Storm life cycle modulates extreme hydroclimate impact risk: a Great Lakes Region case study

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Key Points:

- Storm life-cycle state at Great Lakes entry organizes the risk of extreme extra-tropical cyclone impacts
- Extreme evaporation risk is systematically higher in Fall (SON) for storms that enter the region later in their life cycle
- Extreme precipitation risk is also elevated for later-entry storms, with the clearest signals emerging in Summer in the upper Great Lakes

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Abstract

Extratropical cyclones (ETCs) drive hydroclimate variability in the Great Lakes, yet their impacts vary widely between events. Here, we classify ETCs into two storm types using an unsupervised clustering approach based on storm properties and evolution. The resulting classes differ systematically in life cycle stage at Great Lakes entry. Using bootstrap-estimated risk ratios and risk differences, we show that storms entering later in their life cycle have a higher risk of extreme evaporation during autumn (SON) across all five lakes. In contrast, precipitation responses are weaker, more spatially heterogeneous, and most evident in summer over the upper lakes. Differences in storm genesis location do not fully explain these patterns, indicating that storm evolution at interaction provides a more informative organizing axis. These results demonstrate that storm life cycle stage governs the risk of extreme lake–atmosphere fluxes and offer a transferable framework for storm-centric impact assessment.

Plain Language Summary

Large storms called extratropical cyclones are a major driver of extreme weather in the Great Lakes, but their impacts vary widely from storm to storm. In this study, we show that storms can be grouped into two main types based on when they reach the Great Lakes during their life cycle. Storms that arrive later in their development are more likely to produce extreme evaporation during the fall, increasing the likelihood of these events across all five lakes.

Differences in extreme precipitation are weaker and less consistent. The clearest rainfall signals appear during summer in the upper Great Lakes, while other regions show little systematic difference between storm types. We also find that the two storm types tend to form in different locations, with later-developing storms forming farther west.

Overall, our results show that how a storm evolves plays an important role in shaping extreme weather risks in the Great Lakes. Because large lakes interact with storms in similar ways around the world, this approach may also help assess extreme weather risks in other regions.

1 Introduction

Large lake regions are tightly coupled lake–atmosphere systems that are sensitive to hydroclimate variability, particularly precipitation and evaporation (Anyah & Semazzi, 2009; Notaro et al., 2013; Raible et al., 2021; Kunkel et al., 2022). Evaporation from large lakes can strongly influence downstream weather, including lake-effect precipitation. This process is pronounced in the North American Great Lakes, where relatively warm lake temperatures enhance moisture availability and modify near-surface atmospheric conditions, with impacts on local and regional weather (Scott & Huff, 1996; Angel & Isard, 1997; Vavrus et al., 2013; J. Wang et al., 2022). These interactions can extend beyond the lakes themselves, influencing regional climate variability and extremes across broad spatial scales (Hawcroft et al., 2012; Xiao et al., 2018; J. Hanrahan et al., 2021; Clare et al., 2023).

The Laurentian Great Lakes are a large, interconnected freshwater system that provides a well-observed testbed for studying hydroclimate variability. Lake levels are sensitive to imbalances among precipitation, runoff, and evaporation (Quinn, 2009; J. L. Hanrahan et al., 2010; Gronewold et al., 2016). Despite a relatively dense observational network, evaporation remains poorly constrained and is often inferred from models or reanalysis products. Extreme evaporation events play an important role by enhancing heat and moisture exchange, driving lake-effect precipitation, and contributing to lake level variability, with direct implications for infrastructure, navigation, water supply, and flood risk (Neff & Nicholas, 2005).

Extratropical cyclones (ETCs) are a dominant driver of hydroclimate extremes in the Great Lakes Region (GLR), including changes in precipitation intensity and frequency (Angel & Isard, 1998; Hawcroft et al., 2012; Raible et al., 2021). These synoptic-scale systems account for a large fraction of extreme precipitation events and are central to assessments of hydroclimate risk and water resource management (Pfahl & Wernli, 2012; Kunkel et al., 2022). Changes in storm tracks and large-scale circulation are expected to modify ETC behavior, with implications for precipitation extremes (Angel & Kunkel, 2010; Hawcroft et al., 2012; Raible et al., 2021). Observations indicate shifts in the spatial distribution of ETC activity, including northward shifts affecting the Great Lakes (Hutson et al., 2024), with clear seasonal structure (Chang et al., 2016; Gertler & O'Gorman, 2019; Fritzen et al., 2021).

