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Data-Driven Analysis and Scenario Modeling of Hurricanes

Rudra Brahmbhatt
Mechanical & Industrial Engineering
University of New Haven
West Haven, CT, USA
rudra15083@gmail.com

Marzieh Soltanolkottabi
Assistant Professor
Mechanical & Industrial Engineering
msoltan@newhaven.edu

Ali Tolooie
BBA Program Director & Assistant Professor
Supply Chain Management
Mercer University
Macon, GA, USA
tolooie_a@mercer.edu

Abstract

Hurricanes create severe disruptions to infrastructure, supply chains, and emergency response systems, particularly in coastal regions. Accurate forecasting of hurricane paths is essential for preparedness and resource allocation, but relying on a single predicted path can create high uncertainty because hurricanes may shift direction before landfall. This study presents a data-driven framework for generating multiple possible hurricane trajectory scenarios using historical hurricane track data covering 173 years, from 1851 to 2023. Historical hurricane paths recorded at six-hour intervals are clustered using K-means based on trajectory similarity. For each cluster, an average path is generated by averaging latitude and longitude coordinates, creating representative hurricane movement scenarios. As a storm progresses, its observed position is compared with historical tracks within a selected spatial radius. At each six-hour step, the radius is gradually reduced, and scenario probabilities are recalculated using the proportion of hurricanes assigned to each cluster within the current spatial window. This sequential process allows uncertainty to decrease as more storm-position information becomes available. Instead of directing all emergency resources toward one deterministic path, the proposed framework supports planning across multiple plausible paths with associated probabilities. The results show that early-stage hurricane movement contains several feasible paths, while later stages become more focused as probability concentrates around fewer scenarios. This approach supports pre-hurricane preparedness, resource allocation, and disaster response planning under uncertainty.

Keywords
Hurricane trajectory forecasting; clustering; scenario analysis; disruption estimation; disaster preparedness.

1. Introduction
Hurricanes are among the most destructive natural hazards, causing extensive physical, social, and economic disruption in coastal regions. Accurate forecasting of hurricane trajectories is critical for predicting storm impacts,

guiding resource allocation, and supporting emergency preparedness and disaster response. While numerical weather prediction (NWP) models and ensemble forecasts provide detailed trajectory and intensity predictions, their inherent uncertainties during early storm formation and rapid intensification can limit operational usefulness. Small deviations in storm tracks may lead to major differences in exposure, landfall impact, and resource requirements. Therefore, relying on a single forecast line can over-concentrate supplies, shelters, transportation capacity, and response teams in one corridor while leaving alternative impact areas underprepared. To address this challenge, data-driven clustering methods can identify recurrent hurricane trajectory patterns from historical archives and support a multiple-path forecasting structure with scenario probabilities. This allows the model to show several possible hurricane paths before landfall instead of presenting only one predicted route.

K-means clustering is adopted due to its simplicity, scalability, and interpretability. Historical hurricane tracks are partitioned into distinct clusters based on spatial patterns and trajectory similarity, grouping storms with comparable movement characteristics. For each cluster, an average trajectory is computed, where an averaged clustered path is obtained by averaging the latitude and longitude coordinates along the clustered tracks. These representative paths serve as technical proxies for typical storm trajectories, enabling characterization of historical hurricane behavior and supporting the development of realistic scenario sets. Compared with hierarchical and density-based clustering methods, K-means provides superior computational efficiency and well-defined centroids that can be directly incorporated into downstream probabilistic forecasting models. In this study, these centroid-based paths are not used merely for classification; they are treated as representative hurricane scenarios derived from long-term historical behavior. This allows the model to convert nearly 173 years of prior hurricane movement into a compact set of operationally meaningful path alternatives.

