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RESEARCH ARTICLE

Innovation in Practice

AI sea ice forecasts for Arctic conservation: A case study predicting the timing of caribou sea ice migrations

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Abstract

1. Every autumn on the south coast of Victoria Island (Nunavut, Canada), endangered Dolphin and Union (DU) caribou (*Rangifer tarandus groenlandicus x pearyi*) wait for sea ice to form before continuing their southwards migration to the mainland. Delayed freeze-up, less stable ice conditions and ice-breaking by vessels are putting migrating caribou at risk, but unpredictable freeze-up times pose challenges for conservation planning. Having early warning of when the caribou sea ice crossing is likely to take place could guide more targeted measures (e.g., ice-breaking vessel management).
2. In this case study, we use a multi-stakeholder approach to explore the potential of using observed and forecast sea ice concentration (SIC) to predict when DU caribou are likely to cross the sea ice. We examine links between caribou movement records and coincident satellite observations of SIC collected between 1996–2005 and 2015–2019. We establish probabilistic "percent-crossed" metrics to convert SIC freeze-up profiles into anticipated sea ice crossing-start date ranges and maps. Finally, we assess the potential of using IceNet, an AI-based 25 km resolution SIC forecast model, to predict these crossing-start ranges in 2020–2022.
3. We identify a clear link between SIC freeze-up profiles and crossing-start times, with median SIC reaching 98.8% (IQR = 94.1%, 100%) when caribou start their crossings. Our percent-crossed metrics are effective in converting SIC records into crossing-start date maps which can guide human experts. IceNet results show promise, predicting crossing-start ranges comparable to those observed in 2022 up to three weeks before the first observed sea ice crossing. In 2021,

IceNet's predicted ranges are systematically early, but improve between three- to one-week lead times.

4. *Practical implication*: AI sea ice forecasts could provide early warning of DU caribou sea ice crossing times, informing mitigation of ice-breaking vessels and providing a blueprint applicable to other ice-dependent species. Our case study contributes practical considerations, limitations and areas for future research to drive innovation in this emerging field forward. Ultimately, forecasts could be integrated into human-expert centred decision-support tools, guiding dynamic conservation and management for Arctic species.

KEYWORDS

Arctic Northwest Passage, Artificial Intelligence (AI), Dolphin and Union caribou, dynamic conservation, GPS tracking, migration, *Rangifer*, sea ice forecast

1 | INTRODUCTION

Sea ice is a vital habitat for many Arctic species; from polar bears seeking prey, to seals rearing pups and migrating cetaceans (Laidre et al., 2008; Post et al., 2013). The sea ice and its associated ecosystem are also fundamental for coastal Indigenous Peoples' way of life, supporting food security and cultural practices, which have developed over millennia. Yet average Arctic temperatures are rising, at a rate as much as four times that of the global average (Rantanen et al., 2022), and sea ice is being lost. September sea ice extent has halved in the last 40 years (Serreze & Meier, 2019). Climate projections indicate the Arctic Ocean could be virtually sea ice free in the summer as early as the 2030s (Kim et al., 2023). As Arctic species navigate their increasingly unpredictable and fast-diminishing sea ice habitat, they simultaneously face intensifying pressure from fishing, shipping, tourism, and oil and gas industries drawn to the opening ocean (Bird et al., 2008; Dawson et al., 2014, 2018; Mudryk et al., 2021; van Luijk et al., 2022).

It is imperative to safeguard wildlife and livelihoods in this fast-changing Arctic seascape. However, designing and implementing effective area-based conservation and management in the face of uncertain environmental conditions is challenging (Cashion et al., 2020). There are calls for dynamic management strategies that can integrate environmental forecasts and be responsive to resulting changes in ecosystems and their components (Abrahms et al., 2023; Gissi et al., 2019; Tittensor et al., 2019). Sea ice forecasts could be informative in predicting seasonal wildlife distributions on a more dynamic basis (Kovacs et al., 2011), as the movement of many Arctic species are intrinsically linked to sea ice conditions (Laidre et al., 2008). However, physics-based numerical models have struggled to capture the complex atmosphere-ice-ocean interactions necessary for accurate, high resolution sea ice forecasts (Blanchard-Wrigglesworth et al., 2015; Wayand et al., 2019). Recently, AI modelling has emerged as a promising alternative for sea ice forecasting (Andersson, Hosking, Pérez-Ortiz, et al., 2021), with AI systems now advancing more rapidly than their physics-based counterparts as part of the broader "AI weather forecasting revolution" (Bi et al., 2023; Lam et al., 2023; Price et al., 2024). With the ability of AI models to learn sea ice behaviour from diverse data sources, this new generation of forecasting systems could provide the accuracy, resolution and speed required to support conservation and management decisions in the future.

In this paper, we explore the feasibility and potential of using AI sea ice forecasts to inform Arctic conservation through a targeted case study. We focus on the Dolphin and Union (DU) caribou (*Rangifer tarandus groenlandicus x pearyi*), a genetically distinct subspecies of caribou endemic to the Kitikmeot Region of Nunavut, Canada (Mcfarlane et al., 2016). As well as forming a key part of the local ecology, DU caribou play a critical role in the lives and livelihoods of the local Inuit and Inuvialuit people (Hanke et al., 2021, 2024; Poole et al., 2010). However, the numbers of DU caribou have suffered sharp declines in recent years, falling from an estimated 34,558 (95% CI = 27,757 to 41,359) individuals in 1997 to just 3815 (95% CI = 2930 to 4966) in the most recent 2020 survey (Species at Risk Committee, 2023). The herd is assessed as Endangered by the Committee on the Status of Endangered Wildlife in Canada (COSEWIC, 2017). Effective avenues for conservation must be explored to prevent their permanent demise.

One of the distinct characteristics of the DU herd is its biannual migration across sea ice. In the spring, before the ice melts, caribou cross from mainland Canada to Victoria Island to access summer calving grounds. In the autumn, after calving, they congregate on the south coast of Victoria Island waiting for sea ice to re-form (the *staging period*) before crossing back to overwinter on the mainland (Poole et al., 2010). A reduction in sea ice quality in the region has caused increasing numbers of the caribou to perish, sometimes in their hundreds, during ice crossings in recent years (Hanke et al., 2021). Sea ice crossings can also be disrupted by leads (linear open water tracks) in the ice created by transiting ice-strengthened vessels (Dumond et al., 2013; van Luijk et al., 2022). This is of concern as the region (surrounding nearby community Cambridge Bay) has experienced the third highest increase in vessel traffic in

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Nunavut in recent decades (Dawson et al., 2018). In response, the Victoria Island Waterways Safety Committee (VIWSC) was formed to collaboratively identify, assess and manage cumulative risks from shipping—highlighting "impacts of icebreaking activities on caribou migration, food security, and hunter safety" as a key priority (Doucette & Mansfield, 2024).

In 2019, VIWSC "icebreaking" workshops identified seasonal periods and locations where caribou and people use sea ice to find an approach for pro-active management of shipping risks (Doucette & Mansfield, 2024). During the autumn, it was noted that the caribou "may start crossing as soon as sufficient ice has formed, which is variable on a year-to-year basis" (Ekaluktutiak Hunters and Trappers Organisation, 2019). Telemetry studies indicate that between 1999 and 2006 the average overall autumn crossing date was 1 November, but varied over 25 days annually during this period (Poole et al., 2010). More recent data (collected since 2015) suggests autumn sea ice crossings have shifted later in November in line with later freeze-up dates (Leclerc & Boulanger, 2018, 2020). The resulting management decision was to implement a Notice to Mariners (NOTMAR) communication system spanning these observed crossing periods. Between 15 October to 30 November, the NOTMAR recommends vessels to give notice, with follow up call/emails, 1 week prior to transiting through designated winter caribou protection zones, to a pre-defined list of local contacts (NOTMAR, 2020). Local partners also have access to near-real time maritime vessel traffic data via an online platform and can communicate with vessel operators to alert of hazards (Doucette & Mansfield, 2024). The NOTMAR includes voluntary measures to: slowdown to minimum safe speed if caribou or people are encountered, use local information to avoid passing in front of caribou or people, and avoid opening multiple leads (NOTMAR, 2020).