ETCs evolve through distinct life cycle stages, with each stage associated with different dynamical and thermodynamic characteristics (Booth et al., 2018). The mature phase is typically associated with strong winds, enhanced moisture transport, and well-developed frontal structure, all of which influence precipitation and air–lake fluxes. Interaction with large lakes during this stage can amplify local and downstream impacts (Anyah & Semazzi, 2009). As a result, storm evolution plays a central role in shaping hydroclimate impacts.

Despite this, the relationship between storm evolution and impacts on large lake systems remains poorly resolved. Many studies relate ETC frequency or intensity to precipitation and evaporation without accounting for life cycle stage, implicitly treating storms as temporally uniform (Agustí-Panareda et al., 2005; Eichler & Higgins, 2006; Fritzen et al., 2021; Hutson et al., 2024). Conversely, studies of storm evolution rarely link storm structure directly to lake-specific impacts. Classification approaches based on storm origin or track provide useful context but do not fully capture variability in storm impacts on regional hydroclimate (Riemer & Jones, 2010). As a result, the relationship between storm life-cycle state and lake impacts remains less well quantified.

In this study, we take a storm-centric, Lagrangian approach to linking ETC evolution with extreme lake-surface hydroclimate events, specifically precipitation and evaporation extremes, using the Great Lakes as a testbed. We analyze a dataset in which each

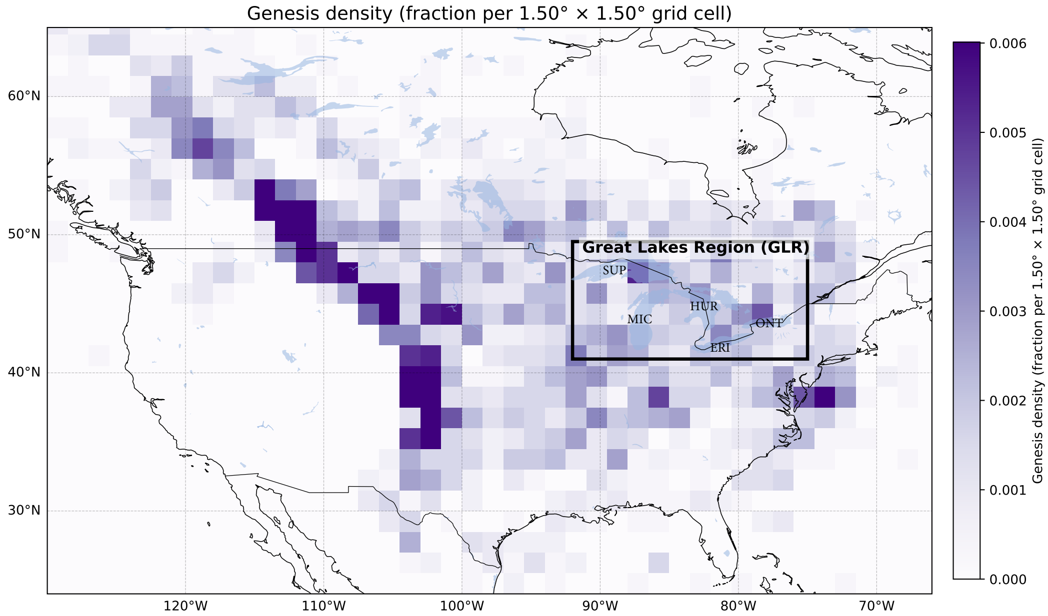

Figure 1. Heatmap of ETC genesis from the CFSR dataset (1979–2019), expressed as the fraction of storms per 1.5° grid cell. The Great Lakes Region (GLR) is outlined in black, and the individual Great Lakes are labeled.

ETC is treated as an individual event and paired with the corresponding lake-specific precipitation and evaporation anomalies that occurred during its passage through the GLR. This per-storm framework allows us to evaluate how differences in storm evolution relate to differences in extreme hydroclimate responses. While ETCs are contributors to Great Lakes hydroclimate variability, the present analysis does not estimate the fraction of all extreme lake-surface events attributable to ETCs; instead, we examine how ETC properties modulate the likelihood of extremes within the population of ETC events.

Using unsupervised classification, we allow storm evolution to emerge as an organizing feature without prescribing categories. We focus on simple proxies for storm maturity and residence time within the Great Lakes Region (GLR), providing a coarse representation of storm evolution during lake interaction. While simplified, these metrics enable us to assess whether storm evolution organizes the risk of extreme hydroclimate impacts. The framework is transferable to other large lakes, inland seas, and regions influenced by ETC-driven extremes.

