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Climate change contributes to the decline in off-reservation tribal harvest availability in the Great Lakes region

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Climate change threatens the lifeways of Indigenous Peoples, impacting their rights to self-determination and sovereignty. In the Laurentian Great Lakes region, Indigenous communities have experienced harvest declines of wild rice (Ojibwemowin: Manoomin; Dakodiapi: Psiŋ; Latin: *Zizania palustris*), a sacred aquatic plant central to their culture. Here we analyzed 1985–2020 wild rice density and harvest data in relation to key climate variables. Our results indicate that wild rice stem density in the fall is higher in years that have (1) lower early-summer water levels due to decreased precipitation, and (2) longer lake-ice duration due to colder winter temperatures. Overall, wild rice available for tribal harvest off-reservation has declined regionally by ~5–7% annually—declines that are likely to continue due to anthropogenic climate change, specifically increased early-summer precipitation and warmer winters. This decline has infringed on Indigenous lifeways by reducing off-reservation tribal harvest, a right guaranteed by treaties with the U.S. government.

Climate change disproportionately disrupts Indigenous Peoples' land-based lifeways[1,2], which are legally protected by their inherent rights to self-determination[3] and sovereignty[4]. Despite these outsized impacts and direct consequences for their survival, Indigenous Peoples have been largely excluded from mainstream climate research[5]. For the Indigenous Peoples of the upper Laurentian Great Lakes, concerning climate change impacts on their sacred food[6,7], wild rice (*Zizania palustris* L.), have been observed[8–12] as this region experiences warming exceeding average global rates[13]. For the Ojibwe, one of three Peoples among the Anishinaabeg, wild rice was integral in the prophecy guiding their migration to this region[14] and now serves as a cultural foundation protected for harvest under treaties signed with the United States[6,15,16]. While wild rice is also culturally important for the Dakota, who call it Psiŋ, as well as for other Indigenous Peoples, this paper mostly incorporates Ojibwe perspectives, including the use of the Ojibwemowin word for wild rice, Manoomin[6], with capitalization honoring its personhood[17].

Two centuries ago, Manoomin was abundant across the shallow surface waters of the upper Laurentian Great Lakes region and portions of eastern North America[18,19], but today it has disappeared almost entirely from Michigan[20,21] and from one third of the watersheds in Minnesota and Wisconsin where it was found about a century ago[22] (Fig. 1). Over the last few decades, tribes and inter-tribal organizations have reported continued declines of Manoomin[23,24]; however, detecting recent multi-year trajectories of change and associated impacts on tribal harvesters has been elusive against the backdrop of Manoomin's natural multi-year cycles[25]. Further, studies have identified both land-use and climate changes to be among the general causes for this decline: drainage, ditching, damming, and other water management, coupled with changing precipitation patterns and winter conditions, have together shifted habitats outside of Manoomin's preferred water level niche, favoring other plant species in many places[6,20]. Despite these observations, no formal quantitative assessments of specific relationships between climate conditions and Manoomin abundance have been conducted to date. Filling this knowledge gap informs care for Manoomin in the face of climate change, efforts central to supporting Ojibwe lifeways and upholding treaty obligations.

This study quantifies declines in Manoomin density and harvest over the last three decades, ties these losses to climate disruptions during Manoomin's vulnerable life stages, and shows threats to Indigenous lifeways. To accomplish this, we employed environmental science within both the mainstream ('Western') knowledge system and the Ojibwe gikendaasowin (Ojibwe knowledge system). Environmental science within Ojibwe

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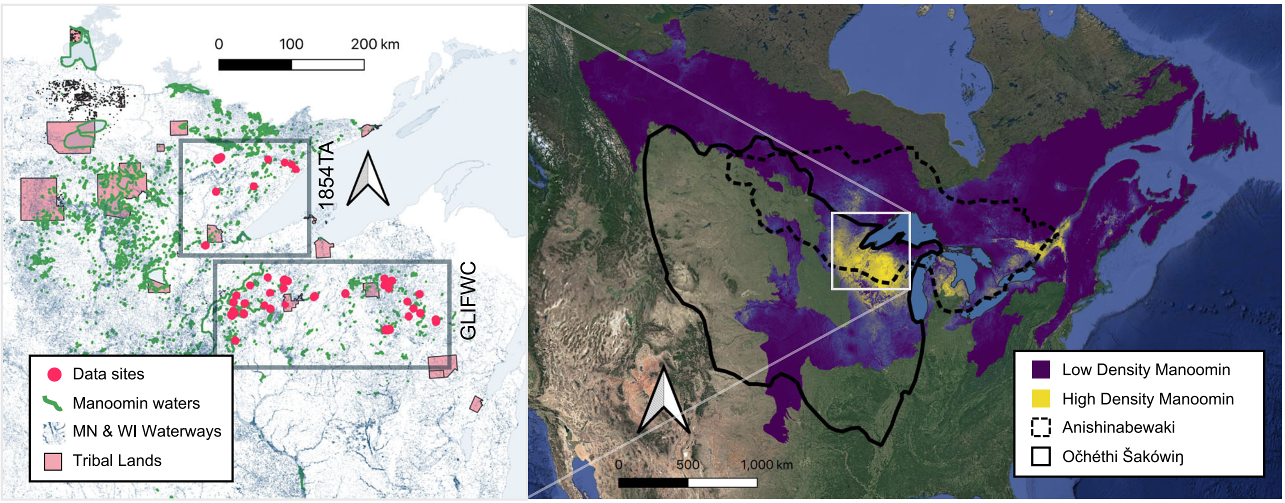

Fig. 1 | Map of study area. Map of data sites at the regional scale (left) and the continental scale (right). Regional scale map also includes Manoomin waters[104,105], Minnesota and Wisconsin waterways[106,107], and tribal lands[108]. The continental scale map also includes modeled Manoomin distribution[109], and the traditional territories of the Anishinaabeg (Ojibwe, Potawatomi, Odawa) and Očhéthi Šakówiŋ (Lakota, Dakota, and Nakota speaking people)[110]. Satellite Imagery: Google, ©2024.

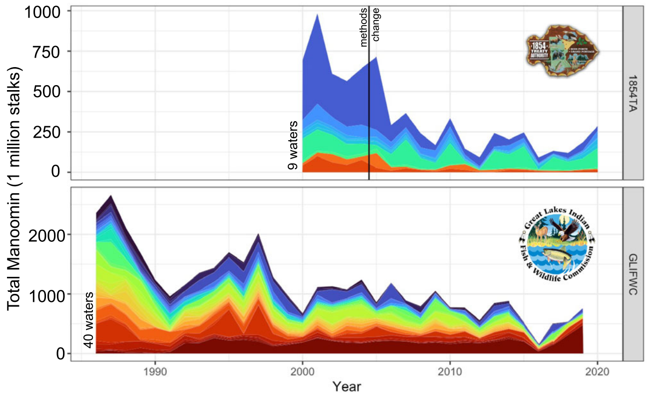

Fig. 2 | Manoomin abundance within study sites. Summed wild rice density through time for both the GLIFWC and 1854 Treaty Authority datasets. Each color represents a different lake. Note the sampling method changed in 2006 for the 1854 Treaty Authority dataset, indicated with a black line. Organization logos reproduced with permission (GLIFWC ©2025, 1854TA ©2025).

gikendaasowin, also referred to here and more generally across different Indigenous knowledge systems as Traditional Ecological Knowledge (TEK), is science embedded in an Indigenous worldview developed through generations of Indigenous Peoples living in close relationship to their homelands[17,26,27]. When invoked together, mainstream science and Ojibwe gikendaasowin deepen our understanding of the Manoomin socio-ecological system in ways unattainable from each one alone[28–30]. Given the dominance of mainstream environmental science within the academy, we strove for equitable collaboration by learning from Indigenous methodologies[31] and leaning on TEK as the 'intellectual scaffold' for our approach[32,33]. Specifically, the fundamental understanding of interconnectedness within TEK directed our tribal-university partnership formation[34,35] and our methodological assumption that knowledge production and colonial power dynamics are inextricably linked with the environment[17,36].