The NOTMAR framework is a flexible two-way communication system which incorporates on-the-ground observations (e.g. from hunters and vessel operators) of *real-time* caribou movements. However, *near-future* information on expected peak sea ice crossing periods would help mitigate impacts ahead of time and allow refinement of the notice period on an annual basis (Doucette & Mansfield, 2024). Here, we explore whether AI sea ice forecasts could be used to anticipate the timing of autumn sea ice crossings, to drive these more refined area-based management strategies. As a demonstration model we use IceNet, which shows promising results in forecasting daily pan-Arctic sea ice concentration (SIC) at 25 km resolution (Andersson, Hosking, Krige, et al., 2021; Andersson, Hosking, Pérez-Ortiz, et al., 2021). We adopt a multi-stakeholder approach, developing our objectives and methods with an interdisciplinary team which includes AI-forecasting experts, regional government biologists, conservation practitioners, software engineers, and remote sensing and sea ice experts (all listed co-authors). Our research had three main objectives; these were: (i) to quantify links between autumn SIC formation and the timing of DU caribou sea ice crossings, by linking movement records from telemetry tracked caribou with the passive microwave derived SIC products used to train IceNet, (ii) develop metrics which can convert SIC time series to anticipated sea ice crossing times, and (iii) explore the utility of the IceNet prediction system for local communities, conservation planners and regional governments, while also assessing its limitations and potential future improvements to enhance the accuracy of sea ice crossing predictions.

2 | MATERIALS AND METHODS

2.1 | Study region, sea ice conditions and migration patterns

The region of interest in this study lies between Victoria Island and mainland Nunavut in the Canadian Arctic Archipelago, and includes the eastern Dolphin and Union Strait, Coronation Gulf, Dease Strait, and western Queen Maud Gulf (Figure 1). During the summer, the region is fully open water for several months, transitioning to a continuous cover of land fast ice which remains for several months over the winter (Montpetit et al., 2023). There is substantial temporal and spatial variability in autumn freeze-up patterns (Paquette et al., 2023; Poole et al., 2010). Typically, freeze-up levels suitable for caribou crossings are expected between 15 October and 30 November, which is the timeframe designated for caution in the NOTMAR (NOTMAR, 2020). Freeze-up also consistently occurs from east to west, with areas initially freezing over with a layer of new ice before solidifying into more stable grey ice (Poole et al., 2010).

Dolphin and Union caribou begin their southwards migration from post-calving summer and autumn ranges on Victoria Island. When they reach the Victoria Island coastline, they are forced to wait for stable grey ice conditions to form before continuing their migration over sea ice, eventually reaching mainland winter ranges (Poole et al., 2010). We note that in this study we focus on the sea ice crossing segment of the autumn migration specifically. Depending on the location within the study region, sea ice crossing distances range between approximately 20 to 70 km, with caribou generally completing the crossing in a matter of days (for more details we refer readers to Poole et al., 2010). While a small number of caribou may remain on Victoria Island (e.g. due to poor body condition preventing migration), this study focuses on inferring the general behaviour of the herd that undertakes the sea ice crossing.

2.2 | Data and models

2.2.1 | Satellite telemetry (collar) dataset

The data used in this study captures the movement patterns of 131 mature female DU caribou fitted with collar trackers; herein referred to as the collar dataset. For more details of capture and collaring procedures, please see Leclerc and Boulanger (2018, 2020) and Roberto-Charron (2021). We note that DU caribou bulls are not fitted with collars due to their necks expanding during the rutting season; however, there is strong evidence that during the autumn

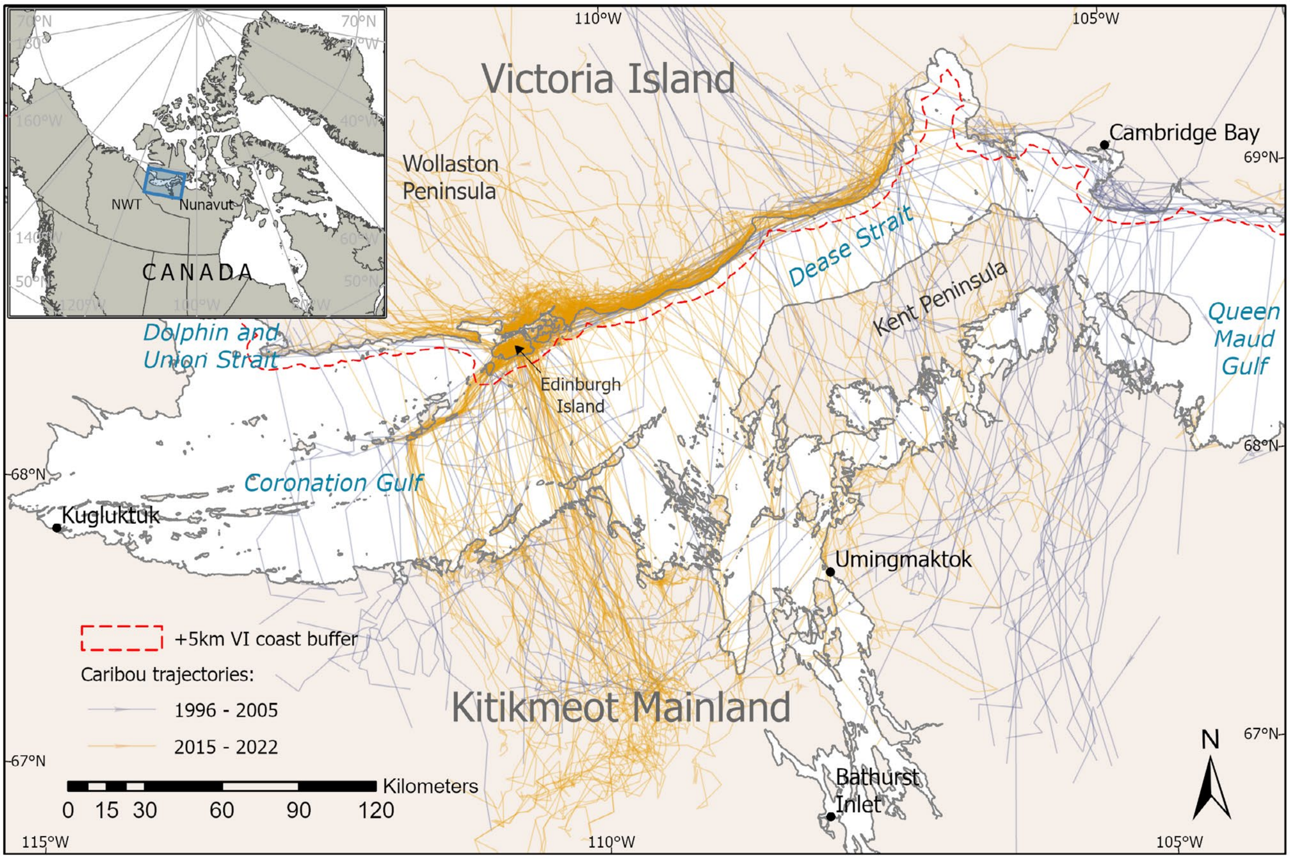

FIGURE 1 Map showing study region and autumn migration routes recorded for mature female DU caribou between 15 October and 15 December, as the caribou migrate south from Victoria Island to the Kitikmeot mainland. Telemetry tracks are coloured by two time periods in which they were recorded, between 1996–2005 (blue) and 2015–2022 (orange). The 5 km Victoria Island coastline buffer used for extracting sea ice crossing-start points is shown as a red dashed line. Base map sourced from OpenStreetMap (OpenStreetMap, 2023).

sea ice crossing, males and females migrate together (Species at Risk Committee, 2023). In this paper, we refer to each GPS location recorded by a collar as a *fix*, and the frequency of records as the *fix rate*. Collars were deployed across seven different campaigns spanning the periods 1996–2005 and 2015–2022, with fix rates varying both between and within years (Table S1). We used a restricted date range of collar records collected between 15 October and 30 December for each year to cover the period of the autumn migration only. Collars can remain active for several years; hence, there are often multiple autumn sea ice crossing trajectories recorded for each individual caribou. From the 131 individuals, there were a total of 263 of these autumn migration trajectories for use in the analysis (Table S2).