2 The extratropical cyclone impacts dataset

To examine linkages between ETC properties and impacts on evaporation and precipitation in the GLR, we derive per-storm data from the NCEP Climate Forecast System Reanalysis (CFSR) (Saha et al., 2010), which has a horizontal resolution of $0.5° \times 0.5°$ and assimilates a wide range of observations.

ETCs are identified and tracked over 1979–2019 using the Crawford and Serreze (CS) detection algorithm applied to mean sea level pressure (MSLP) (Crawford & Serreze, 2016; Crawford et al., 2021). We retain storms that enter the GLR (38–52°N, 72–96°W; Figure 1). To isolate synoptic-scale systems, we require a minimum radial pressure difference of 7.5 hPa and a radius of at least 250 km at one or more timesteps. Storm radius is defined using the outermost closed isobar, with the maximum taken over the storm's residency in the GLR. The resulting dataset includes 3317 ETCs sampled at six-hourly resolution.

We extract precipitation (P) and evaporation (E, derived from latent heat flux and surface temperature) for each storm. Impacts are computed over a window from 24 hours prior to GLR entry to 48 hours after exit, centered on minimum MSLP. We analyze storm-integrated P and E, with evaporation expressed as an anomaly relative to a 1981–2000 climatology. Lake-wide averages are computed using latitude-weighted means.

We characterize storm evolution using per-storm metrics derived from the CFSR-based ETC inventory. Storm structure is represented by minimum central pressure, maximum pressure gradient, maximum radius, and maximum propagation speed, each evaluated over the storm's residency in the GLR. Interaction with the lake system is quantified as the fraction of each storm's lifetime spent within the GLR.

To represent storm life cycle stage at lake interaction, we define a maturity proxy as the fraction of storm lifetime elapsed at first GLR entry:

$$M = \frac{t_{\text{entry}} - t_{\text{genesis}}}{t_{\text{lysis}} - t_{\text{genesis}}} \tag{1}$$

where t_{genesis}, t_{entry}, and t_{lysis} denote the times of cyclogenesis, first GLR entry, and dissipation. Larger values indicate storms that enter later in their evolution.

This metric does not fully describe storm structure or evolution but provides a consistent measure across events, allowing us to test whether storm maturity and GLR residence time organize differences in extreme precipitation and evaporation risk.

3 Methods

In this section, we describe the unsupervised classification framework used to identify distinct classes of ETCs (3.1), along with the definition of extremes and the probabilistic metrics used to assess relative impact risk (3.2).

3.1 Unsupervised classification as a hypothesis generator

We use unsupervised classification to identify covariance structure between storm properties and lake interactions without imposing *a priori* assumptions. Such approaches are well suited to complex Earth system problems, where structure emerges from combinations of variables rather than single thresholds (Sonnewald et al., 2019, 2020, 2023; Maze et al., 2017; Jones & Ito, 2019; Jones et al., 2019, 2023).

We apply Gaussian mixture modeling (GMM), which represents the joint distribution of storm characteristics as a weighted sum of multiple multivariate Gaussian distributions, each representing a different cluster of storms, and provides probabilistic assignment of storms to classes. The feature space is constructed from per-storm properties and interaction metrics summarizing storm intensity, structure, and evolution, including minimum central pressure, maximum pressure gradient, maximum storm radius, maximum propagation speed, fraction of storm lifetime spent within the GLR, and the relative timing of GLR entry within the storm lifecycle (Section 2). Together, these variables provide a compact and physically interpretable representation for classification.

We evaluate GMMs with varying numbers of classes using model selection metrics that balance goodness of fit and parsimony (Supporting Information, Figure S1). Solutions with 2–4 classes are defensible, but the final choice is guided by a scientific objective (Rosso et al., 2020; Jones et al., 2023). We therefore select a two-class solution based on interpretability, class coherence and seperability, and robustness across sensitivity tests (Supporting Information, Figures S2-S4). Similar parsimonious approaches have been used to distinguish large-scale ocean structure in the North Atlantic (Desbruyères et al., 2021).

Our emphasis on a simple classification reflects the use of unsupervised modeling as a hypothesis generator rather than a definitive taxonomy (Kaiser et al., 2022). Higher-order structure may be present, but the two-class framework provides a basis for assessing differences in extreme precipitation and evaporation risk without overfitting or obscuring physical interpretation.