With this methodological grounding, we leveraged local observations, understandings, values, and data from within TEK to generate relevant research questions and hypotheses, inform the appropriate choice of statistical methods, and draw meaningful interpretations of quantitative model outputs (see "Methods"). Tribal priorities and TEK initiated and informed long-term data collection of Manoomin abundance: two inter-tribal organizations, the 1854 Treaty Authority (1854TA)[24] and the Great Lakes Indian Fish and Wildlife Commission (GLIFWC)[23] (Figs. 1 and 2), collected, respectively, 20 years and 34 years of Manoomin density data across a total of 49 historical Manoomin waterbodies in Wisconsin and Minnesota with different sampling methods. In addition, GLIFWC surveyed tribal and non-tribal members on their harvest yields across Wisconsin for 27 years. Knowledge of Manoomin's boom-and-bust abundance patterns and unique local relationships[6] advised our choice of methods: we assessed the density data for periodicity using spectral analysis[37] and for temporal trends and relationships with climate using statistical models that evaluated site-specific, regional, and non-linear relationships[38]. Further observations on Manoomin's sensitivity during early life stages[6] guided our hypotheses that winter, spring, and early-summer conditions would impact Manoomin growth. We engaged both TEK and mainstream science to represent these factors with specific climatic predictor variables. The results show that climate change in this region—specifically, increasing early-summer precipitation, higher mean winter temperatures, decreased snowfall, and shorter ice duration across this region—negatively impacts Manoomin density, contributing to declines in off-reservation harvest and thus threatening Indigenous lifeways.

Results

Manoomin trends over the last three decades

To understand Manoomin's varying abundance through time, both fluctuations and persistent trends in Manoomin density were characterized. Out of 49 waterbodies, 67% had significant multi-year cycles of density ranging from 2 years to 7 years (median cycle = 3 years), and 41% had multi-decadal cycles (median cycle = 20 years) (Supplementary Table 1). Additional modeling (Methods) captured each waterbody's unique temporal patterns and overall regional trends (Fig. 3), explaining 65% and 69% of the deviance in density for the 1854TA and GLIFWC datasets, respectively; 34% for the GLIFWC Wisconsin tribal harvest data; and 23% for the GLIFWC Wisconsin non-tribal harvest data. The regional trend of off-reservation Manoomin density for both datasets was statistically significant over the last two to three decades, with mean annual decrease in density of 6.8% (95% CI [−10.6, −2.8], 1985–2019) and 5.6% (95% CI [−12.0, 1.3], 1998–2020) for the GLIFWC and 1854TA datasets, respectively. Most of this decline was concentrated in the mid-1980s through mid-2000s. In Wisconsin, off-reservation tribal harvest exhibited a statistically significant mean annual decrease of 2.0% (95% CI [−6.4, 2.7], 1992–2019) harvest weight per trip. Non-tribal harvest did not show a net decline over the 1992–2019 analysis window but decreased for a period during 2000–2010, then rebounded.

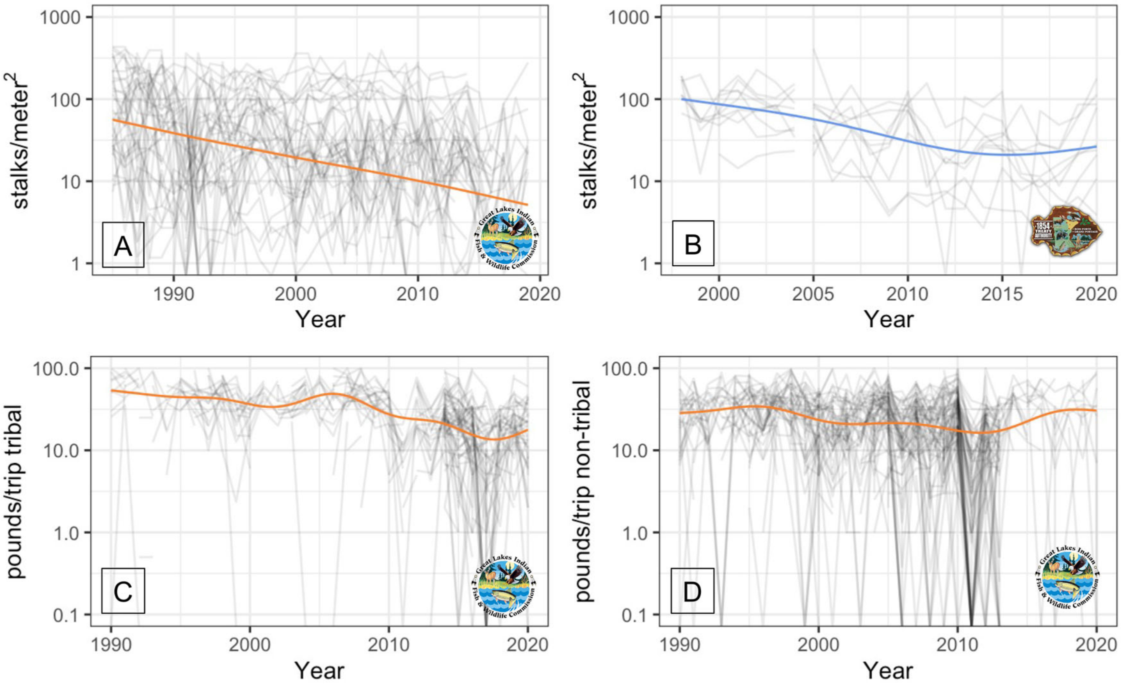

Fig. 3 | Manoomin density and harvest trends. Generalized additive model (GAM) smooth curves for **A** GLIFWC Manoomin density through time, **B** 1854 TA Manoomin density through time, **C** Wisconsin tribal harvest through time, and **D** Wisconsin non-tribal harvest through time. In all plots, gray lines represent raw, waterbody-level data. Solid colored lines are the overall GAM-smoothed curves through time. Organization logos reproduced with permission (GLIFWC ©2025, 1854TA ©2025).

Climate impacts on Manoomin density

The tested hypotheses about regional Manoomin-climate relationships were derived from TEK and constrained by data availability. Specifically, local observations within TEK[6] show connections between longer (multi)decadal periodicities of Manoomin abundance and oscillations of spring and early-summer precipitation, and between cold, snowy winters and high Manoomin abundance. Four hypotheses emerged: higher precipitation during the submerged and floating leaf stages (spring and early summer) decreases density, more days with a minimum temperature above 4° °C (growing degree days) increase density, higher mean winter temperature decreases density, and greater snow accumulation increases density (Table 1).