Figure 1 shows the study region and a summary of the autumn migration trajectories. The main sea ice crossing routes used by the caribou are in the east to Kent Peninsula and in the west using the island chains from Edinburgh Island. As DU caribou travel in groups (in the 2019 aerial survey observed group sizes were 8.4 ± 7.3 individuals on average (Leclerc & Boulanger, 2020)), satellite telemetry tracks can be used to infer herd spatial and temporal movements. During deployment campaigns, collars are distributed across the Dolphin and Union winter range, from the west side of Bathurst Inlet to the east side of the Kent Peninsula, to capture the variation in movement across individuals (or groups of individuals; Leclerc & Boulanger, 2018, 2020; Roberto-Charron, 2021).

2.2.2 | Observational sea ice concentration data

Sea ice concentration (SIC) is defined as the percentage of a passive microwave satellite image grid cell that is covered by ice, ranging from open water (0%) to full ice coverage (100%). We use passive microwave radiometry satellite brightness observations that are converted to SIC values using the well-established Ocean and Sea Ice Satellite Application Facilities (OSI-SAF) algorithm. The passive microwave radiometry record provides some of the longest and most continuous records of SIC because it is not affected by cloud cover or light levels and has been in-orbit since the late 1970s.

The (OSI-SAF) products used in this study are derived from the Special Sensor Microwave Imager/Sounder sensors. These products have provided daily, pan-Arctic data on SIC at 25 km resolution (25 km × 25 km pixel size) since 1979 (Lavergne et al., 2019). We downloaded OSI-SAF data from the European Organisation for the Exploitation of Meteorological Satellites data portal (OSI SAF, 2017, 2019). To assess potential performance gains from using higher spatial resolution data, we also compared against the University of Bremen product derived from the Advanced Microwave Scanning Radiometer 2 (AMSR2) sensor, which started recording SIC in 2012 at a 6 km resolution (Spreen et al., 2008). We downloaded the SIC dataset derived from the AMSR2 sensor from the University of Bremen data portal.

2.2.3 | IceNet model and forecasts

The IceNet model is based on a U-Net convolutional neural network architecture (Ronneberger et al., 2015), and is accessible via an open-source repository (https://github.com/icenet-ai/icenet). It is trained to forecast future OSI-SAF SIC conditions by learning from over 30 years of historical training data, including past and present SIC fields and atmospheric reanalysis data (Andersson, Hosking, Pérez-Ortiz, et al., 2021). IceNet's monthly pan-Arctic 25 km SIC forecasts were shown to outperform the leading physics-based model, SEAS5, at two-month lead times and beyond, while using a fraction of the computational cost (Andersson, Hosking, Pérez-Ortiz, et al., 2021). Following the initial publication, IceNet has been adapted to forecast 25 km SIC at a daily timescale for up to 93 days lead time (Andersson, Hosking, Krige, et al., 2021).

The daily version of IceNet we employ for this study is an ensemble of 10 individual U-Net models, each separately trained using daily OSI-SAF SIC and climate records from 1979 to 2014 (Table S3). We validated models using data from 2015 to 2019. Data from 2020 to 2022 were left as an unseen test set to assess results. Missing OSI-SAF dates pre-2015 were excluded from the training phase ($n=291$), and a small number of missing dates in the validation and test years ($n=3$) were filled using temporal linear interpolation (for a full list of missing files see OSI-SAF product user manual; EUMETSAT, 2023). Final IceNet outputs are presented as the mean across the 10-model ensemble.

2.3 | Analytic approach

2.3.1 | Multi-stakeholder development approach

Our method was developed using a multi-stakeholder approach to ensure relevant expertise and knowledge continually informed the system's design. An interdisciplinary team of scientists and stakeholders provided expertise in key areas, including regional biology, remote sensing of sea ice, AI sea ice forecasting and polar conservation and management. This approach facilitated ongoing refinement of the design of the tool, with the aim of providing practical outputs to guide human experts in their decision-making rather than a fully automated approach. For example, using SIC forecast maps and metrics in conjunction with other weather forecasts, real-time collar locations, and expert ecological knowledge. Team discussions also highlighted the need for probabilistic outputs, for instance summarised as percentiles or likelihood of caribou crossing, such that uncertainty could be clearly captured and assessed by users of the tool.

Beyond the core team, we engaged a broader network of stakeholders at key points during the project. Inuit partners were regularly updated on the research on the DU caribou herd by Government of Nunavut representatives. The local hunters and trappers community was supportive of the work, provided comments, and received the final project report. A DU caribou user-to-user meeting (November 2022) provided an opportunity to present project findings and seek further feedback. At the end of the project, representatives from government organisations involved in the NOTMAR system were invited to a wider stakeholder meeting. This event provided an opportunity to discuss the project findings and their application, including the potential for the outputs to be integrated into the current management approach. An example of feedback from the wider stakeholder engagement was reiterating the importance of the privacy of real-time caribou telemetry data. Emphasis was that if real-time data were to be integrated into the tool, strong data privacy should be built into any software infrastructure, with access limited to authorised individuals only.

2.3.2 | Crossing-start detection algorithm

Through visual assessment of animations depicting caribou migration patterns in relation to SIC data products, we observed that sea ice conditions at the Victoria Island coast were a strong precursor for sea ice crossing-start times. We therefore refined our objective, focusing specifically on predicting when caribou begin their sea ice crossings rather than the duration or routes taken. To achieve this, we developed a novel crossing-start detection algorithm. First, we defined a "crossing-start contour" which is the Victoria Island coastline (from Open Street Map's land polygon dataset; Open Street Map data, 2023) with a 5 km buffer added away from the coast (hereon the "VI-buffer"). This buffer accounts for potential inaccuracy in the coastline and collar data and means that all crossing-start points can be defined at a consistent distance from the coast. Then, we made small manual adjustments to the VI-buffer to incorporate expert knowledge of the region and caribou crossing routes, to include islands very close to the mainland, which the caribou use for staging. The final VI-buffer is displayed in Figure 1.

Using the VI-buffer, our crossing-start detection algorithm processes each autumn migration trajectory as follows:

1. Intersect the caribou trajectory with the VI-buffer. Label each GPS fix as either on Victoria Island (=1) or not (=0).
2. Search the trajectory for the point where the caribou leaves the VI-buffer and does not return (i.e. a GPS fix of 1 followed by only 0 s). If the trajectory ends in a 1, mark it as invalid.
3. Estimate the point and time the caribou crosses the VI-buffer by linearly interpolating between the last GPS fix on Victoria Island and the first GPS fix of the sea ice crossing (assuming constant speed and travelling in a straight line). This defines the crossing-start point for the trajectory.

The longer the time interval between the last fix on Victoria Island and the first fix of the sea ice crossing, the less certain we can be of the estimated crossing-start point time and location (when and where the caribou crosses the VI-buffer). In this study, we selected an upper limit of 3 days difference; however, this could be adjusted depending on different user specifications. Of $n = 263$ autumn migration trajectories, $n = 37$ were marked as invalid, and a further $n = 29$ had fix intervals above 3 days (Table S2). This resulted in $n = 197$ autumn migration trajectories ($n = 53$ pre-2014 and $n = 144$ post-2014) for our final analysis.

2.3.3 | Linking SIC and crossing-start times

To quantify the link between crossing-start time and passive microwave derived SIC data, we extract the OSI-SAF and AMSR2 SIC time series recorded at each crossing-start point (Figure 2). We sample SIC ±46 days either side of each crossing-start date, resulting in a 93-day SIC time series equivalent to the length of an IceNet forecast. To assess the relationship, we plot the distribution of SIC values recorded across all crossing-start points in the training dataset. We also summarise the distribution of SIC values recorded on the crossing-start dates.