Building upon these clusters, computing the probability that a newly forming hurricane will follow a given cluster-average path provides a rigorous method for real-time forecasting. This probabilistic approach allows for dynamic updating of scenario likelihoods as the storm evolves, capturing the uncertainty inherent in early-stage track prediction. Such a framework enables scenario-specific forecasts, which improve the operational relevance of predictions for emergency managers and planners. By integrating historical patterns with real-time observations, the model provides actionable insights that enhance early warning systems and preparedness strategies, while explicitly quantifying the likelihood of alternative storm trajectories.

Accurate trajectory forecasts are most useful when guiding resource allocation. Optimizing both the quantity and location of resources and facilities ensures timely delivery, while integrating probabilistic hurricane trajectories with location-allocation models helps minimize delays and improve preparedness. Relying on only one predicted path can over-concentrate resources and leave nearby communities underprepared if the storm shifts. By contrast, allocating resources across several probability-weighted paths allows emergency managers to balance preparedness across plausible impact regions, improving robustness under uncertainty.

In this study, we propose a unified framework that combines K-means clustering and probabilistic trajectory estimation. The framework leverages decades of historical hurricane track data to generate cluster-based scenario paths, dynamically updates probabilities for active storms, and quantifies potential disruption along each scenario. By linking probabilistic forecasts with operational resource planning, the approach provides a scalable, interpretable, and operationally relevant methodology that enhances both the predictive accuracy of hurricane trajectories and the efficiency of disaster response operations. This integrated approach bridges the gap between meteorological forecasting, machine learning, and disaster operations research, supporting evidence-based decision-making under uncertainty and contributing to more resilient coastal communities.

2. Literature Review

Accurate prediction of hurricane and tropical cyclone trajectories is essential for disaster preparedness, emergency planning, and resource allocation. Traditional numerical weather prediction (NWP) and ensemble-based forecasting systems provide detailed path and intensity forecasts, but they remain subject to substantial uncertainty during storm genesis, early track development, and rapid intensification. To address these limitations, researchers have increasingly explored statistical, probabilistic, and data-driven approaches that use historical storm behavior to identify recurring track patterns and improve forecasting under uncertainty. For example, (Tim Hall, 2005) showed that cluster-based average tracks can support semi-parametric tropical cyclone trajectory modeling, while (Jing & Lin, 2020) developed an environment-dependent probabilistic tropical cyclone model for the North Atlantic Basin that linked storm behavior to environmental variables. Similarly, (Cheung, 2021) demonstrated that historical track-pattern information can be used in a medium-range tropical cyclone forecasting system, highlighting the growing value of trajectory-based predictive methods beyond purely physics-based forecasting.

A major stream of research has focused on clustering hurricane and typhoon tracks to identify representative movement patterns. (Nakamura, 2009) introduced a mass-moment K-means approach for classifying North Atlantic tropical cyclone tracks using centroid and variance information, showing that K-means can summarize complex storm trajectories into interpretable average paths. Regional studies have further confirmed the usefulness of K-means-based track classification. (Robertson, 2007) applied cluster analysis to typhoon tracks in the western North Pacific and showed that centroid-based clustering can identify meaningful large-scale movement patterns, while (Yan, 2025) found that K-means clustering in the South China Sea produced well-separated track groups with distinct lifespan, wind-speed, precipitation, and genesis characteristics. At the same time, alternative clustering and trajectory-pattern methods have also been explored. (Kim, 2011) used fuzzy c-means clustering to classify typhoon tracks and showed that soft cluster membership is useful when storm-track boundaries are not sharply separated. (Seo, 2016) applied a self-organizing map to tropical cyclone tracks and identified distinct trajectory clusters across the western North Pacific, while (Chang, 2020) used a self-organizing-map-based framework to compare projected typhoon tracks with historical trajectories for dynamic flood forecasting. (Don, 2016) further demonstrated that regression mixture models can cluster ensemble tropical cyclone forecasts into representative storm evolution paths. In operational hazard applications, (Kowaleski, 2020) used clustered ensemble hurricane tracks from Hurricane Irma to generate representative storm-surge and inundation scenarios. Collectively, these studies show that trajectory clustering is a powerful tool for extracting dominant path structures and generating scenario-based interpretations of tropical cyclone movement.