3.2 Definition of extremes and risk metrics

We define extreme precipitation and evaporation events using percentile-based thresholds computed separately for each lake and season. For precipitation, we define extremes as events exceeding the 95th percentile of storm-associated lake-mean overlake precipitation calculated over masks for each lake from the entire 1979–2019 period in the CSFR. For evaporation, we define extremes using the lower 5th percentile of evaporation anomalies, corresponding to the most negative (i.e. strongest upward) lake–atmosphere moisture flux events. This approach accounts for strong seasonal variability while avoiding assumptions about the underlying distribution of impacts. We quantify differences in extreme-event likelihood between storm classes using probabilistic risk metrics, including the risk ratio (RR) and risk difference (RD), which compare the probability of exceeding a given threshold conditional on storm class membership (Class 1 and Class 2):

$$\mathrm{RR} = \frac{P(\mathrm{Extreme} \mid \mathrm{Class\ 2})}{P(\mathrm{Extreme} \mid \mathrm{Class\ 1})} \tag{2}$$

$$\mathrm{RD} = P(\mathrm{Extreme} \mid \mathrm{Class\ 2}) - P(\mathrm{Extreme} \mid \mathrm{Class\ 1}) \tag{3}$$

These metrics quantify probabilistic differences in impact risk conditional on storm class membership, as opposed to deterministic attribution. To assess uncertainty in these estimates, we use nonparametric bootstrap resampling. Confidence intervals are computed by repeatedly resampling storms with replacement and recalculating the risk metrics across bootstrap realizations. This framework emphasizes probabilistic interpretation and robustness rather than deterministic attribution, and supports comparisons across lakes, seasons, and storm classes.

4 Results from a two-class model

Gaussian mixture modeling identifies two distinct classes of ETCs affecting the GLR (Figure 2). The strongest separation between the two classes occurs in metrics describing storm evolution and interaction timing with the Great Lakes. Type 1 storms enter the GLR earlier in their lifecycle, characterized by lower maturity proxy values and a smaller fraction of their total lifetime spent within the GLR (Figure 2(a,b)). In contrast, Type 2 storms typically interact with the GLR later in their evolution and remain within the region for a larger fraction of their lifetime. These differences indicate that the two ETC classes primarily separate storms based on the timing of Great Lakes interaction relative to storm development.

The two classes also exhibit systematic differences in other storm properties, including radius, minimum central pressure, maximum propagation speed, and maximum pressure-gradient metric (Figure 2(c-f)). However, these intensity and structural characteristics show substantially less separation than the lifecycle and interaction metrics. Together, these results indicate that the two ETC classes primarily reflect differences in the timing of Great Lakes interaction within the storm lifecycle, rather than differences in peak intensity or size.

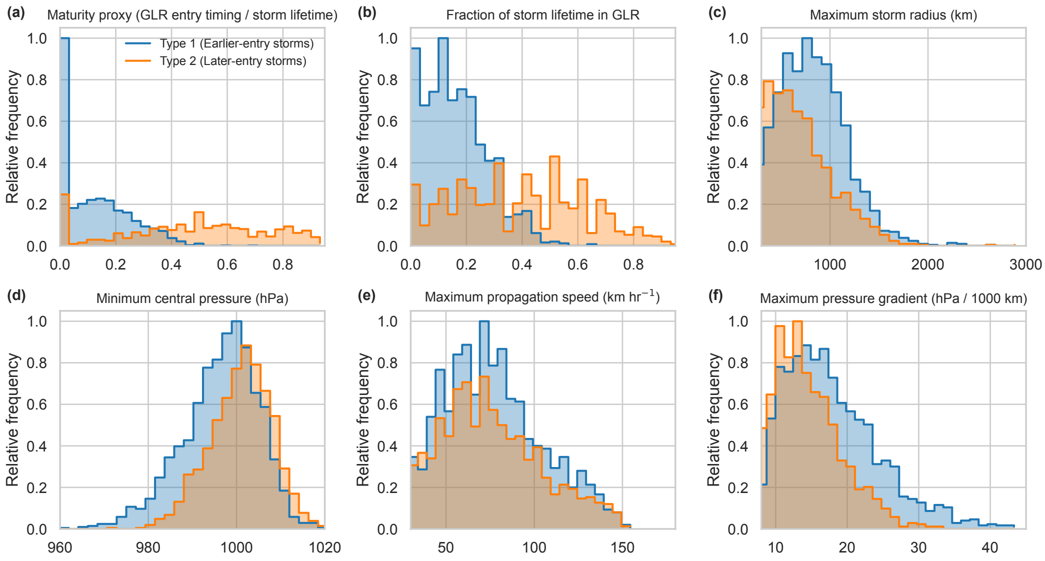

Figure 2. Histograms of storm properties for the two classes: (a) maturity at GLR entry, (b) fraction of storm lifetime in the GLR, and lifetime maxima of (c) storm radius, (d) central pressure (minimum), (e) wind speed, and (f) pressure gradient.

