BAMS In Box

Making Seasonal Outlooks of Arctic Sea Ice and Atlantic Hurricanes Valuable —Not Just Skillful

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In recent years, a big effort has been made by part of the climate community toward the development of climate services in order to make climate information decision oriented. In a climate forecasting context, this means identifying climate variables, thresholds and/or events of relevance to users. Once identified, these elements, which generally do not coincide with variables typically forecasted by the scientific community, are analyzed to determine whether they can be predicted both reliably and skillfully at the appropriate time scale. This process generally requires a sustained dialogue between the different parties involved before coming to a fruitful conclusion. Here, we discuss two such efforts that attempt to bridge the gap between climate forecasting and application for two phenomena already receiving a fair amount of attention from the general public: hurricanes and Arctic sea ice.

The first seasonal forecast model of tropical cyclone (TC) activity was published in the late 1970s by Nicholls (1979). However, due to a general skepticism regarding seasonal forecasting of TCs in the meteorological community at the time, its author did not begin issuing publicly available seasonal tropical cyclone forecasts for the Australian region until the late 1980s (N. Nicholls 2019, personal communication). Relying in part on a newly discovered relationship between Atlantic hurricanes and El Niño–Southern Oscillation, William Gray at Colorado State University (CSU) thus became the first to issue TC outlooks in real time in 1984 (Gray 1984). While CSU has been producing uninterrupted forecasts since then and was the only group doing so for the Atlantic through the mid-1990s, many groups have since initiated seasonal hurricane forecasts of their own. The number of groups issuing seasonal predictions for the Atlantic increased dramatically in the mid- to late 2000s, likely due in part to the extremely active 2004 and 2005 Atlantic hurricane seasons. Seasonal predictions of TC activity are now produced for each basin where TCs are observed, and for most TC basins, predictions are issued by multiple groups. For the Atlantic basin alone, 26 groups, ranging from private weather companies to universities to national weather services, are now producing publicly available seasonal outlooks. This increase in the number of groups issuing these forecasts is also owed in large part to the development of new technologies as well as easily accessible climate data, which has made it relatively straightforward for any group (or individual) to develop their own forecasting system.

Seasonal sea ice forecasts began more than two decades later than seasonal hurricane forecasts. But after the record low sea ice extent (SIE) in September 2007, which fell 26% below the previous year and took many scientists by surprise, there was a growing effort in the scientific community to develop reliable methods to predict the minimum SIE a few months in advance. This effort was led by a grassroots project organized through the Study of Environmental Arctic Change (SEARCH) called the Sea Ice Outlook (SIO; www.arcus.org/sipn/sea-ice-outlook). Each year starting in June, the SIO would collect and synthesize sea ice "outlooks" of the pan-Arctic September SIE and share results on its web page. SIOs were requested each month up to the September minimum. In 2014, the effort was formally funded by several U.S. agencies and rolled into the Sea Ice Prediction Network (SIPN; www.arcus.org/sipn). In 2017, based on the SIPN, the sister project SIPN South (http://acecrc.org.au/sipn-south) was initiated to meet the growing demand for sea ice forecasts in the Southern Ocean.

Perhaps surprisingly, despite a 25-yr head start, there is no such equivalent organized network in the hurricane community. However, a similar platform has recently been brought online that gathers all freely available Atlantic hurricane outlooks as they are made available by the 26 different groups now issuing them. Each year since 2016, the site has collected and displayed seasonal hurricane forecasts issued from late March through early August. Spearheaded by the Barcelona Supercomputing Center and CSU and supported by a private sponsor (XL Catlin—now AXA XL) but relying on the volunteer participation of the forecasters, the hurricane collation site (www.seasonalhurricanepredictions.org) arose from the desire of these three institutions to centralize the various outlooks, which are typically publicly available but scattered across different domains. This stands in contrast with a coordinated community effort that offers its view on the upcoming hurricane season.

