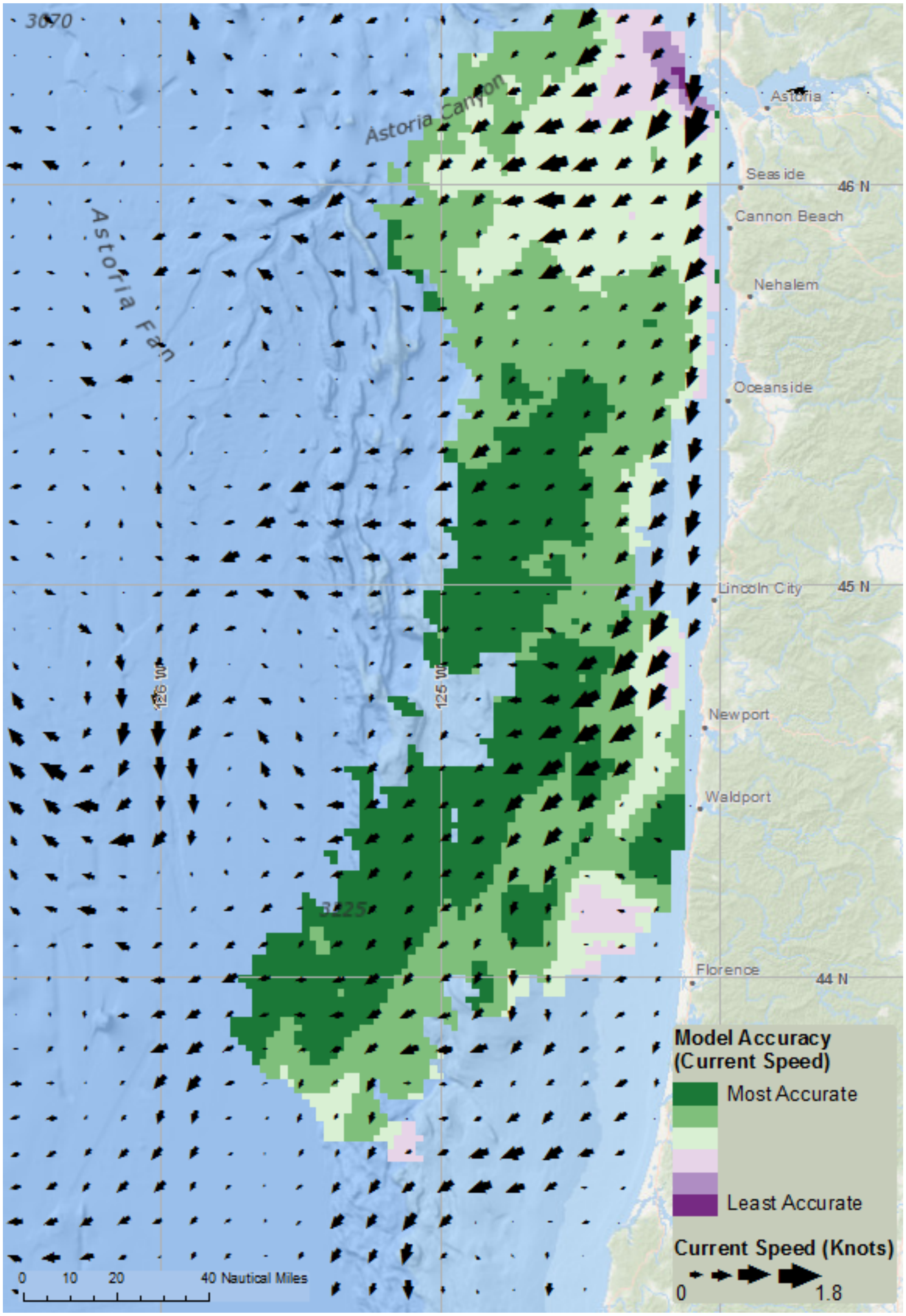

Figure 19: Map showing the ROMS model accuracy metric broken into 6 categories, using a purple-to-green color ramp. Surface currents are shown as black arrows.