To convert a given SIC time series to a predicted crossing-start date, we first apply a rolling mean average with window length ω to reduce the effects of noise, and then search for the date at which the smoothed SIC time series first passes above a given SIC threshold (sic_thresh). This gives us a predicted crossing-start date which can be compared to the observed crossing-start date extracted using the crossing-start detection algorithm. To find optimal smoothing parameters we search for ω and sic_thresh values, which minimise the mean absolute day error (MADE) on the test set (see Methods S1 for more details). We found $\omega = 40$ produced the best results for OSI-SAF (minimum MADE = 6.35) and $\omega = 50$ for AMSR2 (minimum MADE = 6.13) datasets.

2.3.4 | Percent-crossed metrics and maps

Using our chosen ω values, we compute predicted crossing-start dates for a range of SIC thresholds (from 0.5 to 1 with an interval of 0.01). For each threshold, we recorded the percentage of caribou that had crossed before the predicted date (i.e. observed crossing-start date ≤ predicted crossing-start date). We define the SIC conditions which equate to n percent of the caribou crossing as the *n%-crossed* SIC *criteria* (where n can be chosen at any value between 0% and 100%). This allows for a probabilistic interpretation of outputs, for example, estimating time intervals when 10%–90% of the herd would be expected to cross. To produce spatiotemporal outputs, we apply *n*%-crossed SIC criteria to forecast SIC time series to generate *n%-crossed maps*. These show the dates at which each grid cell is expected to meet the *n*%-crossed SIC criteria. The *n*%-crossed SIC criteria were computed using 1996–2019 records for OSI-SAF and 2015–2019 records for AMSR2. Years 2020–2022 were reserved for testing the sea ice crossing prediction system.

2.3.5 | Evaluating IceNet's performance in the study region

We use a similar analysis to Andersson, Hosking, Pérez-Ortiz, et al. (2021) to evaluate the sea ice forecasting ability of this

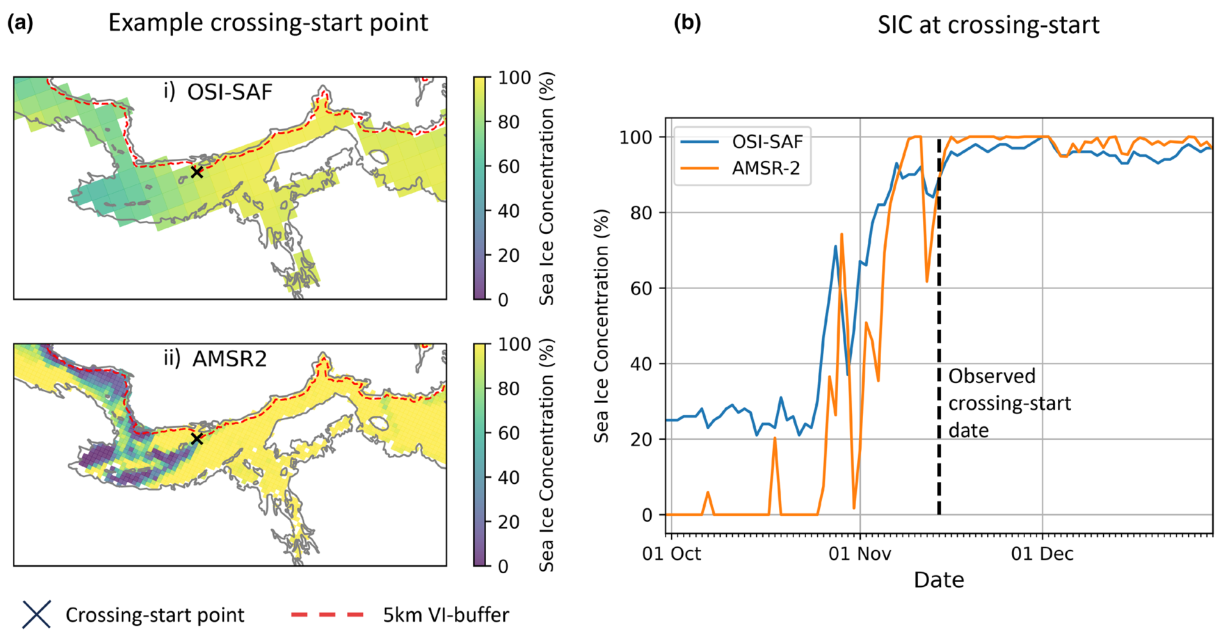

FIGURE 2 (a) An example crossing-start point (black cross) extracted using the crossing-start detection algorithm. This is overlaid on (i) OSI-SAF and (ii) AMSR2 sea ice concentration observations recorded on the crossing-start date. (b) Example OSI-SAF and AMSR2 SIC profiles extracted at the crossing-start point, with black dashed line showing the observed crossing-start date.

daily-resolution variant of IceNet, and make comparisons against the European Centre for Medium-Range Weather Forecasts SEAS5 model (Johnson et al., 2019). SEAS5 is one of the best performing dynamical SIC forecast models, allowing us to benchmark the accuracy of our AI approach against leading non-AI alternatives. We note that the version of SEAS5 assessed here is a 25-model ensemble; however, due to restricted computational resources for training, the version of IceNet consists of a 10-model ensemble—this gives SEAS5 an advantage due to lower variance in the ensemble mean.

We assess the accuracy of the forecasts both at the pan-Arctic scale and in the study region. We bias correct SEAS5 forecasts (a routine approach for calibrating climate models; Andersson, Hosking, Pérez-Ortiz, et al., 2021) by subtracting the mean error field for a given date and lead time, computed as an average over the years 2005–2014. Each forecast lead time date is compared against observational OSI-SAF data using the SIC mean absolute error (%). Since SEAS5 forecasts are only initialised on the 1 of each month, we restrict comparisons to these initialisation dates for the 2015–2022 validation and test years ($n=96$ forecasts). We present results as the mean error for each of the 93-day lead times, with bootstrapped 95% confidence intervals for the mean.

2.3.6 | IceNet crossing-start prediction analysis

To compare predicted crossing-start dates to those observed in the test years, we show date ranges by extracting the earliest date in the 10%-crossed map to the latest in the 90%-crossed map, taking only grid cells which were used by caribou in that year. We also show the inter-quartile range of predictions (the earliest 25%-crossed date to the latest 75%-crossed date). These are plotted against crossing-start dates observed in the test years. We validate the approach by applying the methods to observed OSI-SAF and AMSR2 time series. We apply OSI-SAF n%-crossed SIC criteria to IceNet forecasts to assess the success of the final prediction system. We compare IceNet forecasts generated one, two, and three weeks before the first observed crossing-start date in each year (IceNet_1w, IceNet_2w and IceNet_3w respectively). These lead times were recommended as appropriate levels of early warning for stakeholders from shipping and conservation agencies.

3 | RESULTS

3.1 | The relationship between SIC and crossing-start times

Our analysis of the relationship between SIC and crossing-start times reveals a clear pattern; the distribution of SIC freeze-up profiles shows that crossing-start times coincide with SIC reaching high levels (Figure 3). The link is clearer in AMSR2 (Figure 3b, (i)) than OSI-SAF (Figure 3a, (i)), however, we also observe higher variability in AMSR2 data prior to the crossing-start date, likely due to the higher resolution product capturing more SIC variation at the coast. Distributions of SIC values on the crossing-start date are higher and less variable in AMSR2 (median 98.8% (IQR = 94.1%, 100.0%)) than in OSI-SAF (median 90.0% (IQR = 83.0%, 95.8%)).

Using our percent-crossed analysis (Section 2.3.4) we were able to convert this SIC information into probabilistic mappings, showing the percent of caribou (in the pre-2020 collar dataset) which had crossed by various SIC thresholds (Figure 4). We see that the likelihood of crossing increases as SIC thresholds increase in a similar pattern for both OSI-SAF and AMSR2. These mappings allow end-users to select different percent-crossed values depending on their requirements, fulfilling needs highlighted in our stakeholder discussions.