While the first hurricane forecasts were based on statistical relationships between TC activity and key climate predictors such as ENSO and Caribbean basin sea level pressures (Gray 1984), the increase in climate model resolution has allowed the development of dynamical model-based forecasts, wherein hurricane-like vortices are detected and tracked in initialized climate simulations (Vitart and Stockdale 2001). However, because this type of forecast requires expensive infrastructure compared to the comparatively simpler statistical models, few groups are now issuing dynamical forecasts. At present, most groups are producing so-called hybrid forecasts, which rely on both statistical relationships between TCs and the large-scale environment and initialized climate simulations by dynamical models (for an estimate of the large-scale fields during the hurricane season). The increase in computational power has also fostered the development of innovative technologies, as machine learning techniques have started to be applied to the TC forecasting problem. While still in their infancy, they have the potential to yield new insights on the large-scale factors modulating TC formation. Since 2018, two groups have begun issuing hurricane outlooks based on machine learning techniques, and more are likely to follow.

For sea ice forecasts, various methods were used initially, including heuristic estimates, simple linear regression models and dynamical coupled ice–ocean models. However, with time, the use of dynamical models for sea ice forecasts has grown, including both coupled ice–ocean models forced by atmospheric reanalysis data or fully coupled climate models, with and without initialization by data assimilation. And while early forecasts simply provided estimates of the pan-Arctic sea ice extent, today's forecasts also include sea ice thickness, spatial maps of sea ice probability (presence of ice or not) and timing of sea ice breakup and ice advance. These metrics are arguably of more use to various stakeholders than the pan-Arctic sea ice extent, whether it is local communities planning for the seasonal hunt, or shipping companies trying to avoid the ice. This effort has been recently extended through separate funding to include a year-round portal for subseasonal to seasonal forecasts (Wayand et al. 2019). In comparison, the hurricane website includes an outlook for four different basin-wide statistics (named storms, hurricanes, major hurricanes and accumulated cyclone energy—an integrated measure of frequency, intensity, and duration), thus only providing information on the expected overall level of hurricane activity (see Table 1 for a comparative overview of both portals).

Table 1. Comparison of sea ice and hurricane outlook platforms.

	Sea ice outlook	Hurricane outlook
Region	Arctic	North Atlantic
Operational since	2014	2016
Period targeted	September	June–November
Variables forecasted	Total sea ice extent Sea ice probability (2D) Ice free date (2D) Regional sea ice extent (Alaska region, Beaufort and Chukchi Seas)	Number of named storms Number of hurricanes Number of major hurricanes Accumulated cyclone energy
Forecast submission	June, July, August	Continuous March–August
Number of forecasts archived (2018)	813	133
Type of forecasts	Statistical Dynamical (fully coupled models and ocean-ice model only) Hybrid Heuristic	Statistical (including machine learning) Dynamical Hybrid
Participating groups (as of 2018)	39	26
Type of organizations	Universities (30) Government agencies (2) General public (7)	Universities (8) Government agencies (6) Private weather companies (12)
Data available	Upon request	Directly, CSV format

Figures 1 and 2 show the hurricane and sea ice outlooks for the recent years. For hurricanes, seasonal forecasts issued in 2015 and 2016 were quite good—with the median outlook correctly predicting the observed number of hurricanes (four) in 2015 and missing by only one hurricane (eight predicted vs seven observed) in 2016. However, the median forecast in 2017 and 2018 underpredicted hurricane activity—with both median forecasts predicting three fewer hurricanes than were observed. In 2017, the median forecast was for 7 hurricanes, while 10 were observed. In 2018, the median forecast was for five hurricanes, while eight were observed. Hurricane forecast skill does improve with a decrease in lead time, with moderate skill emerging in June and August forecasts showing the largest skill (Klotzbach et al. 2019). Perhaps surprisingly, we do not detect a clustering of the August forecasts with respect to the April and June forecasts over the 2015–18 period, except for 2017 when most forecasters revised their forecast upward due to anomalous warming of the tropical Atlantic just ahead of the start of the season. Despite this adjustment, few forecasters predicted the hyperactive 2017 hurricane season.