Conclusions

Guiding Frameworks

Quantifying and communicating the uncertainty in deterministic models in a way that is both mathematically rigorous and meaningful to end-users (such as commercial fishermen) is a complex problem. The OCF team used a transdisciplinary process to overcome internal disciplinary boundaries, which resulted in a cumulative understanding of this problem that no single team member could have reached alone. The key to achieving this was the incorporation of stakeholder perceptions of risk and uncertainty into a guiding framework that informed and integrated the methodologies of each team member.

An additional benefit of learning about stakeholder perceptions was the discovery of the underlying motivations around their decision-making, which allowed the OCF team to understand how the fishermen processed the uncertainty associated with ocean condition forecast models. In this case study, once the perceptions of the fishermen were understood, it was clear that the focus on generating model uncertainty metrics should be shifted to accuracy metrics. The team was only able to reach this result after abandoning the pursuit of the technical definition of uncertainty and instead listening to how the fishermen perceived uncertainty. Their perceptions of uncertainty aligned well with the technical definition of accuracy, which was a metric that could be generated for both of the ocean condition models involved in the study. Generally, the team found that collaboration between data users and data providers is more effective if one party is willing to temporarily surrender their preconceived notions of definitions and processes in order to open their minds to the other party's understanding of the same concepts. This allows both parties to shift their understanding of specific concepts to better align with the actual content of what is being communicated. This practice could be extensible to other groups of stakeholders and scientists who are engaged in collaboration.

Bridging the Divide: Spatial and Temporal Resolution

This study revealed a problem that is common in areas of research attempting to bridge the divide between science and application: the mismatch of the spatial or temporal scales of available data with user needs. Throughout the transdisciplinary process, an important theme that emerged was the difference in the perception of time between data scientists and fishermen. For example, data scientists tend to use units of time that are easily reduced to discrete values, such as a range of dates. Similarly, they rely on spatial information collected at discrete locations. Fishermen, on the other hand, simultaneously think about time in the short-term and long-term. For them, the concept of time and where they travel is often heavily influenced by shifting environmental and social factors, as well as their own priorities. If these differences are not addressed, it can lead to disconnects in communication, which influence the usefulness of any resulting forecast products. Understanding how to recognize and bridge disconnects is crucial to the process of designing and building useful products. Two examples of disconnects faced by the OCF team include the following:

An example of a temporal resolution disconnect the team faced was calculating RMSE in the surface currents for the ROMS model. Commercial fishermen would prefer to have a model evaluation performed in increments of 7 days or less because they relate ocean conditions to rapidly changing atmospheric conditions. However, the calculation of RMSE on such a short time scale does not result in a robust model accuracy metric from a mathematical perspective due to the lack of data points.

An example of a spatial resolution disconnect the team faced was overcoming the inability to verify WW3 model output at all places where fishermen might use it, due to the lack of buoy observations. To overcome this disconnect, the team devised a methodology to make predictions on model performance throughout the modeled domain. The team validated this methodology at times when accuracy was most important to commercial fishermen, such as the winter months. This demonstrated how stakeholder perceptions can not only influence methodology, but can also influence problem formulation for scientific research, and therefore the resulting products.

Bridging the Divide: Data Formats and Model Output

Standard data formats differ between ocean scientists, computer programmers, and cartographers. This can make generating meaningful visualizations a challenge, depending on the nature and format of model output and program input. Data formats are often selected based on training, software availability, and individual preference. It is important to consider how these seemingly minor technical differences may act as a barrier to collaboration between data scientists and those charged with visualization, and these differences in model output and software input should be made explicit in any collaboration involving the handoff of data.

Forecast Products

The OCF team developed tools to quantify and visualize model accuracy in a way that may be helpful to fishermen in their decision making process. In order to create accuracy metrics, the ocean modelers had to generate model accuracy quantification across the model domains. For the ROMS model assessment, RMSE was calculated between the modeled surface currents and HF radar observations. For the WW3 assessment, a machine learning algorithm was used to make spatial predictions about model error. This algorithm was designed to detect patterns in the model performance where observations were available, then it used spatial information to extrapolate this pattern throughout the grid. Both model metrics were then used to create map-based visualizations in an effort to communicate this information about model accuracy to fishermen.