A related body of literature has linked forecast uncertainty to emergency logistics, preparedness, and resource allocation. (Rios, 2025) developed a location-allocation model for food distribution in post-disaster settings, while (Zhang, 2021) proposed a stochastic scenario-based framework for pre-positioning facility locations and relief resources under uncertainty. More specifically for hurricane applications, (Zhang, 2019) developed a two-stage stochastic programming model for hurricane preparedness that jointly optimized points of distribution, medical supply levels, and transportation capacity before and after uncertainty was revealed. (Turnquist, 2012) proposed a dynamic allocation approach for the pre-positioning and short-term delivery of emergency supplies under uncertain post-disaster demand, and (Batta, 2013) developed a hurricane supply pre-positioning model that explicitly considered the possible destruction of pre-positioned resources during the disaster itself. These studies collectively show that resource allocation decisions are highly sensitive to forecast uncertainty and that probabilistic scenario information is essential for effective pre-landfall planning.

Although prior studies have established the value of clustering, probabilistic modeling, and disaster logistics, an important research gap remains at their intersection. Existing trajectory clustering studies have largely focused on classification, regional track characterization, or ensemble scenario summarization, while probabilistic forecasting studies have often emphasized environmental predictors or medium-range prediction rather than dynamically updated cluster-based scenario likelihoods. Similarly, logistics studies have incorporated disaster uncertainty, but they typically assume scenario inputs are already available rather than deriving them from a sequential historical trajectory analysis. Therefore, few studies explicitly combine historical hurricane track clustering, real-time sequential probability updating, and operational resource-planning relevance within a unified framework. This study addresses that gap by using K-means-based representative hurricane trajectories and stage-specific probabilistic scenario updating to support pre-landfall preparedness and resource allocation under uncertainty.

3. Methodology

To leverage historical hurricane data for predicting future movement patterns, K-means clustering was applied using spatial track features that capture trajectory similarity and proximity to the originating region. K-means is an unsupervised learning algorithm that partitions data into K clusters by minimizing the within-cluster sum of squared distances from cluster centroids. The method is computationally efficient and well suited for large historical hurricane datasets, enabling the identification of dominant and recurring hurricane movement patterns. In addition to computational efficiency, K-means was selected because it provides interpretable centroid-based representative paths that can be directly translated into scenario trajectories for forecasting. For each cluster, a representative trajectory was obtained by averaging the latitude and longitude coordinates at corresponding time steps, yielding mean paths that capture typical hurricane behavior while reducing the complexity of historical track data. Alternative clustering or trajectory similarity methods could also be considered; however, K-means is particularly suitable in this study because it produces clear cluster-average paths that align well with the scenario-based objective of the proposed framework.

Hurricane trajectory clustering was implemented in Python using the scikit-learn library. K-means clustering was applied to normalized latitude-longitude trajectory vectors, with feature scaling performed using Min-Max normalization to ensure equal contribution of spatial dimensions. The approach leverages the efficiency and robustness of scikit-learn for handling multivariate trajectory data.

To capture the evolving nature of hurricane movement, a sequential spatial filtering process was applied. Geospatial filtering was implemented in Python using the Pandas library for storm track handling and the Geopy library to compute great-circle distances between hurricane positions and evolving center points. This approach enables accurate identification of hurricanes within a specified spatial radius while accounting for the curvature of the Earth.

As an illustrative example, a randomly selected point (16.35,−80.5) was used as the initial center, located within a region characterized by high historical hurricane trajectory density, thereby ensuring adequate data availability for clustering. Historical hurricanes passing within a prescribed radius of this location were clustered using K-means, and the corresponding cluster-average trajectories were computed and visualized. After a 6-hour interval, the center was updated to (17.5,−82.1) and the procedure was repeated with a reduced spatial radius. This process was iteratively applied at successive 6-hour intervals with updated centers and decreasing radii, terminating at the final point (28.7,−91.8) at the 36-hour forecast horizon. At each stage, clustering was performed on hurricanes within the defined spatial window, and cluster-average paths were generated.