To further evaluate the relative importance of individual storm characteristics in defining the two classes, we trained supervised classifiers to reproduce the GMM assignments and assessed feature contributions using multiple approaches, including random forest feature importance and permutation importance (Supporting Information, Figure S5). Both approaches identified the maturity proxy and fraction of storm lifetime spent within the GLR as the dominant predictors of class membership, while radius, intensity, and propagation characteristics contributed comparatively little. These results suggest that the classification is primarily organized by lifecycle timing and GLR interaction timing rather than by differences in storm intensity or structure.

For evaporation anomalies, a strong and spatially coherent risk signal emerges in autumn (SON). Across all five lakes, Type 1 (early–life cycle) storms exhibit a systematically lower likelihood of producing extreme evaporation events than Type 2 (late–life cycle) storms, with risk ratios consistently below unity and positive risk differences across the basin (Fig. 3). Median risk differences range from approximately 4% in Lake Superior to roughly 7% in Lake Ontario, with uncertainty intervals remaining above zero for all lakes. Importantly, these results reflect evaporation anomalies, with the seasonal cycle removed, indicating that the signal does not arise from the climatological dominance of fall evaporation but instead reflects differences in storm characteristics.

In contrast, evaporation extremes in winter (DJF), spring (MAM), and summer (JJA) do not exhibit a robust or spatially consistent dependence on storm class. In these seasons, risk ratios generally span unity and risk differences are indistinguishable from zero within uncertainty bounds, with only weak and isolated deviations (e.g. in Lake Erie) that lack basin-wide coherence (Supporting Information, Figure S6).

Precipitation extremes also show a seasonally constrained response, albeit with differences between the upper and lower lakes. During summer (JJA), earlier–entry storms are associated with a lower probability of extreme precipitation in the upper Great Lakes (Lakes Superior, Michigan, and Huron), where risk ratios fall below unity and median risk differences remain positive. In contrast, precipitation extremes in Lakes Erie and

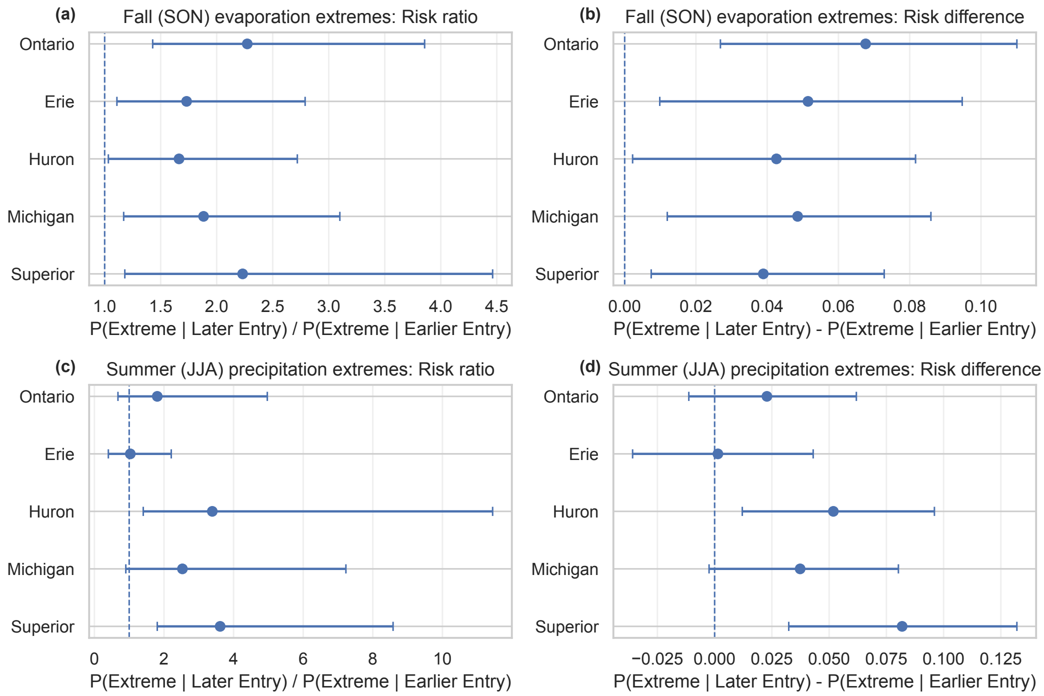

Figure 3. Risk ratios (a, c) and risk differences (b, d) between storm classes for seasons with the strongest signals: evaporation extremes (a, b) in autumn (SON) and precipitation extremes (c, d) in summer (JJA). Points show bootstrap medians; error bars indicate the range of bootstrap estimates. Values greater than 1 (RR) or 0 (RD) indicate elevated risk for later-entry storms.