For sea ice, pan-Arctic September SIE forecasts generally fail to capture large deviations from the long-term trend (Hamilton and Stroeve 2016; Stroeve et al. 2015), regardless of the method used. The median forecast is only weakly correlated with observed data (Pearson correlation coefficient of 0.13), but is still slightly superior to trivial forecasts like persistence (0.08) or trend extrapolation (0.01) (none of which are significantly different from zero at the 5% level based on a one-sided t test). Interestingly, the forecast skill does not necessarily improve with shorter lead times as one would expect. Perhaps even more interesting is the fact that the median outlooks are highly correlated (0.89) with the verification data from the previous year. That is, the median outlook of year n is strongly influenced by how anomalous the observed conditions were in year $n - 1$ [a similar result was noted in Hamilton and Stroeve (2016)]. So in effect, when viewed as a whole, groups tend to forecast the previous year's conditions. Unfortunately, we do not have a sufficient amount of retrospective

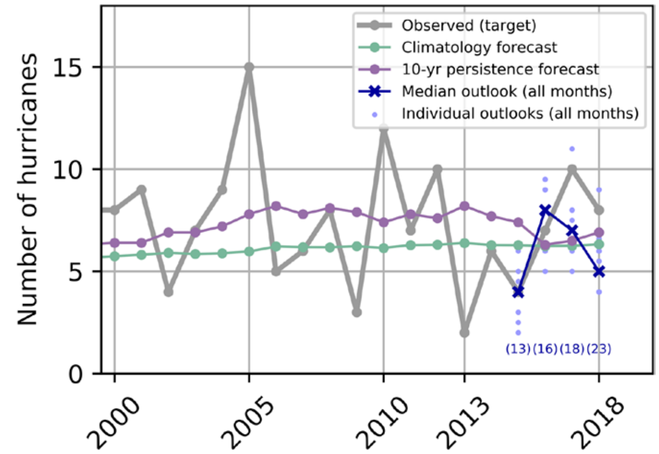

Fig. 1. Forecasts of North Atlantic basinwide hurricane number and verification data. The observed number of hurricanes for each season is shown in gray (Landsea and Franklin 2013). The light blue dots are all of the latest individual hurricane outlooks collected since 2015 (one dot per group). The dark blue line is the median of those outlooks. The green and purple lines are two benchmark forecasts: the climatology forecast is defined as the average of all hurricane counts from 1969 to the current year minus one (green), and the 10-yr persistence forecast is defined as the average of all hurricane counts from the 10 preceding years (purple). The numbers along the *x* axis indicate the number of forecast that have been submitted for a given year for that particular variable.

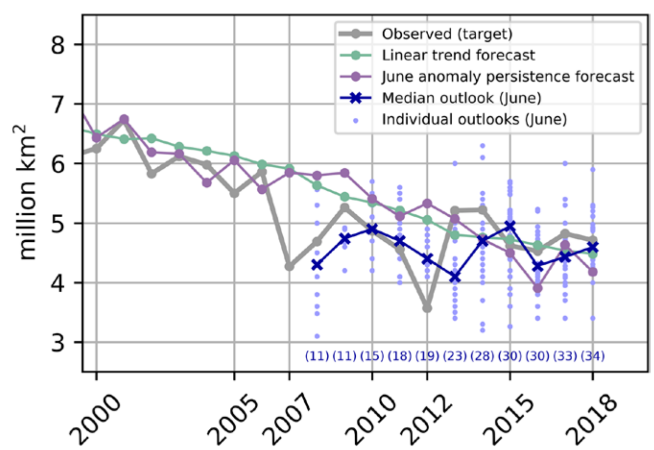

Fig. 2. Forecasts of September Arctic sea ice extent and verification data. The National Snow and Ice Data Center (NSIDC) sea ice index, version 3 (Fetterer et al. 2017), is shown in gray as observational reference for verification of the forecasts. The light blue dots are all individual June sea ice outlooks collected since the inception of the project in 2008 (252 forecasts in total). The dark blue line is the median of those outlooks. The green and purple lines are two benchmark forecasts: a linear trend forecast based on September extents available until the year preceding the forecast (green) and an anomaly persistence forecast (purple). To produce the latter, May anomalies were added to the September climatology. The numbers along the *x* axis indicate the number of forecasts that have been submitted for a given year for that particular variable.

forecasts to determine whether something similar occurs in the context of hurricanes. Correlations of CSU June forecasts, which go back to 1984, for the number of Atlantic hurricanes issued on 1 June with the previous year's observed hurricanes was 0.27, compared to 0.36 for the actual year, suggesting that hurricane forecasts behave differently, which is probably linked to the strong influence of ENSO on Atlantic hurricanes and their forecasts.