At each 6-hour time step, cluster probability was computed empirically as the ratio of the number of historical hurricanes assigned to a given cluster within the current spatial window to the total number of historical hurricanes contained in that window. Thus, the cluster probabilities represent the relative likelihood of alternative trajectory scenarios at that specific stage of hurricane evolution. These probabilities were recalculated at each successive window using the filtered hurricane subset for that stage.

No explicit temporal dependence between successive windows is assumed. At each 6-hour step, cluster probabilities are recalculated independently using the proportion of historical hurricanes assigned to each cluster within the current spatial window. The sequential aspect comes from updating the spatial center and filtering hurricanes at each stage, rather than from a formal time-dependent transition model. This interpretation clarifies that the resulting probabilities should be viewed as stage-specific relative scenario likelihoods rather than transition probabilities carried forward across time.

The sequence of selected center points from (16.35,−80.5) to (28.7,−91.8) was then connected to form a hypothetical hurricane trajectory. The cluster probabilities associated with each point along this trajectory indicate the most likely directions of hurricane movement over successive 6-hour intervals and provide a probabilistic interpretation of real-time hurricane path evolution. In this way, the proposed framework captures how uncertainty is initially high, with several clusters having similar likelihood, and then progressively decreases as more trajectory information becomes available and some paths become more probable than others. This allows the model to generate multiple plausible pre-landfall paths with associated probabilities, which can support resource allocation and preparedness planning under uncertainty.

4. Data Collection

This study used a historical hurricane track dataset provided by the course instructor. The dataset contains 54,743 observations representing 1,972 storms recorded between 1851 and 2023, from which 565 hurricanes with unique storm IDs were selected for the present analysis. Each record includes storm-specific and spatio-temporal information such as storm ID, storm name, date, time, storm status, latitude, longitude, maximum sustained wind speed, minimum central pressure, and wind extent measurements by quadrant. For the purposes of this study, the primary variables used were storm ID, date, time, latitude, and longitude, as these directly describe hurricane trajectory evolution over time.

The dataset consists primarily of observations recorded at six-hour intervals, which makes it well suited for sequential trajectory analysis and dynamic scenario updating. Prior to modeling, the selected hurricane records were organized by unique storm ID so that each hurricane could be represented as a complete trajectory rather than as a set of isolated position points. The trajectory data were then structured into time-ordered spatial sequences to support clustering and path comparison. In addition, variables not required for trajectory construction, or fields containing placeholder values for unavailable measurements, were excluded from the core trajectory modeling process where appropriate.

The processed dataset served as the basis for identifying recurring historical trajectory patterns and constructing representative scenario paths. These trajectories were used within the proposed framework to perform clustering, generate cluster-average paths, and estimate scenario probabilities for evolving storms. Furthermore, the dataset supported model validation by enabling comparison between observed hurricane tracks and the representative trajectories assigned by the clustering framework. This data collection and preparation process ensured that the historical hurricane records were suitable for both probabilistic forecasting and evaluation of the proposed methodology.

5. Results & Discussion

The results of the proposed sequential clustering framework show that hurricane path forecasting should be interpreted as a probabilistic process rather than a single deterministic prediction. At the early stage of storm evolution, the probabilities of the identified cluster paths are nearly similar, which indicates high uncertainty in the future movement of the hurricane. This is expected because only limited positional information is available at the beginning, and multiple historical paths remain plausible. As the hurricane progresses and additional six-hour trajectory observations become available, the path probabilities begin to separate, with one or a few trajectories receiving higher probability than the others. This change indicates that uncertainty is decreasing and that the likely direction of the hurricane is becoming more precise. Even near the pre-landfall stage, however, more than one path may still remain feasible. Therefore, instead of waiting for a single exact landfall prediction, the proposed framework provides multiple possible paths with associated probabilities that can support pre-hurricane resource allocation and preparedness planning.