The OCF team cannot make a recommendation about whether or not these metrics and visualizations should be made available in ocean condition forecasting tools. From the data provider perspective, a technique that fails to quantify accuracy accurately adds to the uncertainty present when interpreting model output. The new techniques devised (specifically the WW3 spatial predictions) would not normally be recommended for public use since they have not been thoroughly vetted. However, in the true transdisciplinary spirit, end user opinions must be considered to determine the utility of these uncertainty metrics. These opinions can influence the recommendation as to whether or not they should be made available in ocean condition forecasting tools.

Limitations

The OCF team faced several obstacles throughout the course of the year related to limited project completion time and limited access to data. Forming strong team relationships and developing an understanding of how to combine each team member's disciplinary research takes time. Completing project tasks while developing these transdisciplinary building blocks takes more time than it would normally. Research timelines were not optimally compatible because the data collection and analysis from the interviews was not available to the team until the second half of the project. There was also limited ability to collect additional feedback from fishermen within the project's timeframe, and therefore the outcomes of the project are our 'best guesses,' as they have not been vetted by fishermen.

Data limitations included limited access to historical ROMS forecasts and the limited spatial availability of HF radar for surface current validation. The limited spatial availability of NDBC buoys for wave model output validation drove the machine learning method to create a gridded output to assist with visualization. Finally, all team members were limited by other life events and commitments throughout the course of the year, including full course loads, graduation plans, illnesses, injuries, business ventures, and achieving a work-life balance.

Future Work

The OCF team has laid the groundwork for collaboration amongst researchers that can contribute to the quantification and communication of deterministic model uncertainty, as well as strengthening relationships with the commercial fishing community around this topic. In speaking with commercial fishermen and various ocean condition data providers throughout this research, it is clear that both groups gain trust or confidence in the model in a similar way— by comparing model output to observations at buoys or through personal observation. This similarity in thinking could be leveraged as a starting point, or boundary object, between the two groups in potential future collaborations to further create accuracy metrics or to validate model data. Furthermore, given that commercial fishermen are constantly observing and evaluating the physical ocean environment and relating forecasts to what they observe, the following research questions could be potential areas of collaboration that would benefit them as a group and contribute to the broad problem of how to quantify and visualize model uncertainty.

- How does forecast accuracy vary by season?
- How does forecast accuracy vary in space over time?
- How do these spatial and temporal variations correlate with environmental conditions that are frequently observed by fishermen?
- How can observations from the commercial fishermen be integrated into model validation techniques?
- What kinds of forecast accuracy visualizations are preferred (and easily understood) by fishermen?

Not only could these questions guide future research, but additional forecast products could be derived from advancements in ocean condition observation technology. This technology can be integrated into current techniques to create spatial solutions. A plan has recently been funded to implement HF radar in Washington that would allow future model uncertainty quantification in areas that were unavailable at the time of this research. Accelerometers, the same devices that buoys use to measure wave data, now come standard in smartphones. A process could be developed to collect this data from fishermen, thus increasing the spatial coverage of wave observations.

For forecast products and visualizations, next steps should include setting up a team of beta users to provide feedback on multiple iterations of tools and imagery. The feedback from these end-user studies can refine and inform visualizations (such as maps and charts) to further increase their utility.

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The Bow Ramp (Blog), photo of Coast Guard crossing: http://bowramp.blogspot.com/2006_05_01_archive.html

Statement of Contributions

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Approach	Initial Draft: Ashley Ellenson

	Editing and Final Draft: All
Transdisciplinary Process	Initial Draft: Jessica Kuonen Team Personality Figure: Jane Darbyshire Figure 2: Jessica Kuonen Editing and Final Draft: All
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Methods: Wave Model Results: Wave Model	Initial and Final Drafts: Ashley Ellenson Figure 3: Matthew Mauch Figures 4-7: Ashley Ellenson Editing: All
Methods: Regional Ocean Modeling System Results: ROMS	Initial and Final Drafts, Figures: Matthew Mauch Editing: All
Methods: Visualization Results: Visualization	Initial and Final Drafts, Figures: Jane Darbyshire Editing: All
Conclusions	Initial Draft: Jessica Kuonen Editing and Final Draft: All
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