3.2 | Metric outputs and maps

To visualise and interpret the spatiotemporal links between SIC and crossing-start, the relationship in Figure 4 can be used to generate n%-crossed maps. These maps indicate, for each coastal grid cell, when n% of caribou in the pre-2020 collar dataset would have started migrating, based on SIC criteria. In Figure 5 we show example 10%-crossed maps generated using observational OSI-SAF data; for corresponding AMSR2 and IceNet outputs, see Figures S1 and S2. We note in the case of OSI-SAF and AMSR2 "initialisation date" here refers to the first date of the 93-day time series extracted from the observational data, creating an exemplar forecast for comparison with IceNet predictions. We present three example initialisation dates at 2-week intervals before and during the sea ice crossing (17th October, 31st October and 14th November), comparing between 2021 and 2022. Real-time caribou locations for each initialisation date are overlaid on each map to illustrate how this information can guide users in identifying which grid cells are most likely to be selected for crossing. We note that in 2021 the freeze-up and crossing-start dates were particularly late; on average 10 days later than the mean crossing-start date recorded between 2015 and 2022. This late crossing is well captured by the 10%-crossed maps, which show longer time horizons for the 17th and 31st October initialisations in 2021 compared to 2022.

3.3 | IceNet performance

In terms of raw SIC forecasting accuracy, IceNet outperforms SEAS5 at all lead times, both in the pan-Arctic outputs and in the study region (Figure 6). Bootstrapped 95% confidence intervals for the mean errors do not overlap, showing the differences are significant. In the study region, mean SIC errors compared to OSI-SAF are 5.5 ± 0.5% for IceNet (when averaging across lead times) and 12.0 ± 0.7% for SEAS5. We note that in the study region, mean errors for both models remain relatively level as lead time increases, rather than

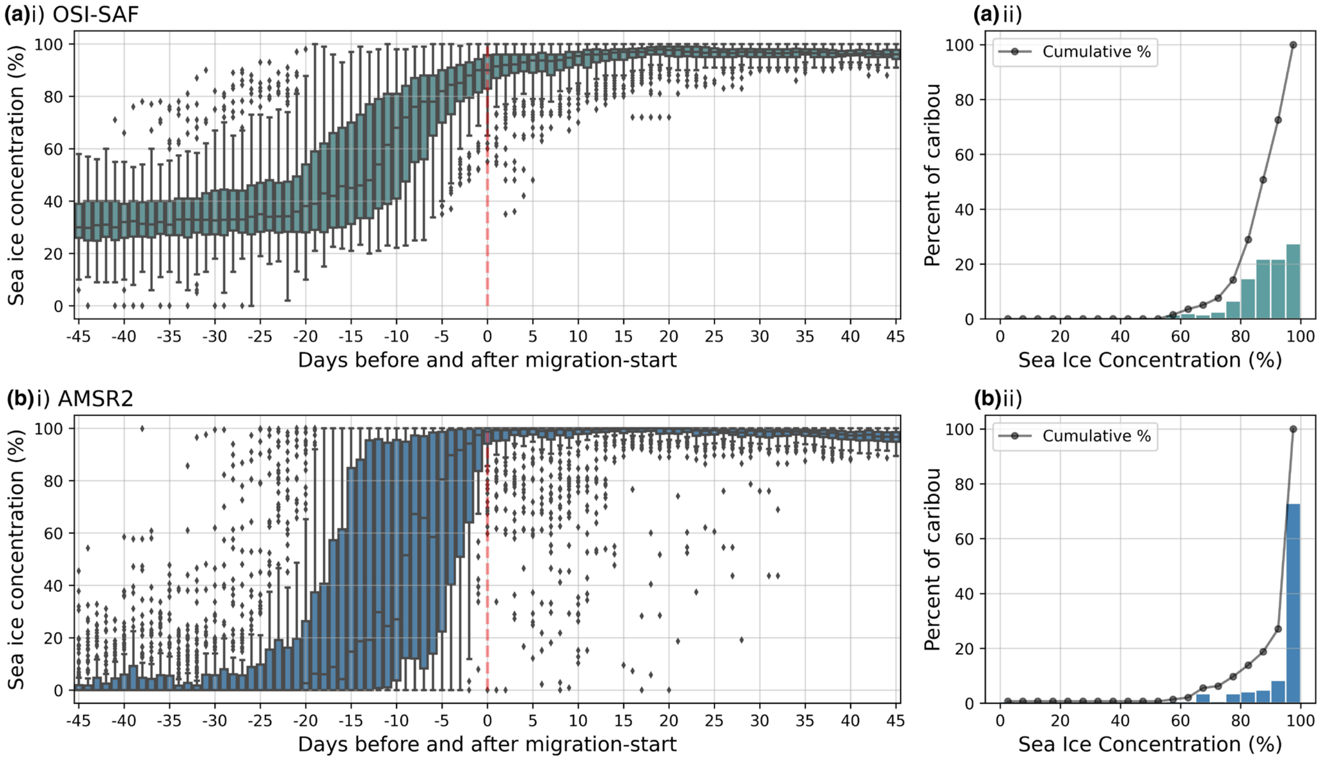

FIGURE 3 Comparison of SIC data extracted from all crossing-start points using (a) 25 km resolution OSI-SAF ($n=197$) and (b) 6 km resolution AMSR-2 ($n=144$) satellite records. We show (i) the daily distribution of SIC values recorded at crossing-start points ± 45 days from the crossing-start date and (ii) the distribution of SIC values recorded on the crossing-start date (day = 0).

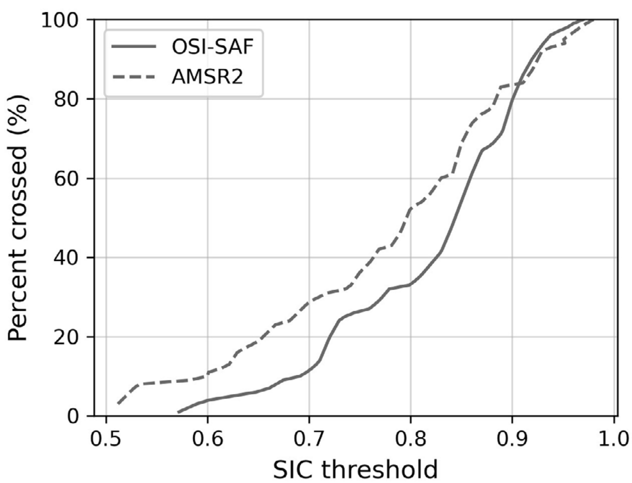

FIGURE 4 Curves showing the percentage of caribou (from pre-2020 satellite telemetry collar observations only) that had crossed by each SIC threshold. Results computed for both OSI-SAF and AMSR2 SIC datasets.

increasing as expected in the pan-Arctic case. This is likely because, for much of the year, the region is either completely frozen or completely ice free, which makes long-range forecasts quite accurate overall, with main sources of error occurring in the relatively short freeze-up and break-up seasons.

To assess IceNet's ability at forecasting crossing-start times we summarise the spatiotemporal data represented in Figure 5 into date ranges. We take the earliest date in the 10%-crossed map to the latest in the 90%-crossed map as whiskers, selecting only grid cells actively used by collared caribou for crossing that year. Similarly, boxes represent the earliest date in the 25%-crossed map to the latest in the 75%-crossed map. In Figure 7 we show IceNet's predicted crossing-start ranges for 2021 and 2022; results for 2020 are presented in Figure S3 due to the low number of observational data points that year ($n=3$). We note that while this allows us to compare predicted date ranges against observational data (the crossing-start times from collared caribou which are shown as grey points), it is important to highlight that this is a simplification of the problem that is better captured by mapped spatiotemporal information.

Using OSI-SAF as a benchmark, our predicted date ranges accurately encompass the observed crossing-start dates in the test years. AMSR2 data most accurately captures the late freeze-up in 2021 but predicts slightly later than observed in 2022. IceNet results are promising, with predicted crossing-start ranges comparable to those achieved with OSI-SAF data, especially in 2022. In 2021, IceNet_3w forecasts a range approximately two weeks earlier than OSI-SAF, but results improve as lead time decreases. Results for all IceNet lead times, including results for 2020, are presented in Figure S4.