While the total hurricane count is one of the most commonly forecasted hurricane variables, it is of relatively little use to many stakeholders due to its limited application. Although not included on the platform itself, many groups are also issuing forecasts for the number of landfalling storms for different parts of the basin, which generally include different segments of the continental U.S. coastline where financial impacts of landfalling storms are the largest. However, even these landfall forecasts are of limited use because they are not explicitly tailored to a stakeholder's decision-making process. In reality, the lack of tailoring to stakeholder needs—in the tropical cyclone space at least—is likely due to the following:

1) The sheer scope and complexity of stakeholders that are actively interested in tropical cyclone predictions—these stakeholders range from emergency planners and aid agencies to financial risk managers such as re/insurance companies.
2) The desire by typical stakeholders to have predictions of a tightly defined risk, which has not yet been attempted in any very explicit way, rather than the scientific hazard itself.

It can be said that risk is a function of hazard, vulnerability, and exposure; this way of thinking is deeply ingrained in the catastrophe modeling industry, which attempts to quantify societal impacts of perils. Although, as mentioned earlier, seasonal tropical cyclone landfall forecasts are now being attempted, the fact that they still remain disconnected from a fully coherent picture of vulnerability and exposure, as pertains to a precise decision-maker, means that they will likely remain of limited direct use to stakeholders, even if proven skillful. Rather than landfalling predictions being useless though, it is clear that these attempts are facilitating the conversation between the academic communities that are focused on the hazard, and those applied communities focused on the risk, such that predictions may be tailored to explicit decision-making chains in the future. In that sense, the hurricane seasonal forecasting community should consider emulating the SIPN, which, with time, has evolved to better meet stakeholder needs.

Hurricane and sea ice forecasting have more in common than it might initially appear. In the context of global climate change, the processes to be forecasted are likely not stationary. That is, forecasting hurricanes and sea ice is more about chasing a moving target than one at rest. To face this reality, fundamental research continues in parallel to the efforts presented in this manuscript. Identifying new physical mechanisms that offer predictability at seasonal time scales would indeed improve our skill at forecasting sea ice or hurricanes, but also drive our understanding beyond simple predictor–predictand empirical relationships that might break down as mean states change (Caron et al. 2015). Another point of convergence between the two fields of research is the notion that at the time scales considered, forecasts can only be expressed in probabilistic terms. Indeed, while climatic preconditioning drives in part the sea ice retreat and hurricane activity over one season, it is well known that weather—unpredictable beyond two weeks—both modulates sea ice evolution and the timing and location of hurricane formation. Probabilistic forecasts, even if well calibrated, are prone to misinterpretation by audiences outside the forecasting community itself (Gigerenzer et al. 2005). This reality underlines the need to provide expert guidance when these forecasts are communicated to the public and stakeholders. Finally, a third common aspect is the awareness that forecast skill and value are different concepts. As first pointed out by Murphy (1993), a forecast can be correct in terms of correspondence with matching observations but unexploitable for stakeholders. Sea ice and hurricane forecasting have historically attempted to forecast region-wide quantities relevant for forecast verification purposes such as total sea ice extent or basinwide count over a given season. While such diagnostics can readily be used to evaluate retrospective forecasts, they often have little utility for those who need information to make a decision. The sea ice forecasting community is crossing the line by proposing a range of new user-oriented diagnostics, as explained above. We are hoping that the hurricane community can follow suit.

Despite dramatic progress in recent years in the fields of Arctic sea ice predictability (Chevallier et al. 2017) and prediction (Zampieri et al. 2018) as well as in hurricane forecasting (Klotzbach et al. 2019), the authors are unaware of any stakeholders reliant on these forecasts for planning and risk mitigation or transfer purposes, both because the variables currently forecasted are not useful for these purposes and because a reliable estimate of the skill of more useful variables (e.g., timing of sea ice breakup, odds of an hyperactive hurricane season) have yet to be established. The continuation of international cooperative initiatives like SIPN and the seasonal hurricane prediction platform will be key to move forecasts beyond the academic framework and make them useful in an operational context of climate services, like weather forecasting did at the end of the twentieth century.

Additional information

The sea ice and hurricane outlook data, as well as the scripts used to generate Figs. 1 and 2, can be obtained from the following Github project: https://github.com/fmassonn/paper-hurricanes-seaice.git.

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