5.1. Numerical Results

This subsection presents the numerical findings of the two illustrative hurricane cases used in this study. The main objective of these results is to show how the number of plausible paths and their relative dominance evolve over time as more trajectory information becomes available.

Case 1: Trajectory clustering at point 1

For Case 1, the sequential clustering framework was applied from the initial center point (16.35,−80.5) to the final point (28.7,−91.8) using decreasing spatial radii over successive six-hour intervals. The numerical results show that at the initial stages, multiple clusters are present, indicating that the hurricane can still follow several different historical movement patterns. At 0 h and 6 h, three clusters were identified. At 12 h, the number of clusters increased to four, representing the highest uncertainty stage in this case. After that, the number of feasible paths began to reduce, with two clusters at 18 h, three clusters at 24 h, two clusters at 30 h, and finally one cluster at 36 h. This pattern clearly shows that trajectory uncertainty is high in the early stage and gradually decreases as more hurricane path data become available.

Table 1. Spatio-Temporal Windowing Parameters and Resulting Number of Clusters

Time (hrs)	Center (lat, lon)	Radius (km)	Number of Cluster
0	(16.35, -80.5)	200	3
6	(17.5, -82.1)	180	3
12	(19.2, -84.3)	160	4
18	(22.1, -86.8)	140	2
24	(24.9, -88.2)	120	3
30	(27.1, -90.5)	100	2
36	(28.7, -91.8)	80	1

An important inference from Table 1 is that the model does not immediately force the hurricane into one predicted route. Instead, it preserves multiple plausible paths in the early and intermediate stages, which is more realistic for hurricane forecasting. As the storm evolves, some paths become more likely than others, reflecting the fact that the model is learning from the newly observed trajectory points. Thus, the results indicate that early forecasts should be interpreted with caution, while later forecasts become increasingly focused and operationally useful.

Case 2: Trajectory clustering at point 2

Case 2 represents a later-stage hurricane segment extending from (26,−87.5) to (32.3,−88.7). In this case, the hurricane is already located in a more mature movement region with dense historical path information. The clustering results show that the generated scenario paths are more coherent and aligned with the evolving hurricane track. Compared with Case 1, the uncertainty in Case 2 is relatively lower because the storm has already moved beyond the broad genesis-stage region. As a result, the dominant paths become more distinguishable, and the probability concentration shifts more clearly toward the most likely trajectory directions.

The numerical implication of Case 2 is consistent with the overall logic of the proposed framework. When only a small amount of path information is available, the probabilities of different clusters remain close to each other. However, after several hours of observed movement, the model can differentiate better among possible paths, and a few clusters begin to dominate. This demonstrates that the framework can capture the gradual reduction of uncertainty not only in an early-stage hurricane but also in a later-stage storm segment.

Overall, the numerical results from both cases show a common trend: initially, the hurricane has several plausible future paths with nearly similar likelihood, but as more trajectory data become available, some paths gain higher probability and the prediction becomes more precise. This is a key result of the study because it supports the use of probabilistic scenario forecasting for real-time decision-making under uncertainty.