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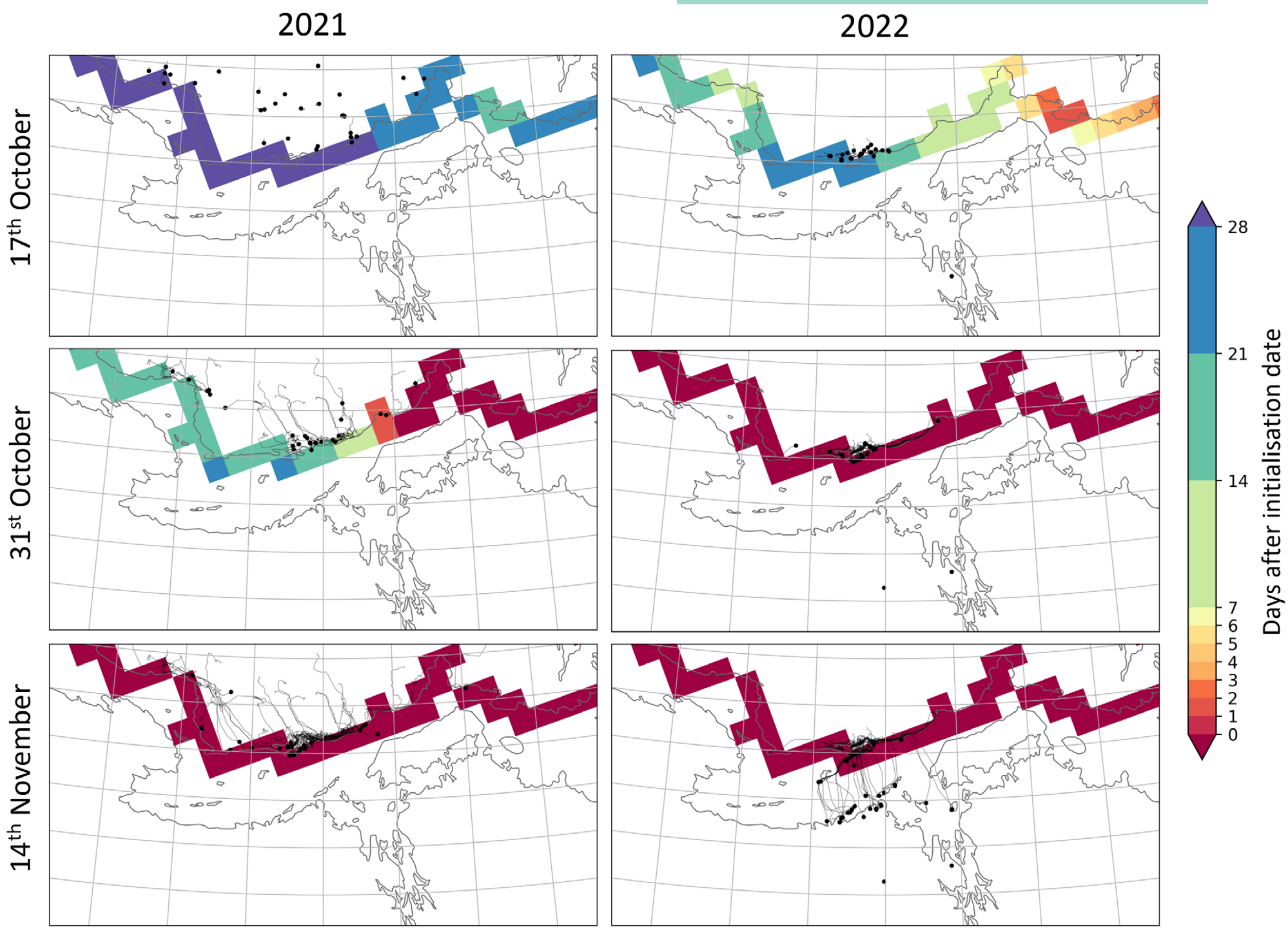

FIGURE 5 Example 10%-crossed maps produced on three initialisation dates (17 October, 31 October and 14 November) for 2021 and 2022. Colours show the number of days after the initialisation date that each grid cell is expected to meet the 10%-crossed SIC criteria (the SIC conditions where 10% of caribou in the observational data would have crossed). Dark red (<0 days) means the 10%-crossed SIC criteria have already been met. Black points show the locations of collared caribou on each initialisation date.

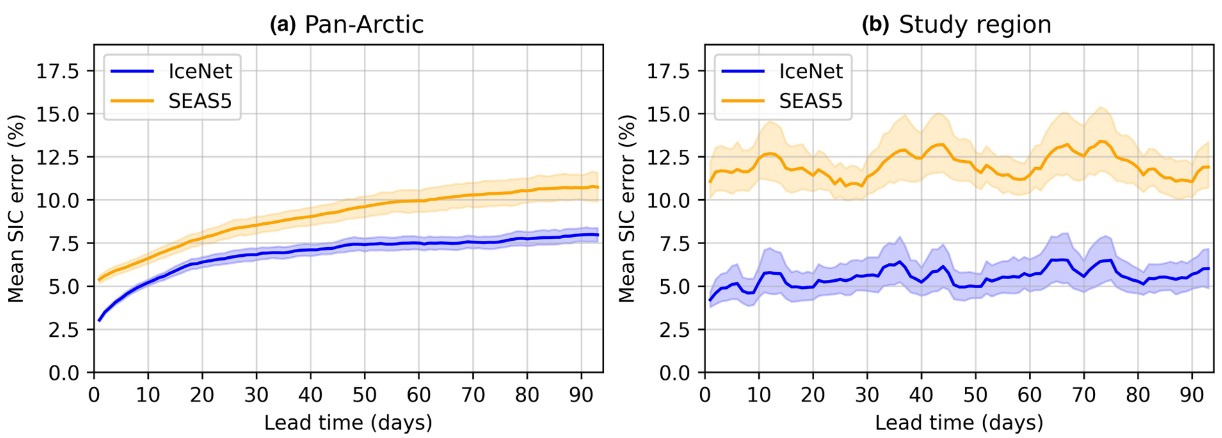

FIGURE 6 Mean SIC error (%), where error is the mean absolute difference between forecast SIC and OSI-SAF SIC, taken across 96 forecasts from 2015 to 2022. Error bars represent the bootstrapped 95% confidence intervals for the mean. We show results (a) for the pan-Arctic and (b) for the study region only.

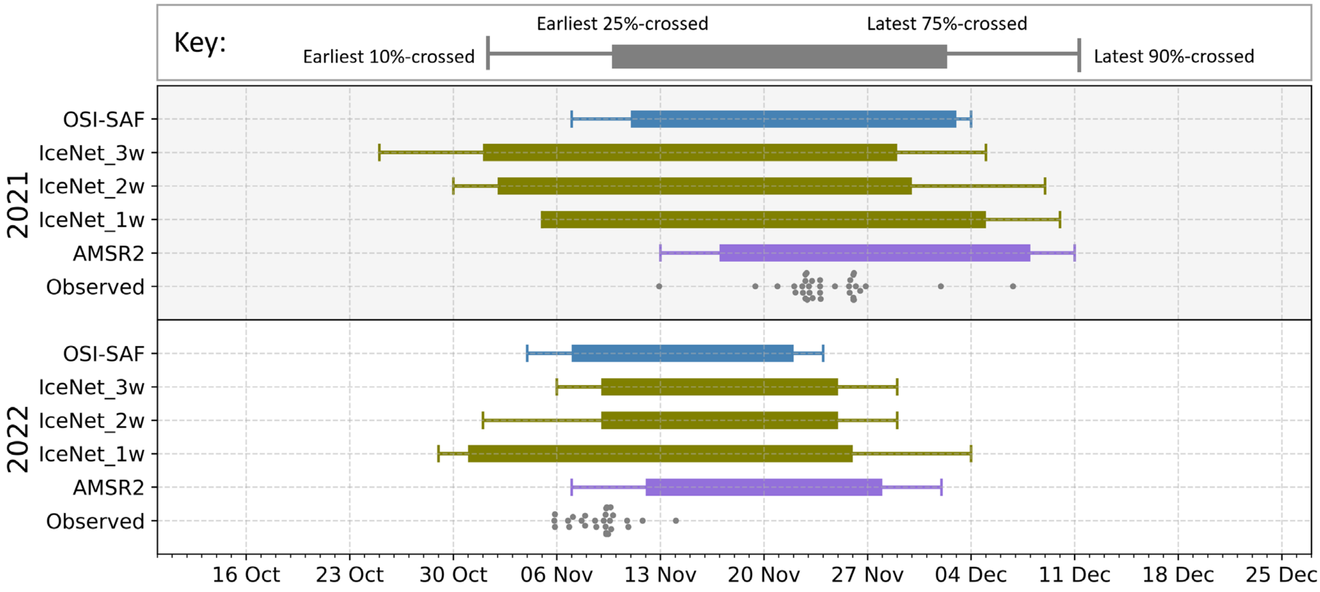

FIGURE 7 A comparison of predicted crossing-start ranges generated using OSI-SAF, AMSR2 and IceNet. IceNet outputs are demonstrated for three different lead times–one-, two- and three-weeks before the first observed crossing-start date in that year (IceNet_1w, IceNet_2w and IceNet_3w respectively). Whiskers show the earliest date in the 10%-crossed map to the latest in the 90% crossed map, considering only grid cells actively used by migrating caribou that year. Boxes show the earliest date in the 25%-crossed map to the latest date in the 75%-crossed map, also restricted to actively used grid cells. Grey dots show the observed crossing-start dates for the collared caribou in each year ($n=34$ in 2021, and $n=27$ in 2022).