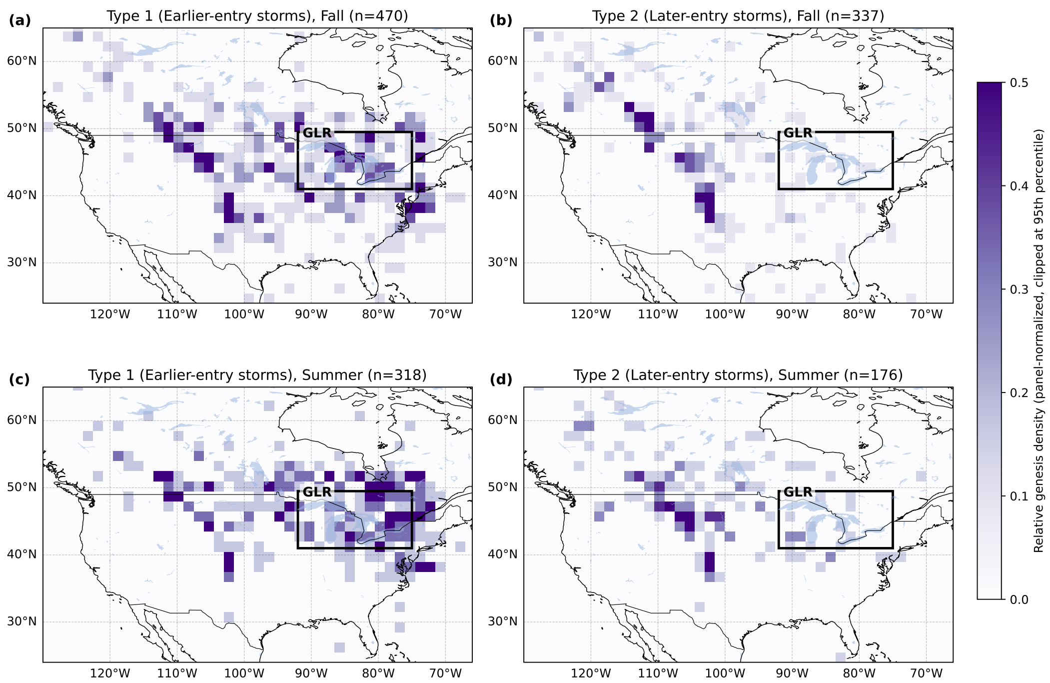

Figure 4. Storm genesis density by class and season. Panels show relative cyclone genesis frequency (panel-normalized and clipped at the 95th percentile) for (a) Type 1 (earlier-entry), autumn (SON), (b) Type 2 (later-entry), autumn (SON), (c) Type 1 (earlier-entry), summer (JJA), and (d) Type 2 (later-entry), summer (JJA).

Ontario during summer show no statistically distinguishable class dependence. Outside of summer, precipitation extremes do not display systematic differences between storm classes across the basin.

Taken together, these results indicate that storm life cycle differences most strongly modulate extreme impacts through autumn evaporation across all lakes and summer precipitation in the upper Great Lakes. Other seasons show comparatively weak or absent class dependence, underscoring the importance of both seasonality and storm evolution in shaping ETC-driven hydroclimate extremes.

The two storm classes also exhibit systematic differences in their geographic origins, as reflected in the spatial distribution of cyclogenesis locations (Figure 4). Late–life cycle storms tend to originate farther west. In contrast, early–life cycle storms display a more diffuse set of origins, spanning a broader range of longitudes and latitudes. This west–east contrast produces a visible imprint of orographic forcing in both classes, with the Rocky Mountains acting as a dominant organizing feature in storm lee cyclogenesis.

However, these origin differences do not by themselves explain the observed differences in extreme precipitation and evaporation risk. Storms from similar genesis regions can produce markedly different impacts upon entering the GLR, depending on their stage of evolution and the duration of their interaction with the lakes. In this sense, storm origin provides useful contextual information but offers limited explanatory power for impact variability when considered in isolation. Instead, storm maturity at Great Lakes entry and residence time within the region provide a more direct and physically relevant framework for interpreting differences in extreme lake–atmosphere fluxes.