To test these hypotheses, we modeled Manoomin density through time and in relation to climate datasets[39] (see "Methods", Fig. 4 and Table 1). For both the GLIFWC and 1854TA datasets, higher precipitation in spring and early summer, during Manoomin's floating leaf stage, was associated with lower density (GLIFWC: $p < 0.001$; 1854TA: $p < 0.001$). Precipitation during spring, Manoomin's submerged stage, also had a significant correlation with Manoomin density, but this was a positive correlation for the GLIFWC dataset ($p < 0.001$) and negative for the 1854TA dataset ($p = 0.007$). The effects of growing degree days were also inconsistent across datasets: they had a significant negative correlation with Manoomin density in the GLIFWC dataset ($p = 0.04$) but no significant effect for the 1854TA dataset ($p = 0.09$). Mean winter temperature had a significant negative correlation with Manoomin density for the 1854TA dataset ($p = 0.04$), but the correlation for the GLIFWC dataset was just above the significance threshold ($p = 0.06$). The regional and water-body specific trends through time were significant in both models (GLIFWC $p < 0.001$; 1854TA $p < 0.001$). The effects of snow were consistently positive but not significant for both datasets. This lack of significance may be partly attributable to another term in the model (the site-specific random effects) that captured similar variability as the snow data (Methods), potentially underestimating the strength of the snow-Manoomin relationship. The models explained 76% and 74% of the deviance in the GLIFWC and 1854TA data, respectively.

We further explored in-lake impacts of floating-leaf stage (early-summer) precipitation and dormant stage (winter) conditions on fall Manoomin density using water level data[24] for the waterbodies monitored by 1854TA, and ice duration data[40] for lakes nearby the waterbodies monitored by GLIFWC, based on data-type availability (Methods, Fig. 4, Rows 4 and 2, respectively). The results show that shallower water levels during the floating-leaf stage ($p < 0.001$) and longer ice duration ($p < 0.001$) were both positively correlated with Manoomin density (Fig. 4B and 2F, respectively). Water levels for the other growing stages did not have statistically significant effects. Models for both the GLIFWC and 1854TA datasets explained 76% of deviance in the data.

Relevant climate changes for Manoomin

Temporal changes in climate over time were also assessed. All weather variables showed significant change over time ($p < 0.05$) since 1985 (Fig. 5). We additionally increased the analysis window for four records that extended back to1900, and all weather variables were again significant ($p < 0.05$) except for growing degree days (Fig. 5). Winter temperature, snowfall, and submerged stage precipitation have increased on average by 1.5 °C, 20 cm, and 4 cm, respectively, since 1900, with significant nonlinearity. Precipitation during the floating-leaf stage has not increased on average over either time scale, but the magnitude of the last peak (2012–2020) increased by 3 cm compared to previous multi-year oscillations since 1900.

Lake-ice duration and water level temporal trends were also evaluated. Generally, ice duration has declined, especially in the late 1990s, and water levels in submerged and floating-leaf stages have increased since 1998 (Fig. 6). All of these variables also exhibit substantial multi-year oscillations.

Relationships with Indigenous harvest

Informed by TEK (see "Methods"), we hypothesized that Manoomin harvested by tribal members increases with Manoomin density. Furthermore, we hypothesized that preceding years' harvest would not negatively impact Manoomin density, as suggested by TEK[6,15] and past studies[41,42], and could possibly even improve future harvest.

To assess these hypotheses, two more models were developed: one investigating the relationship between the weight of Manoomin harvested

Table 1 | Summary of Models and Results

Life stage	Month	Predictor variable	Response variable	Hypothesized correlation	Resulting correlation: GLIFWC	Resulting correlation:1854TA
Dormant	October–March	Winter temperature	Manoomin density	Negative	Not significant	Negative
		Ice duration		Positive	Positive	No data
	December–March	Snow		Positive	Positive	Not significant
Submerged	March–May	Precipitation	Manoomin density	Negative	Positive	Negative
		Water levels		Negative	No data	Negative
Submerged–harvest	March–September	Growing degree days		Positive	Negative	Not significant
Floating leaf	June–mid July	Precipitation	Manoomin density	Negative	Negative	Negative
		Water levels		Negative	No data	Negative
Emergent–flowering	Mid July–mid August	Precipitation	Manoomin density	None	Not significant	Not significant
		Water levels		None	No data	Not significant
Harvest	August–September	Year	Manoomin density	~4-year cycles	2–7 year cycles (67% of waters)	Not enough data
		Year		(Multi)decadal long cycles	10–30 year cycles (41% of waters)	Not enough data
		Year		Decline through time	−6.8% per year	−5.6% per year
		Manoomin abundance	Tribal harvest	Positive	Positive until 250 stalks/m^2	No data
		Previous harvest		None	Positive	No data
		Year	Total harvest	Decline	Tribal: −2.0% per year	No data
					Non-tribal: variable without significant decline	

Summary of hypotheses, modeled variables, and resulting correlations.

by tribal members and Manoomin density, and another investigating the relationship between current-year and previous harvests (see “Methods”). The first model showed a positive correlation between Manoomin density and tribal harvest per trip up to 250 stalks/m^2, after which harvest declined (Fig. 7). It also revealed a significant decline in harvest per trip over time. In the second model, the average harvest per trip for the previous two years had a significant positive correlation with harvest in the current year. In total, these models explained 19% and 52% of total deviance, respectively.

Discussion

The combination of mainstream scientific and TEK monitoring methods provided a robust characterization of Manoomin abundance. The 1854TA approach privileges mainstream science through extensive ground surveys using unbiased, plot-level measurements that yield higher precision of fewer sites with greater time costs. Monitoring conducted by GLIFWC privileges TEK by employing multiple faster, lower-cost methods of aerial photos, harvester surveys, and simplified ground surveys that allow for long-term and widespread measures to cover a greater number of culturally important sites, even if with lower precision[28]. In sum, the 1854TA dataset prioritizes site-level precision with lower regional accuracy, while the GLIFWC datasets prioritize regional accuracy with lower site-level precision. Combined, these models, with their complementary strengths and limitations, provide robust information on status and trends: we can assume confidence in the results when the datasets show agreement, but differing sampling methods may be a cause when they do not. Guided by TEK, both inter-tribal organizations focused on one plant and important ‘hot spots’ of harvest rather than randomized site selection across multiple species[28]. Therefore, these data do not represent overall ecosystem health or total Manoomin abundance across the region, but instead, regional, off-reservation Manoomin available for Ojibwe harvest.

The short time series lengths (<40 years, 1 data point/year) may weaken the robustness of the multi-year and (multi)decadal oscillations found in Manoomin abundance across the region with spectral analysis, but these variations are consistent with TEK[6,25] and experimental evidence[43,44] of natural cycles. Despite the complexity introduced by this natural interannual variability and site-level variation, models revealed a statistically significant decline of ~5–7% per year in off-reservation Manoomin available for Ojibwe harvest across the region and ~3% per year in off-reservation harvest per trip for tribal members. The similar declines across all datasets suggest robust results, and that declining harvest could be related to declining density. This harvesting trend may also be influenced by demographically aging harvesters’ decreased productivity but increased skill, differences in tribal members’ on-reservation harvest (which is not accounted for in these data), and/or low sample size[45].

Greater precipitation during the floating leaf stage correlated with reduced Manoomin stem density at the end of the growing season. This relationship was robust to the differences in geography and sampling methods between datasets. Further, the significant negative correlation between high water levels during Manoomin’s floating leaf stage and Manoomin density in the 1854TA dataset is consistent with our hypotheses, prior studies[46–50], TEK[6], and historic Ojibwe trade records[18]. High precipitation generally raises water levels, which increases the energy required for Manoomin to reach the surface and photosynthesize[51] and can drown emerging Manoomin stalks[41,52]. Other studies indicate an additional ecological explanation: high water levels decrease seed production[46] by delaying phenology[18,51,53] and therefore, over time, favor perennial species over annually reproducing Manoomin[51]. Together, these results suggest that high precipitation during the floating-leaf stage has caused declines in Manoomin density by raising water levels.