4 | DISCUSSION

4.1 | The relationship between SIC and crossing-start times

Our results show a strong link between SIC reaching high levels and the female DU caribou starting their autumn sea ice crossing between Victoria Island and the Canadian mainland (Figure 3). This shows clear potential in using forecast SIC freeze-up profiles as a precursor for crossing-start times. The distribution of SIC values recorded on crossing-start dates shows values critical for the caribou to migrate across the gulf. While both datasets revealed a similar pattern, crossing-start SIC values were higher and less variable in AMSR2 (median 98.8% (IQR = 94.1%, 100.0%)) than in OSI-SAF (median 90.0% (IQR = 83.0%, 95.8%)), due to finer spatial resolution. In both cases, the requirement for ~90% SIC for caribou sea ice use aligns with values derived from other data sources and traditional knowledge (Paquette et al., 2023; Poole et al., 2010).

The 6 km resolution AMSR2 data provides a more accurate picture of localised SIC variation, at a scale more comparable to the movement of individual caribou. A visual comparison in Figure 8 clearly reveals how AMSR2 can capture small areas of open water blocking the caribou crossing, while this detail is averaged out in the corresponding OSI-SAF data. This motivates the development of higher resolution IceNet forecasts capable of capturing fine scale ice dynamics. We also note there are inherent uncertainties and biases in SIC values derived from passive microwave radiometry data, for example contamination with land in coastal regions, sensitivities to surface melt water, and underestimation of thin sea ice (EUMETSAT, 2023). In comparison to ground-based observational data, OSI-SAF and AMSR2 have biases of −1.0% and −3.9% respectively (Kern et al., 2019), although these uncertainties are lower at high SIC values required by caribou (Heinrich et al., 2006). Nevertheless, passive microwave radiometry data can only provide an estimate and could be compared to direct observations of sea ice from visible or synthetic aperture radar satellites to validate observations.

While our analysis indicates a strong link between OSI-SAF and AMSR2 SIC time series and crossing-start times, it is important to highlight the limitations of using passive microwave SIC datasets as the sole predictor. Sea ice is complex, and there are numerous aspects including ice thickness, surface roughness, and the presence of surface melt water, which could influence the caribou sea ice crossing (Leblond et al., 2015; Paquette et al., 2023). Relationships to these variables could be assessed using supplementary datasets, for example new year-round satellite records of ice thickness (Landy et al., 2022) or Canadian Ice Service charts (Paquette et al., 2023) to build a more complete understanding of how caribou respond to other properties of sea ice. Other weather-related factors such as snow depth, wind strength and storm events could also prevent the caribou from migrating even if ice conditions appear suitable (Gurarie et al., 2019). These elements could be assessed from other forecasts to guide decision-making leading up to expected crossing-start dates. Ultimately, it is important to recognise that the decisions guiding individuals or groups of animals are not influenced by a single environmental variable. For example, complex social dynamics within the herd are also important in guiding migratory movements (Cameron

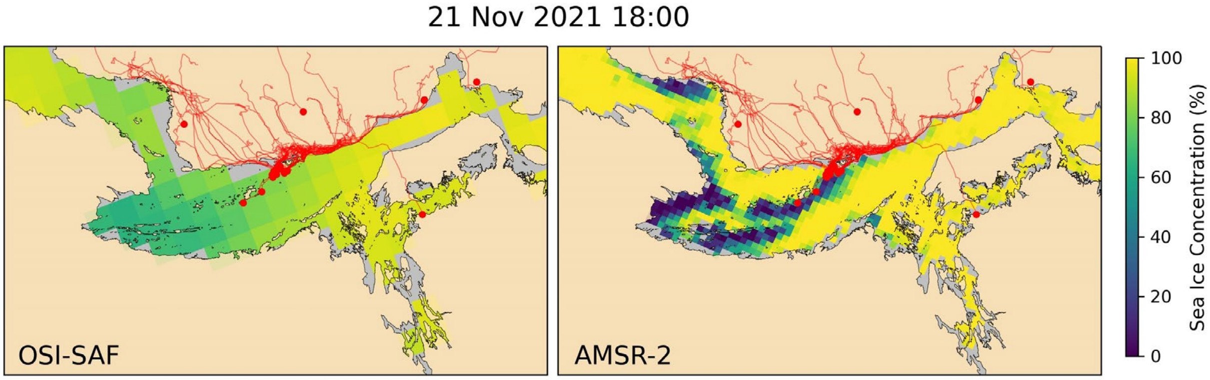

FIGURE 8 A comparison of crossing routes from 21 November 2021, visualised over 25 km resolution OSI-SAF and 6 km resolution AMSR2 sea ice concentration data. In AMSR2, you can clearly see the areas of open water preventing the caribou from leaving island chains in the centre of the gulf; detail that is lost in the lower resolution OSI-SAF data.

et al., 2020; Torney et al., 2018). Pressures such as predator avoidance, the need to access new feeding grounds, and myriad other factors might drive caribou to attempt their sea ice crossing, potentially at different SIC levels (Gurarie et al., 2019; Leblond et al., 2015; Paquette et al., 2023). It is therefore essential that human experts remain at the centre of the decision-making process, so in-depth knowledge (including scientific, Indigenous and local knowledge systems) of the study species and region can be combined with forecast and real-time data to determine appropriate conservation actions.

4.2 | Utility of the sea ice crossing prediction system

When applied to observational OSI-SAF data, our *n*%-crossed SIC criteria produce crossing date ranges which closely match those observed in the test years. The current version of IceNet shows promise in forecasting these results, producing predicted crossing-start ranges comparable to OSI-SAF in 2022, but systematically forecasts an earlier crossing in 2021. This suggests IceNet needs further improvement before it would be fit for operational use, although overall the results are encouraging. As our comparison to SEAS5 shows, IceNet already significantly outperforms one of the leading physics-based systems, highlighting the potential for AI models to offer improved forecast accuracy for conservation decision-making. The fact that AI forecasting systems are now advancing more rapidly than traditional physics-based systems (Bi et al., 2023; Lam et al., 2023; Price et al., 2024) further motivates their adoption as part of future conservation tools.

Interestingly, in 2022 we see poorer crossing date range estimation using higher resolution AMSR2 when compared to the lower resolution OSI-SAF, possibly contradicting the need for higher resolution forecasts. This seems counterintuitive, as the link between crossing-start and SIC is clearer in the higher resolution data. This may be an artefact of using only coastal grid cells to anticipate crossing-start, which are known to be unstable in passive microwave radiometry records due to brightness values from the land contaminating those in the ocean (EUMETSAT, 2023). This may be more pronounced and variable in AMSR2 compared to OSI-SAF, which is captured over a larger area, thereby reducing noise. More advanced spatiotemporal modelling of caribou movements would likely address this. However, it is also important to note in all cases that predicted date ranges are a simplification of the more complex spatiotemporal problem, and information is best captured by map outputs.