5 Discussion

This study examined how ETC life cycle evolution relates to extreme precipitation and evaporation in the Great Lakes. Using a storm-centric framework, we identified two classes that differ in maturity at Great Lakes entry and in the fraction of storm lifetime spent within the basin. These differences correspond to consistent probabilistic shifts in extreme impact risk, particularly for evaporation and, more selectively, precipitation. The results describe shifts in risk rather than deterministic outcomes and suggest that storm evolution provides a useful organizing axis for lake–atmosphere interactions.

Strong autumn evaporation from the Great Lakes is well established and linked to large air–lake temperature contrasts and synoptic forcing associated with ETCs (Lofgren & Zhu, 2000; Laird & Kristovich, 2002; Polderman & Pryor, 2004; Notaro et al., 2013; Hunter et al., 2015; Anderson & Gronewold, 2025). Here we show that these extremes are modulated by storm evolution: storms entering later in their life cycle exhibit higher risk of extreme evaporation across all lakes. This signal persists after removing the seasonal cycle, indicating a storm-dependent modulation of lake–atmosphere fluxes.

Maturity at Great Lakes entry serves as a compact descriptor of storm structure at interaction. Storms entering later in their life cycle may be more likely to exhibit a well-developed cold sector (Neiman et al., 1993; Hart, 2003), broader wind field (Smith et al., 2021; Zick et al., 2022; Hutson et al., 2024), and more spatially coherent circulation (Smith et al., 2021; Vinour et al., 2021; Sheng et al., 2024), all of which can potentially enhance and sustain basin-scale air–lake fluxes. Their greater fraction of lifetime within the GLR is consistent with this interpretation, reflecting both timing of interaction and persistence of favorable conditions. While not a complete dynamical description, this metric organizes the degree to which storms impose sustained forcing on the lake system.

Overlake evaporation extremes may influence broader hydroclimate responses (Woolway et al., 2020; Zhou et al., 2021). Enhanced turbulent fluxes can modify lower-atmospheric moisture availability, potentially influencing precipitation and other coupled lake–atmosphere interactions (B. Wang et al., 2019; Minder et al., 2020; Cao et al., 2022; Ma et al., 2026). While these processes are not resolved here, this highlights the potential for storm evolution to influence hydroclimate responses beyond the surface fluxes analyzed in this study.

To evaluate whether the observed relationships primarily reflect the total duration of storm influence over the GLR, we performed a sensitivity analysis replacing fractional GLR residence time with absolute residence time. This alternative formulation produced less distinct storm classes, lower posterior classification confidence, and weaker seasonal structure in the resulting impact-risk relationships. These results suggest that normalized residence time captures differences in storm evolution that are not apparent from absolute residence time alone.

In contrast to the basin-wide signal in autumn evaporation, precipitation extremes exhibit a more spatially heterogeneous response to storm class. Differences in precipitation risk emerge most clearly during summer and are largely confined to the upper Great Lakes, with weaker or indistinguishable signals in the lower lakes. This pattern likely reflects seasonal shifts in storm tracks: the northward displacement of baroclinic zones during summer reduces the frequency of ETC impacts on Lake Erie and Lake Ontario (Turner et al., 2013; Plante et al., 2015; Hutson et al., 2024, 2026). Precipitation extremes may arise from processes that vary across lakes and events, including moisture availability, frontal structure, and mesoscale lake–atmosphere interactions (Pfahl et al., 2017; Donat et al., 2019; Zhang et al., 2021). Storm maturity may still organize the large-scale dynamical environment, but its influence on precipitation is less direct than for evaporation and is therefore expressed less uniformly. The absence of a basin-wide precipitation signal should not be interpreted as evidence of fundamentally different physical pathways.

The two storm classes exhibit systematic differences in geographic origin, as reflected in their cyclogenesis locations. Late–life cycle storms tend to originate farther west, while early–life cycle storms display a broader and more diffuse genesis distribution. These patterns are consistent with established pathways of lee cyclogenesis and midlatitude storm development, leaving a clear imprint of orographic forcing (Zishka & Smith, 1980; Mahdi et al., 2019).

However, geographic origin does not completely explain differences in extreme lake-surface hydroclimate impacts. Storms with similar genesis locations can interact with the Great Lakes at different stages of their evolution, leading to distinct wind structures, residence times, and air–lake fluxes. The results therefore point to storm maturity at GLR, rather than origin, as a more informative axis for organizing differences in extreme precipitation and evaporation risk. This reframes storm impacts in terms of storm state at interaction rather than birthplace, providing an alternative perspective on lake–atmosphere coupling.