Precipitation and water depth during the submerged life stage had inconclusive, dataset-dependent effects on end-of-season Manoomin stem density. Differing sampling methods could explain the contrasting relationships modeled from each dataset. Alternatively, because Manoomin plants at this life stage are less susceptible to drowning or uprooting, there

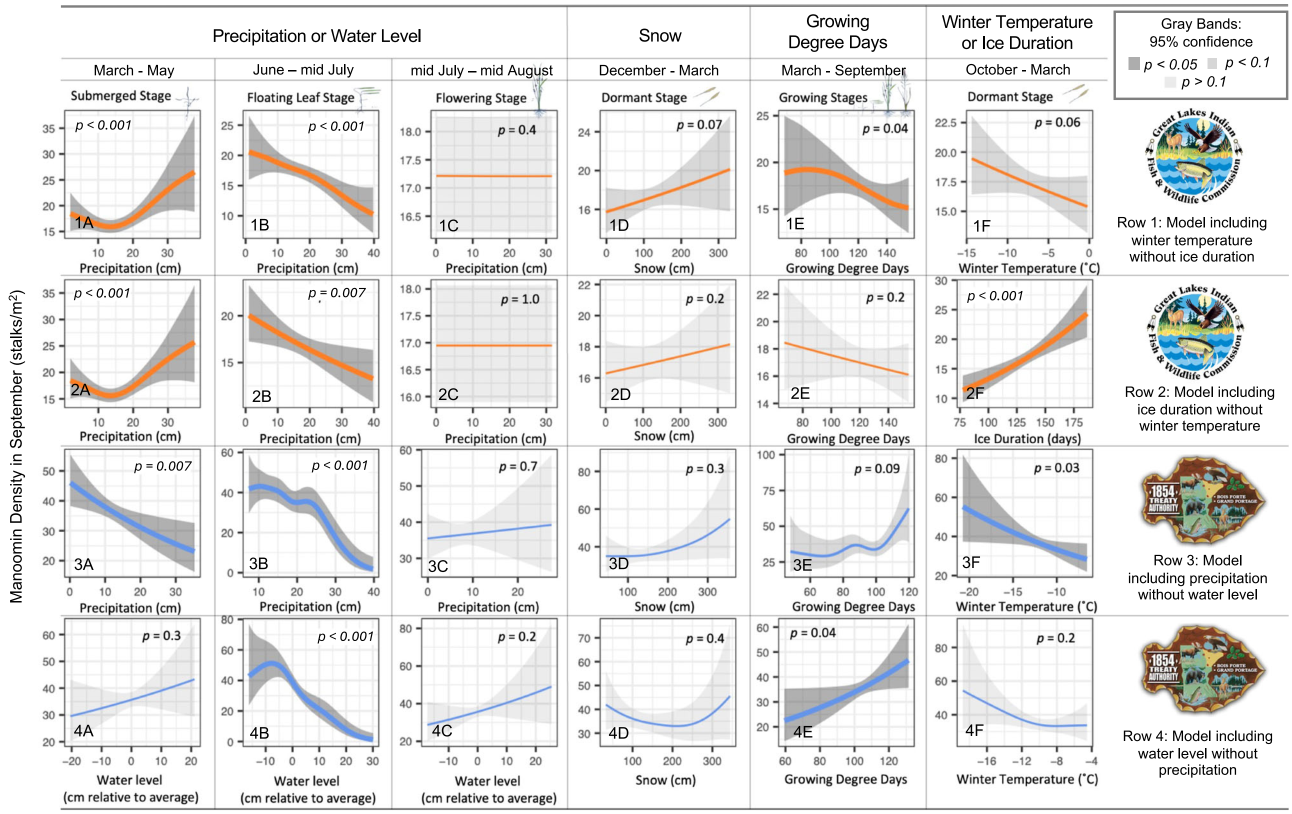

Fig. 4 | Manoomin and climate relationships. Model results (generalized additive model smooth curves) for GLIFWC Manoomin September density (Row 1), GLIFWC Manoomin September density (Row 2), 1854TA Manoomin September density (Row 3), and 1854TA Manoomin September density (Row 4) relationships with seasonal precipitation or water level (Column A, B, and C), snow (Column D), growing degree days (Column E), and winter temperature or ice duration (Column F). Gray bands indicate the 95% confidence intervals. Line and gray band darkness reflects the significance of the modeled relationships, with darker colors and bands indicating statistical significance. Organization logos reproduced with permission (GLIFWC ©2025, 1854TA ©2025).

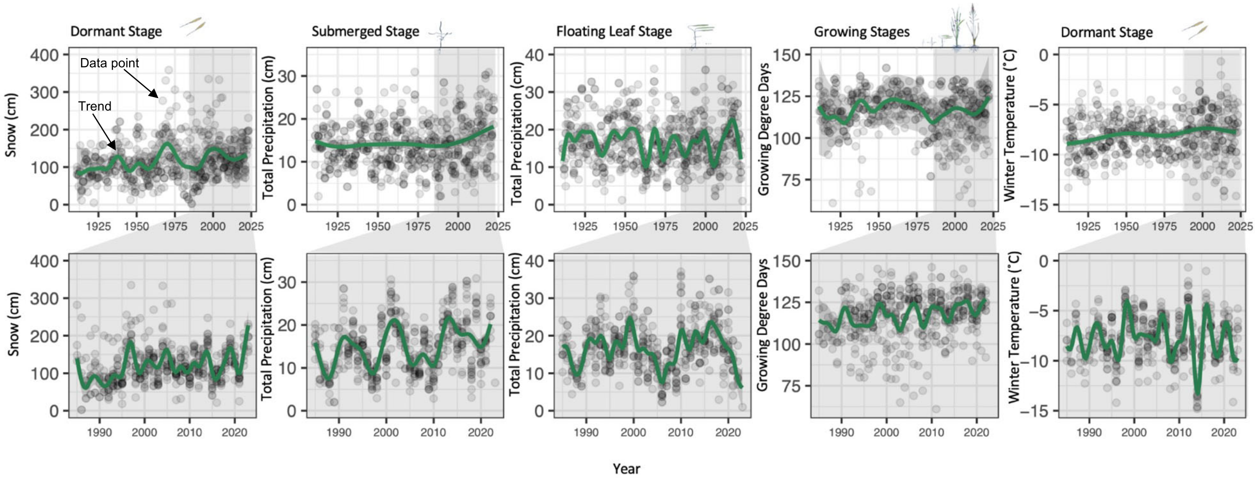

Fig. 5 | Recorded changes in climate variables. Modeled trends (generalized additive model smooth curves) for (top row) climate variables since 1900, and (bottom row) climate variables since 1985. Climate trends are depicted by the graphed line, and climate data points are plotted as circles.

could be subtler, more complex relationships with water levels and precipitation. Higher water levels in the spring submerged stage from spring rains and/or snowmelt may actually benefit Manoomin, as suggested by our GLIFWC model results (Fig. 4, Row 1), because they mix and flush sediments through rice beds, adding nutrients and uncovering seeds, both of which foster initial growth and stabilize long-term abundance[51,54]. However, a correlation with snowfall was not seen for the 1854TA data, possibly because of model structure or because snowfall has an inconsistent, spatially complex, or weak relationship with Manoomin density. Differing sampling methods could be at play here as well. Both precipitation and water levels during the flowering stage were consistently unrelated to Manoomin density, likely because following the floating leaf stage, plants stand above the