Using our analysis, maps showing the date at which each grid cell is predicted to become suitable for crossing can be produced for user-selected probability values. Combining these outputs with real-time collar locations could inform experts when and where caribou are most likely to cross in upcoming days and weeks, complementing information communicated on the ground by hunters and vessel operators via the NOTMAR. Feedback on the provisional system from external stakeholders was positive. Attendees at the DU caribou user-to-user meeting expressed interest in the technology as a tool to manage risks to caribou. One point raised was that the male caribou are not represented in the collar data, meaning male movements could not be captured using the system. In addition, the importance of protecting real-time caribou location data was emphasised (L-M Leclerc, personal communication after presenting at the workshop, November 9, 2022). This feedback highlights the importance of cooperation and inclusion of communities and community organisations as methods are developed further.

4.3 | Future development

The case study brought together a wide variety of expertise and the results have both proved encouraging and provided numerous avenues for future research, development and application. A key limitation of the current approach is that it is restricted to crossing-start times (i.e. the point at which the caribou leave the coast) but does not build in information on the duration or route taken for their sea ice crossings. Methods which factor in this spatiotemporal aspect of the crossing would be a valuable extension, as would incorporating more sea ice variables (e.g. thickness) as discussed in Section 4.1. Upcoming satellite telemetry collar deployments will use a 3-hourly fix rate during sea ice crossing periods (L-M Leclerc, personal communications, January 23, 2023), facilitating studies of fine-scale movements over sea ice in the future (Leblond et al., 2015). It is also important to highlight that satellite telemetry collars are only deployed on a small fraction of the herd and on mature female caribou only. Investigations into how well these collared individuals capture the movement of the wider herd would be beneficial. Finally, here we have focussed solely on the sea ice crossing segment of the autumn migration, due to the clearer link between sea ice formation and crossing times. The timing of the spring migration is more likely motivated by the pregnancy stage in female caribou, with the bulls following later (Species at Risk Committee, 2023). However, sea ice conditions will clearly still be important, and relationships between spring crossing routes and sea ice conditions could be investigated using similar methods. This could be valuable for informing conservation and management, for example to alert when early sea ice break-up might encroach on usual spring migration times which also poses a risk to crossings (Species at Risk Committee, 2023).

Recent advances in AI modelling should be leveraged into developing IceNet, such as vision transformers (Chen et al., 2022; Fan et al., 2021), as well as higher resolution data (for example from AMSR2). The crossing-start approach we have developed is general, and as sea forecasting systems improve, so will the robustness of early warning signals. To facilitate review of information, user-friendly visualisation tools should also be developed, such as a navigable dashboard for visualising IceNet forecasts with derived crossing predictions. Options to upload real-time collar locations and overlay these on forecast outputs could be incorporated to improve user experience and interpretation. These should be built with data privacy in mind to ensure sensitive data is viewable only by authorised users, thus meeting the needs and concerns highlighted by rightsholders and stakeholders. Expanding work to deliver warnings directly to harvesters planning travel on the sea ice was also emphasised by stakeholders, which would require strong engagement with the community, hunters and trappers organisations, and bodies such as the Victoria Island Waterways Safety Committee. As with our methodology development, regular consultation between developers and stakeholders will ensure end-user tools are fit-for-purpose.

4.4 | Lessons and wider applications

In this study, we have used the DU caribou autumn sea ice crossing to explore how AI forecasts could inform dynamic conservation decision-making, by acting as an early-warning indicator for wildlife movement and distribution. This rapidly emerging interdisciplinary field requires case studies such as this to catalyse further development. Our initial findings show the promise in using near-future forecasts of environmental variables to inform dynamic management strategies. However, given the complexity of animal behaviour and the sparsity of observations we recommend future work focuses on human-in-the-loop *decision-support* rather than fully automated *decision-making* systems. Focusing on a specific region and study species has been valuable for identifying avenues for future development to help drive innovation forward. For example, zooming in on the pan-Arctic IceNet forecasts has highlighted areas for improvement (e.g. increasing the spatial resolution) and potential biases in the model and training data. Addressing these will help to realise real-world impact for forecasting systems like IceNet. In addition, our investigations linking collar data and SIC satellite datasets have delivered new findings on the DU caribou relationship with sea ice, helping to further our ecological understanding.

Looking beyond this case study, the concepts explored have the potential to transfer to other species whose behaviour or distribution is closely linked to sea ice conditions. For example, predicting when polar bears are most likely to move off sea ice and onto land close to communities to mitigate against human-wildlife conflict (Abrahms et al., 2023), anticipating Arctic cetacean migration timings to protect vital migratory corridors from shipping impacts (C. Johnson et al., 2022), and forecasting terrestrial haul-out timings for walrus to minimise risk of disturbance and fatal stampedes (Jay et al., 2012). Using forecast sea ice conditions as an indicator for wildlife distribution can also guide fieldwork efforts, for example determining the best times and locations to fly aerial survey transects to optimise data collection and logistics planning. Further study into these different systems can guide new developments in the field, including building flexible downstream user interfaces to synthesise forecast information and derive species-specific metrics and maps. This information could ultimately feed into dynamic spatial management, integrating climate change considerations for more effective biodiversity conservation in the polar oceans (Cashion et al., 2020; Gissi et al., 2019; Tittensor et al., 2019).

AUTHOR CONTRIBUTIONS

Ellen Bowler led the experiments, data analysis and paper writing. Tom R. Andersson, J. Scott Hosking, Rod Downie and Amélie Roberto-Charron conceptualised the project; Tom R. Andersson led the project and stakeholder meetings; Lisa-Marie Leclerc and Amélie Roberto-Charron provided the satellite telemetry dataset and biological expertise; James Byrne, Ryan S. Y. Chan and Oliver Strickson engineered and generated IceNet model outputs and SEAS5 comparisons; Martin S. J. Rogers and Jeremy Wilkinson provided expertise on sea ice and satellite imagery; Rachel D. Cavanagh, Jason Harasimo, Melanie L. Lancaster and Rod Downie input conservation management and regional expertise; all authors contributed to the co-design of methodology. All authors contributed critically to the drafts and gave final approval for publication.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

PEER REVIEW

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1002/2688-8319.70034.

DATA AVAILABILITY STATEMENT

The trained IceNet network weights, IceNet's ensemble-mean SIC forecasts for the 2020–2022 test years, and results linking SIC to caribou crossing start points have been made available on the Polar Data Centre: https://doi.org/10.5285/8738b3cb-52c7-4b36-aa6d-6e15c0b46ba4 (Bowler et al., 2025). Analysis code for this publication is available on GitHub: https://doi.org/10.5281/zenodo.15194685 (EllieBowler, 2025). The IceNet model codebase (https://github.com/icenet-ai/icenet) and pipelining tools (https://github.com/icenet-ai/icenet-pipeline) are accessible on GitHub. Observational SIC data are provided by OSI-SAF (https://osisaf-hl.met.no) and the University of Bremen (https://data.seaice.uni-bremen.de/). SEAS5 forecasts can be obtained from the ECMWF MARS archive (https://www.ecmwf.int/en/forecasts/datasets). The Dolphin and Union caribou satellite telemetry dataset is not openly available; requests for access should be directed to the Government of Nunavut.

RELEVANT GREY LITERATURE

You can find related grey literature on the topics below on Applied Ecology Resources: Migration, Dynamic conservation, GPS tracking.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Table S1. The fix rate of different collars deployed on the Dolphin and Union caribou herd.

Table S2. Number of satellite telemetry collar records per year for the 15th October–15th December autumn migration period.

Table S3. IceNet's input variables and their sources for the observational training dataset.

Method S1. Mean absolute day error (MADE) hyperparameter search.

Figure S1. Example 10%-crossed maps produced on three initialisation dates (17th October, 31st October and 14th November) for 2021 and 2022 using AMSR2 data.

Figure S2. Example 10%-crossed maps produced using IceNet forecasts initialised on three different dates (17th October, 31st October and 14th November) for 2021 and 2022.

Figure S3. Crossing-start ranges for the year 2020, when a postponement in the satellite telemetry collar deployment programme resulted in only $n=3$ observation points.

Figure S4. Crossing-start ranges for different IceNet lead times (the number of days before the first observed crossing in each year).

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