Our storm-centric framing connects to broader efforts to classify ETCs by dynamical and thermodynamical structure. Cyclogenesis spans a high-dimensional continuum of precursor conditions, reflecting variability in upper-level forcing, baroclinicity, and diabatic processes (Graf et al., 2017). Some identified classes, including those associated with strong baroclinicity and upper-level PV anomalies, tend to originate closer to the Great Lakes and are therefore more likely to enter the region earlier in their life cycle. These systems are also associated with strong upward motion and can advect cold, dry continental air over the lakes, favoring enhanced evaporation (Graf et al., 2017). While not diagnosed explicitly here, these connections are consistent with the interpretation that storm evolution and air-mass structure jointly influence evaporation risk.

One limitation is the representation of local-scale processes embedded within ETCs. Features on scales smaller than about 10 km can strongly modulate precipitation, particularly through lake–atmosphere interactions (Cotton et al., 2011; Catto et al., 2019; Kodama et al., 2019). In coarse-resolution reanalyses such as CFSR, these processes are only partially resolved or parameterized. This is especially relevant for mechanisms such as lake-effect snowfall and lake-enhanced precipitation, which can produce spatial heterogeneity in impacts. The precipitation signals attributed to each storm type should therefore be interpreted as large-scale tendencies rather than localized extremes.

Another limitation is the simplicity of the maturity proxy used to characterize storm evolution at Great Lakes entry. This metric collapses a complex, multivariate life cycle into a single scalar quantity. We adopt this simplification to preserve objectivity, scalability, and reproducibility across several thousand events. More detailed, physically grounded definitions of storm maturity that can be applied consistently across long reanalysis records remain an open challenge.

Despite its simplicity, the maturity proxy captures physically meaningful structure in the ETC population and yields coherent, interpretable differences in extreme impact risk. The resulting storm classes align with expected distinctions in storm evolution and lake interaction, revealing systematic relationships between storm state, residence time, and extreme impacts that are not apparent from seasonality or storm origin. We therefore view this proxy as a first-order diagnostic that enables discovery within a storm-centric framework rather than a definitive measure of storm maturity. Future work can refine these diagnostics while retaining the core insight that storm evolution at lake interaction plays a central role in shaping extreme impacts.

The storm-centric framework presented here is transferable to other large lake systems, inland seas, and coastal regions influenced by ETCs. Its core elements, including objective storm tracking, unsupervised classification, and probabilistic risk metrics, are not specific to the Great Lakes and can be applied wherever storm-resolved impact datasets are available. By accounting for storm evolution and residence time, this framework enables more granular assessments of extreme impact risk than approaches based solely on seasonality, storm counts, or geographic origin, without implying deterministic attribution or forecast skill.

The consistent association between storm maturity and extreme evaporation highlights the importance of storm evolution for lake–atmosphere coupling. These enhanced lake–atmosphere exchanges may have implications for broader regional processes, including lake-effect precipitation, although such responses are not evaluated here. While the specific thresholds, proxies, and hydroclimate metrics used here reflect the Great Lakes system, these components can be adapted to other regions while retaining the storm-centric perspective.

Future work can refine the representation of storm evolution while retaining a storm-centric perspective. More detailed maturity diagnostics, including frontal structure, moisture transport pathways, or dynamically defined life cycle markers, could augment or replace the simple proxy used here. Coupling storm-resolved classifications with moisture source diagnostics or process-based air–lake flux models may further clarify the mechanisms linking storm evolution to extreme impacts. While this study does not assess forecast skill, integrating storm-centric classifications into forecasting contexts represents a potential direction for evaluating whether storm evolution can improve probabilistic assessments of extreme lake–atmosphere interactions and their impacts.

This study shows that storm evolution during lake interaction is an important factor shaping extreme hydroclimate variability in large lake regions. By distinguishing ETCs based on life cycle stage and residence time within the GLR, we show that storm evolution provides a physically meaningful axis for organizing differences in extreme precipitation and evaporation risk. Among ETCs affecting the GLR, accounting for storm life-cycle stage helps explain differences in the likelihood of extreme evaporation and precipitation, offering a storm-centric perspective that complements seasonal and climatological analyses without overextending their scope.

Open Research Section

Code and data used in this analysis are archived and publicly available (Jones et al., 2026).

Inclusion in Global Research Statement

This study uses publicly available reanalysis and derived datasets and does not involve fieldwork, local communities, or region-specific research partnerships. As such, no additional inclusion or permitting considerations apply.

Conflict of Interest declaration

The authors declare there are no conflicts of interest for this manuscript.

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