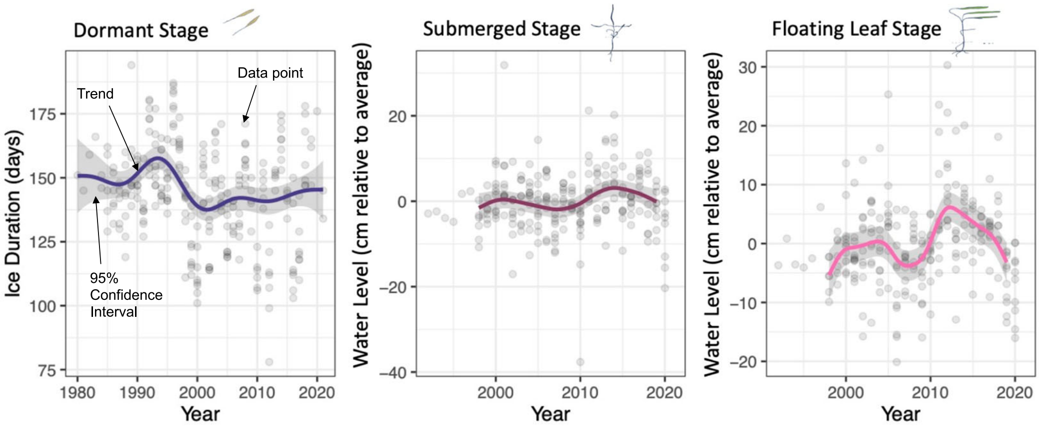

Fig. 6 | Recorded changes in ice duration and water level. Modeled trends (generalized additive model smooth curves) for ice duration, submerged-stage water levels, and floating-leaf stage water levels.

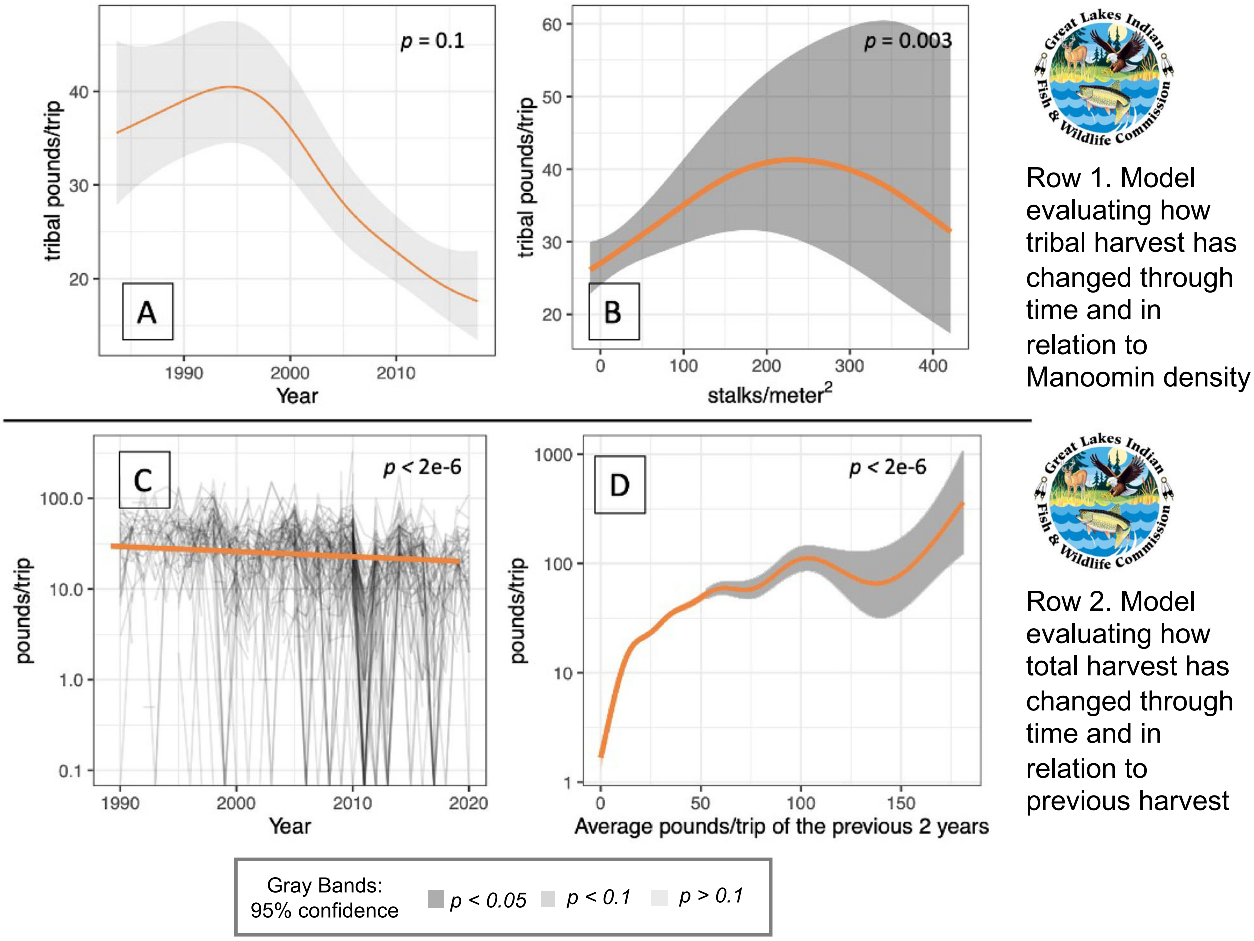

Fig. 7 | Manoomin harvest relationships with density and previous harvest. Model trends (generalized additive model smooth curves) from two models: one including (**A**) tribal harvest through time of study lakes and (**B**) tribal harvest and Manoomin density, and the other including (**C**) harvest through time across all reported lakes and (**D**) previous harvest and current harvest across all lakes. Gray shading around each orange line represents the 95% confidence interval. Organization logo reproduced with permission (GLIFWC ©2025).

water's surface and are physically robust. The lack of precipitation and water level effects for this phenological stage reinforces the TEK understanding that earlier life stages are more sensitive to precipitation and water level.

Colder winter temperatures corresponded with increased Manoomin density at the end of the following growing season for the 1854TA dataset, consistent with observations that Manoomin seeds require seven months at 2.5–5 °C to fully break dormancy and germinate[55] and can withstand temperatures down to and possibly below −10 °C[55,56]. These results suggest that warmer winters likely cause fewer Manoomin seeds to germinate the following year. In addition, colder temperatures may benefit Manoomin relative to perennial plants less tolerant of extreme cold[57]. Although the GLIFWC density data lacked a significant winter-temperature effect, it showed a significant positive correlation with nearby ice duration. Both colder temperatures and longer ice duration generally correspond to thicker lake ice[58]. Thicker lake ice increases the possibility of ice-scouring, which mixes sediment, bringing buried seeds closer to the lakebed surface where they can more readily germinate[18,59]. Ice duration data from nearby lakes likely underestimate ice duration on the Manoomin waters, because these nearby lakes are generally deeper and larger, taking longer to freeze. However, these lakes likely had similar trends in ice durations as the nearby Manoomin waters. Given the limitations of this dataset, further study of lake-ice and Manoomin direct relationships is needed. While our results point to multiple processes through which Manoomin may be vulnerable to milder winters, correlations between growing degree days and Manoomin density were not consistent, suggesting weak or complex relationships and possible impacts of the differing sampling methods.