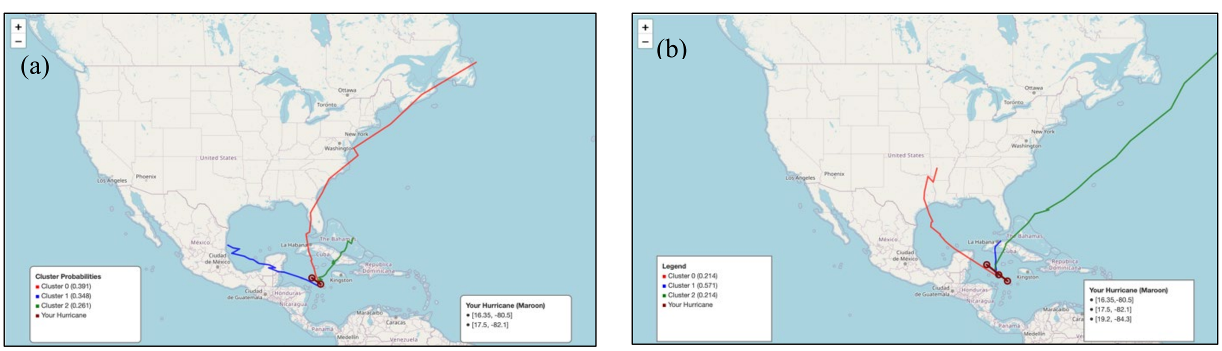
5.2. Graphical Results

The graphical results provide visual evidence of how hurricane path uncertainty evolves over time and how the proposed framework updates the likely scenario paths. These figures are especially important because they illustrate the difference between early-stage uncertainty and later-stage convergence.

Case 1 graphical results

For Case 1, the figures at 6 h, 12 h, 18 h, and 24 h show the real-time hurricane trajectory together with the cluster-based probabilistic scenarios. In the earlier stages, the colored cluster-average trajectories are spread across multiple directions, and their probabilities are relatively similar. This indicates that the model recognizes several plausible future paths and that uncertainty is still high. Such behavior is realistic because, at the beginning of the storm, the available path information is limited and several historical movement patterns remain possible.

As the hurricane continues to move and additional positional data are added, the scenario paths begin to separate more clearly. One or a few cluster paths start to align more closely with the observed hurricane movement, while the remaining alternatives become less dominant. This change visually confirms that the uncertainty is decreasing. In other words, the forecast is becoming more precise not because uncertainty disappears completely, but because the probability distribution starts favoring fewer and more likely paths.



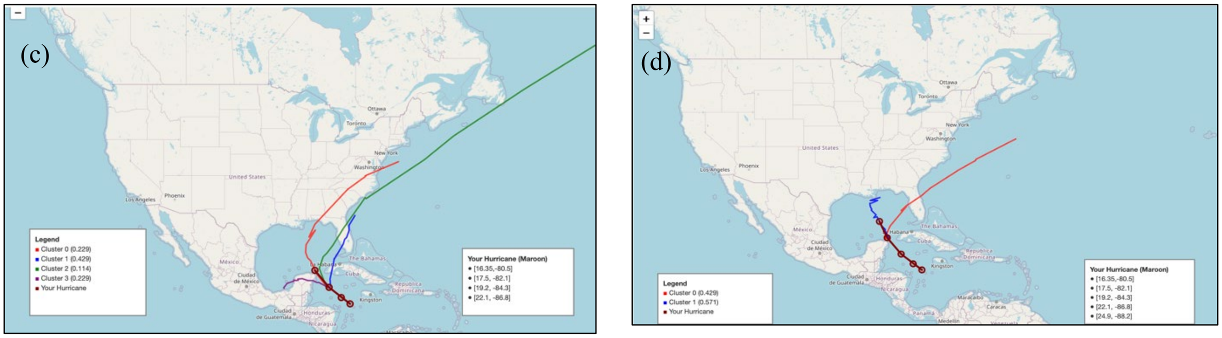


Figure 1. Real-time hurricane trajectory and cluster-based probabilistic scenarios at (a) 6 h, (b) 12 h, (c) 18 h, and (d) 24 hr.

The full Case 1 graphical summary further reinforces this interpretation. The maroon "My Hurricane" path is dynamically matched against historical clustered trajectories, showing how the model adapts over time. The figure demonstrates that the model is not providing a single fixed forecast, but rather updating the probabilities of multiple possible trajectories as the hurricane evolves. This is valuable for planners because it reflects the actual decision environment, where several outcomes remain possible before landfall (Figure 2).