The quantification of climate, water level, and ice duration relationships with Manoomin is complicated by these variables' changes through time (Fig. 5), which are not accounted for in our models. The relationships between Manoomin density and climate variables, water levels, and ice duration could be spurious correlations; however, multiple lines of evidence across multiple datasets support Manoomin's positive relationship with lower early-summer precipitation, lower early-summer water levels, and colder winters marked by more snow and longer ice duration. It is also possible that time is the variable spuriously correlated, or partially so, resulting in an underestimation of Manoomin's relationship with climate, water level, and ice duration. Additionally, many relationships likely influencing Manoomin density and harvest were excluded from this model, such as lake and watershed morphology, watershed and shoreline land-use, herbivory, diseases, permitting processes, reseeding, restoration, and changing phenology[60].

We did include harvest in our analysis and found that the average harvest from the previous two years had a positive relationship with harvest for the current year. Internal dynamics of the multi-year oscillations of Manoomin density may be driving this trend, causing past average harvests to correlate with present harvests. Alternatively, these data may indicate that human harvest can be beneficial—or at least not harmful—for Manoomin populations, supporting our hypotheses, TEK[6,15], and past studies[41,42]. By removing some of the seeds, harvesting may help thin out beds, possibly reducing transmission of brown spot fungal disease[61]. Manoomin may also benefit from the disturbance caused by harvesters pushing through the rice beds, including agitation of sediments to bring buried seeds to the lakebed surface, and knocking seeds into the water that might have otherwise been eaten by birds. Additionally, harvesters may focus their stewardship efforts on the waterbodies from which they harvest the most, supporting greater future density. Because of this potential relationship, both the aging and decreasing number of harvesters over the last several decades[22] may also contribute to the decline of Manoomin due to loss of harvesting knowledge and practice. Additional research, direct experimentation, and TEK are needed to further understand human harvest relationships with Manoomin abundance.

Trends we detected in climate variables are consistent with those previously reported for the region beyond natural oscillations, including increasing winter temperature, increasing totals and variation in spring and summer precipitation[62], and decreasing ice duration[63,64]. Given the relationships we found between these climate variables and Manoomin density, we conclude that climate change, specifically increases in early-summer precipitation, warmer winter temperatures, and decreases in lake ice duration, has already reduced Manoomin density. Longer climate oscillations, as seen in decadal water level cycles observed in the region[65,66], may also contribute to changes in Manoomin density, as suggested by TEK[67], in addition to the overlying signal of climate change.

Looking to the future, this region is projected to receive increases in spring and early-summer precipitation due to anthropogenic climate change beyond natural oscillations[13,68]. Winter precipitation is expected to increase, but with greater partitioning to rain[13,69], and less and earlier snowmelt[70]. Major Manoomin regions—central Minnesota and the shores of Lake Superior—are projected to experience the sharpest declines in snowfall across the region, reaching about 50% reduction by the middle of the 21st century[69]. The warming trend in mean winter temperatures over the last half of the twentieth century[62] is projected to continue and increase[13,68,69]. Ice duration is projected to further decline by approximately 20 days by 2070[64] and 40 days by the end of the century[64,71]. Given the correlations found between these climate factors and Manoomin density, we expect these projected changes to further threaten Manoomin. Other macrophyte communities, especially in shallow lakes at high latitudes, are facing similar threats with the changing climate[72].

The decline of Manoomin, in part driven by climate change, has and will continue to negatively affect tribal communities. Results show that Wisconsin tribal harvest positively corresponds with Manoomin density (up to 250 stalks/m^2), suggesting declines in Manoomin likely contribute to the lower Wisconsin tribal off-reservation harvest rates since 1992. This trend did not hold for very high Manoomin density (>250 stalks/m^2), likely because of difficulties navigating very dense beds during harvest[73]. Climate change has already and will continue to affect harvest in ways unrelated to stalk density: extremely low water levels in August can prevent canoe access to beds for harvesting[18]; storms can prematurely knock rice off of stalks[19,42]; hot, low-wind conditions during the flowering stage may limit pollination for seed production[18,41] and increase prevalence of brown spot fungal disease[61]; excessively hot conditions during harvest can prevent people from harvesting; and all of this variability can make planning for harvest difficult.

The decline in Manoomin over the last decades has disrupted Ojibwe lifeways, family, and health[74,75]. Manoomin cannot simply be replaced by another plant because it is an "integral glue" connecting political, economic, social, spiritual, intellectual, and physical dimensions of Anishinaabeg society[76]. This loss therefore fails to uphold the inherent rights to self-determination and sovereignty[4] of these Ojibwe Nations, as explicitly promised by treaties with the United States[6,77,78] and more broadly recognized by the UN Declaration of the Rights of Indigenous People[3]. Ojibwe Nations continually address this loss through stewardship, research, partnership, and legal action[34,76,79]. Indigenous Peoples from across the world are also experiencing loss of traditional foods and their connected culture and knowledge systems, all driven in part by climate change[80–82]. These are the very people who lead in climate stewardship through mitigation, sequestration, and storage of carbon[83–85] over one quarter of the world's land surface[86]. The loss of Manoomin thus contributes to the erosion of humanity's collective biocultural diversity essential to producing the transformative knowledge for climate solutions[1,80,84,86–90].

In the face of this threat, people can care for Manoomin by limiting additional stressors (e.g., pollution, pesticides, artificially high water levels from anthropogenic dams, disturbance from motorboats, vegetation removal from lake-front properties, high rates of herbivory, increased sedimentation[6]), as well as respectfully partnering with Ojibwe Nations on restoration, research, harvest, and policy change. Additional strategies supported by this research include lowering water levels during the floating-leaf stage to support growth, lowering water levels during the winter to induce deeper freezes, mixing and/or flushing sediments in the early spring to release nutrients and seeds, and cutting back perennial vegetation that out-competes Manoomin.

Methods

Collaborative process

This research was conducted within the Kawe Gidaa-naanaagadawendaamin Manoomin Research Collaborative, a tribal-university partnership with formalized agreements between four Ojibwe Nations (Fond du Lac Band of Lake Superior Chippewa, the St Croix Indians of Wisconsin, the Mille Lacs Band of Ojibwe, and the Lac du Flambeau Band of Lake Superior Chippewa), two inter-tribal organizations (the Great Lakes Indian Fish and Wildlife Commission and the 1854 Treaty Authority), and a group of interdisciplinary researchers at the University of Minnesota-Twin

Cities[34]. Through this partnership, long-term observations and relational understandings within TEK directed the research questions and hypotheses, the choices of methods, the model development, and the interpretation of results.

From the first three years of collaboration, assessing the impact of climate change on Manoomin abundance was determined to be a collective priority across the tribal partners, especially given the high vulnerability of Manoomin to climate change identified by tribal climate adaptation plans[8–10]. The specific hypotheses for climate change impacts on regional Manoomin abundance were developed from TEK shared through tribal documentation[6,8], monthly project meetings, semi-annual project conferences, knowledge-exchange workshops, and time together paddling through rice beds, harvesting, visiting, in ceremony, and feasting. In addition, we hosted 18 virtual meetings to share and discuss water level, water chemistry, and vegetation data from specific Manoomin waters across the region over the winters of 2021 and 2022. These meetings included 19 tribal resource managers from 6 (inter-)tribal organizations across the region, 2 state resource managers, and 18 university researchers, students, and staff. In the summer of 2022, 35 knowledge-holders representing tribal and state agencies, tribal and non-tribal harvesters, academic institutions, and non-governmental organizations gathered in a workshop[91] and shared the most pressing climate change impacts on Manoomin in their waterbody of concern (Supplementary Fig. 1). All of this knowledge, mediated by data-availability constraints, was iteratively refined into testable hypotheses for this study. Additionally, the relational dynamics emphasized within TEK informed the choice of statistical methods, necessitating tools to assess periodicity and non-linear trends and account for unique relationships within each waterbody. Following the initial modeling process, results were discussed with TEK knowledge-holders to inform model refinement and interpretations: variable calculations were adjusted based on additional local observations, further models were created to look at the relationships in new ways such as past harvest relationships with present harvest, and insights and limitations of the results were revealed.

Ethics and inclusion statement

This project was conducted under formalized agreements, such as memorandums of understanding, where roles and research protocols were established, as determined and directed by the partnering tribal organizations and governments[34]. From conception through publication, this research has included tribal members and tribal government/organization staff to ensure local relevance and reciprocity between university researchers and tribal nations. This includes care taken to strengthen tribal nation and organization capacity through funding tribal partners directly on co-written research grants, as well as sharing access to university resources. Additionally, we included necessary protections and benefit-sharing measures regarding traditional knowledge shared within this project, as directed by the partnering tribal governments and organizations. This research would not have been restricted or prohibited within the setting of university researchers, and in fact environmental protection and biorisk-related regulations in this research setting were stronger than in the setting of university researchers. We followed tribal organization and government guidance to avoid any personal risk to research partners. Lastly, we have carefully taken local and regional research relevant to our study into account within our citations.

Datasets: Manoomin density

Data were obtained from the 1854 Treaty Authority (1854TA) and the Great Lakes Indian Fish and Wildlife Commission (GLIFWC). Each organization has been monitoring Manoomin abundance at the end of the growing season across their respective geographic regions for several decades. The 1854TA monitored Manoomin density and biomass on 9 lakes from 1998 to 2020 by averaging Manoomin stalks and plant height in 20–25 0.5-m^2 plots in each lake[24,92]. Their sampling method changed in 2006 when they transitioned from randomized plot locations within a rice bed to a uniform, gridded set of plots[24]. We assumed this transition from biased to unbiased sampling would influence the data, and therefore included a random-effects term to account for this change by allowing for different slopes and intercepts for each sampling method. This additional random-effects term may be redundant, possibly resulting in more conservative modeled relationships; however, we considered it necessary in order to account for the abrupt discontinuity in methods within the dataset.

GLIFWC has been regularly monitoring Manoomin on 40 waters from 1985 to 2019 through a combination of aerial surveys and on-the-water density measurements[23]. Aerial photos were taken with aircraft-based, hand-held cameras at oblique angles. Boundaries of Manoomin stands in each photo were plotted by hand onto waterbody maps to estimate the total acreage of Manoomin[45]. Given the hand-adjusted oblique angle and difficulty of delineating precise stand extent from an aerial photo, these acreage measurements should be considered estimates with significant error. Manoomin density measurements were made by counting stalks in 20 randomly selected 0.5-m^2 plots within a Manoomin bed on each lake. These values were binned into five categories: (1) 0–20, (2) 20–40, (3) 40–60, (4) 60–80, and (5) 80+ average stems per plot. For this analysis, the median number of stalks per plot was used for each bin (bin 1 = 10 stems/plot, bin 2 = 30 stems/plot, bin 3 = 50 stems/plot, bin 4 = 70 stems/plot, and bin 5 = 90 stems/plot). These binned data reduce variability and do not accurately capture densities above 80 stems per plot. Each stalk density was then multiplied by the Manoomin acreage and divided by the entire waterbody area to estimate an average density.

Although the overall sampling method used by GLIFWC contains more error at the site level than the sampling method used by the 1854TA, the lower-effort and simplicity of the method enabled GLIFWC to maintain a consistent survey of Manoomin abundance of 40 lakes for 34 years, providing a long-term dataset for which trends can be analyzed at a regional and multi-decadal scale with fair confidence. And given the smaller sample size, the 1854TA sampling method likely has greater error at the regional scale. While some error exists within both observational datasets, this error was minimized through robust sampling designs. Jointly analyzing these datasets with complementary geographic coverage and methodological strengths and weaknesses creates opportunities for more robust inferences.

Equations relating Manoomin density and plant height to biomass have been developed[92], but were not used because they would introduce additional assumptions and exclude GLIFWC data that lacked plant height. In total, we had 1507 unique data points across 49 waters across the two datasets to include in our analysis.

Dataset: Manoomin harvest

GLIFWC surveyed state (non-tribal) and tribal harvesters annually in Wisconsin from 1992 to 2019[23]. Harvesters were identified by registrations for rice harvesting permits, which are required for all non-tribal harvesters and for tribal harvesters ages 17–64 harvesting off-reservation. All harvesters who had reported a harvest the previous year and a randomly selected half of those who were registered but did not report a harvest the previous year were contacted via phone or mail and surveyed regarding their number of trips, pounds harvested, and harvesting locations off-reservation for that year. The decline in harvest totals may be due to a decline in the survey response rate reported by GLIFWC staff. Due to this phenomenon, we used pounds per trip harvested as the metric of analysis to quantify the amount of harvest per ‘unit effort’[28] given that the declining response rate made it impossible to accurately determine total harvest. In total, we had 2514 unique harvesting data points included for analysis.

Dataset: climate

Daily precipitation, snow accumulation, and maximum and minimum daily air temperature data for 21 different weather stations in the National Weather Service Cooperative Observer Program[39] were obtained from the Midwest Regional Climate Center data portal. The stations were chosen based on closest proximity to each of the Manoomin waters and availability of near-continuous records (>80%) over the study period. These climate variables were aggregated into total precipitation within three life stages of

Manoomin (submerged [Julian day 92–150], floating [Julian day 151–199], flowering/emergent [Julian day 200–229]), number of days in the growing season (Julian day 92–229) with minimum temperature above 4 °C (growing degree days), average preceding winter temperature, and total snow accumulation in the preceding winter (Table 1). Manoomin life stage phenology has likely been changing with climate, which was not accounted for in this analysis. However, all data were aggregated over approximate life stage intervals, and so we assume that small changes in start and end dates for each life stage would have only minor impacts on aggregated totals or averages.

Dataset: ice cover

Because ice-on and ice-off dates were not recorded for the Manoomin waters themselves, ice-on and ice-off data for the closest lake with data extending back to 1985 (with up to a few missing years) were obtained from the National Snow and Ice Data Center (Supplementary Table 1). While nearby lakes likely differed in ice duration due to morphological differences, previous studies have shown location and weather have a greater impact than morphology on ice phenology[93], making nearby lakes a reasonable proxy. Ice duration was calculated by counting the days between ice-on and ice-off records. Ice duration was used as a predictor, rather than ice-on or ice-off dates themselves, because it integrates both freeze-up and break-up date changes into a single metric. Lake ice-on and ice-off dates were used from Crystal Lake, Allequash Lake, Shell Lake, Lake Escanaba, and Trout Lake, and were limited to the 1837 and 1842 Ceded Territories monitored by GLIFWC due to limited data in other regions (Supplementary Table 1).

Dataset: water levels

Bi-weekly water levels were recorded by 1854TA for their 9 Manoomin waters of study from 1998 to 2020[24]. Some water level gauges were placed directly in Manoomin beds while others were placed at easy-access points. To account for this discrepancy, relative water levels were calculated and used for this analysis (deviations from time-averaged values over the entire study period for each growing stage for each lake).

Spectral analysis

Each Manoomin waterbody dataset was individually analyzed to determine the significance and length of Manoomin density cycles, prior to and separate from the modeling of climate and in-lake variables on Manoomin density. To assess the relatively short time series (20–34 data points), we performed the multi-taper method (MTM) on each time series individually to determine significant periodicities[37]. MTM efficiently uses all data and minimizes spectral leakage, making it suitable for the spectral analysis of short datasets. Significance was assessed using an *F*-test, with frequency peaks over 95%, and not exceeding the time series length, considered significant. Frequencies were rounded to the nearest whole number of years for values less than 10 years and rounded to the nearest 10 for values greater than 10 because partial-year periodicities are not likely to occur ecologically, and there is significant error in the estimation of (multi)decadal periodicities given the short dataset. Calculations were performed using the *multitaper* version 1.0-17[94] package in R version 4.3.3[95].

Generalized additive models (GAMs)

GAMs were used to test for Manoomin density, harvest, and climate trends through time, as well as Manoomin-climate relationships. Like generalized linear models, GAMs can assess multiple covariate relationships simultaneously; however, relationships in GAMs are not constrained to be linear. GAMs use smaller basis functions, in this case, cubic splines, added together to make an overall smooth function that can reflect highly non-linear relationships between a variable of interest and multiple predictor variables. The extent of non-linearity is constrained by the maximum number of basis functions, a parameter set within the model (*k*), and a built-in penalty to avoid overfitting. GAMs were chosen because they not only have the ability to represent non-linear, place-specific, and global relationships[38,96–99]—all dynamics present in the Manoomin eco-hydrologic system as emphasized by TEK[6] and the spectral analysis—but GAMs also maintain a higher degree of interpretability compared to other non-linear models[100], essential for addressing the research questions in a collaborative manner.

Multiple GAMs were constructed to evaluate different hypotheses (see Table 1) using the *mgcv* version 1.9-1[101] package in R version 4.3.3[95]. All GAMs were assessed for an appropriate number of basis functions (smoothness) and data distribution, and lack of significant autocorrelation and concurvity (a nonlinear analog of collinearity). Recommended concurvity thresholds (0.8[102]) were exceeded for the site-specific random effects and total snow. These predictors were retained in the models given our ecological hypotheses and to reflect site-specific variability and the nested sampling design (nonindependence of data arising from multiple plots and repeated sampling of each waterbody).

GAMs were first deployed to assess trends of Manoomin density and harvest. These GAMs included one global smooth curve with time to assess the overall density trend across the region, as well as a random-effects term with time for each waterbody to evaluate site-specific trends (local characteristics of individual Manoomin waters) as emphasized within TEK (Supplementary Table 1). The maximum number of basis functions (*k*) within each smooth curve was set relatively high ($k = 20$, twice the default) for each model to account for the possibility of oscillations, as verified by the spectral analysis. If the model failed to converge, *k* was reduced until convergence was achieved. The function *k.check* within the *mgcv* package was then used to verify that *k* was sufficiently large to represent the non-linear relationships within the data[38]. This function revealed that the effective degrees of freedom of each smooth curve were well below the maximum limit set by *k*, and therefore model results reasonably account for the non-linearity in the Manoomin system. Given the difference in sampling methods, the 1854TA density dataset ($n = 202$) and the GLIFWC density dataset ($n = 1305$) were modeled separately, as well as the GLIFWC harvest dataset for tribal members ($n = 1234$) and non-tribal members ($n = 1930$) to distinguish the two populations. The average percent change per year was calculated from the derivatives of the smooth curves[103]. Model results are shown in Fig. 3.

Building from this work, smooth curves were added for each climate variable to the GAMs of Manoomin density to test hypothesized relationships (GLIFWC [$n = 1049$]; 1854TA [$n = 188$]). Specifically, smooth curves were added for precipitation total in each of the submerged, floating leaf, and flowering life stages; snowfall and mean air temperature from the preceding fall and winter (October–March); and growing degree days (days above 4 °C preceding fall harvest). Model results are shown in Fig. 4, rows 1 and 3.

These GAMs were augmented further to explore intermediary variables that relate climate and Manoomin density: water level data were added to the previous 1854TA GAM ($n = 204$), and nearby ice duration datasets were added to the previous GLIFWC GAM ($n = 1025$) based on data availability. Water levels were averaged for each life stage. Precipitation and mean winter temperature were then removed from the 1854TA and GLIFWC GAMs, respectively, because these variables were too similar (exceeding concurvity threshold of 0.8[102]) to the water level and ice duration data. Model results are shown in Fig. 4, rows 2 and 4.

GAMs were additionally employed to evaluate relationships with pounds of Manoomin harvested per trip. One GAM assessed the relationships between GLIFWC survey data of Manoomin pounds per tribal harvester and Manoomin density in the same year (Fig. 7B), regional trend through time (Fig. 7A), and random effects for each waterbody ($n = 273$). The second GAM assessed the pounds per trip through time at sites for both tribal and non-tribal harvesters (Fig. 7C) with the previous two years of harvest (Fig. 7D), and the random effects for each waterbody, including all waterbodies with harvesting data, and not just the ones surveyed for Manoomin density ($n = 1282$).

Lastly, GAMs were used to evaluate climate variable trends through time because they have the capacity to simultaneously capture the non-linear (oscillating), site-specific, and regional trends of multiple time series. The climate variable trends were modeled with GAMs for each of the weather station datasets since 1985 ($n = 444$). Four weather stations had data extending back to the early 1900s ($n = 664$), so an additional set of

GAMs was created to assess longer-term trends in these datasets (Fig. 5). Ice duration ($n = 1035$) and water levels ($n = 188$) were additionally modeled with GAMs (Fig. 6). Each GAM assessed regional trends through time (one single smooth curve for all sites) and site-specific trends (different smooth curves for each waterbody).

Data availability

The Manoomin/Psiŋ (wild rice) density datasets analyzed during the current study are available on the 1854 Treaty Authority Website (https://www.1854treatyauthority.org/reports/reports.html), the GLIFWC Website (https://glifwc.org/reports/), and in the EDI Data Portal repository, https://doi.org/10.6073/pasta/69863ce9768c64da5b1392b2c2660661.

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Author contributions

Madeline Nyblade led the collaborative quantitative analysis and the writing for this paper. Daniel J. Larkin advised and reviewed the quantitative analysis, reviewed and edited this paper, and contributed to leadership within the tribal-university collaborative. Darren Vogt led field data collection of Manoomin density in the 9 lakes studied by the 1854 Treaty Authority. He also contributed knowledge that informed the quantitative analysis, reviewed and edited the paper, and participated in the tribal-university collaborative. Rob Croll contributed knowledge that informed the quantitative analysis, reviewed and edited the paper, and participated in the tribal-university collaborative. G.-H. Crystal Ng reviewed the quantitative analysis, reviewed and edited this paper, and contributed to leadership within the tribal-university collaborative. William Joe Graveen contributed knowledge that informed the quantitative analysis, reviewed and edited the paper, and participated in the tribal-university collaborative. Kristen Hansen contributed knowledge that informed the quantitative analysis, reviewed and edited the paper, and participated in the tribal-university collaborative. Hannah Panci contributed knowledge that informed the quantitative analysis, reviewed and edited the paper, and participated in the tribal-university collaborative. Brandon Byrne led more recent field data collection of Manoomin density on the waters studied by the Great Lakes Indian Fish and Wildlife Commission. He also contributed knowledge that informed the quantitative analysis, reviewed and edited the paper, and participated in the tribal-university collaborative. Bazile Minogiizhigaabo Panek contributed knowledge that informed the quantitative analysis, reviewed and edited the paper, and participated in the tribal-university collaborative.

Competing interests

The authors declare no competing interests.

Additional information

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