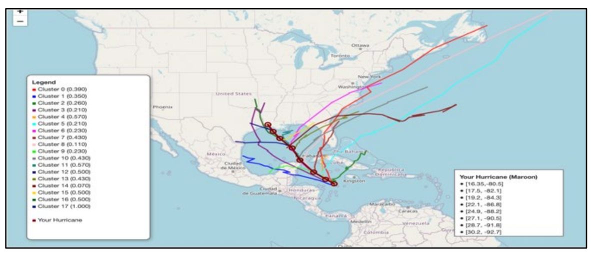


Figure 2. Real-Time Hurricane Trajectory and Cluster-Based Probabilistic Scenarios of case 1

Case 2 graphical results

For Case 2, the graphical result shows the same general probabilistic behavior, but in a later-stage hurricane segment. The maroon observed track aligns with dominant historical clustered paths, and the path alternatives appear more concentrated than in Case 1. This reflects the fact that once the hurricane has already traveled for some time, the model has more evidence to distinguish between likely and unlikely future routes. The figure therefore illustrates a lower-uncertainty forecasting stage, where the most probable movement patterns become clearer.

Together, the graphical results from both cases clearly support the main finding of this study. At the beginning, path probabilities are nearly similar because uncertainty is high. After several hours, the model receives additional trajectory information, and some paths become much more probable than others. Even before the hurricane reaches land, however, multiple possible routes may still exist. This is important because it means that emergency planning should not rely only on one predicted path. Instead, resource planning should consider several likely paths together with their probabilities (Figure 3).

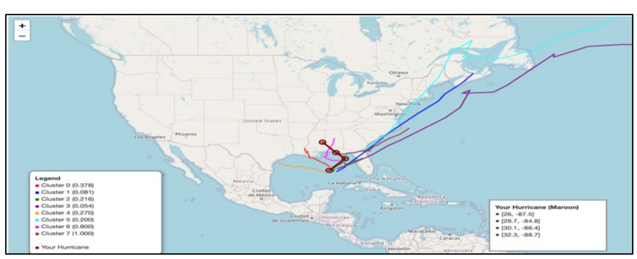


Figure 3. Real-Time Hurricane Trajectory and Cluster-Based Probabilistic Scenarios of case 2

5.3. Proposed Improvement
A useful extension of the proposed framework is to directly integrate path probabilities with pre-hurricane resource allocation planning. Instead of relying on a single predicted path, emergency resources can be distributed across multiple feasible landfall scenarios according to their associated probabilities, allowing decision-makers to better prepare under uncertainty. Future work should also report cluster probabilities numerically and track their evolution over time to provide stronger quantitative support for the observed reduction in forecast uncertainty.

5.4. Model Validation: Generalized Testing Method
Hurricane IDs were randomly split into 80% training and 20% testing sets. Using the training data, 30 clusters were generated with the K-means algorithm to represent dominant trajectory patterns. Each hurricane in the testing set was assigned to the nearest cluster based on spatial similarity to the cluster-average trajectories.

Across 113 testing hurricanes, the mean deviation between observed tracks and cluster-average paths was 48.86 km, with a median deviation of 42.46 km. These small deviations, relative to the spatial scale of hurricane impacts, indicate that the model is both precise and accurate in capturing hurricane trajectories. The close alignment between mean and median deviations further confirms that most hurricanes are well represented by their assigned clusters.

These results confirm that the clustering framework reliably generalizes to unseen hurricanes, capturing dominant trajectory patterns and providing a robust basis for probabilistic forecasting and operational decision-making (Figure 4).

(a)

```
Test hurricane assignment and average per-point deviation:
    Hurricane_ID  Assigned_Cluster  Avg_Deviation_per_Point_km
0       AL092005                21                   42.309173
1       AL052005                27                   65.662467
2       AL212010                 8                   39.640979
3       AL072010                13                   53.403729
4       AL111989                13                   77.719825
..           ...               ...                         ...
108     AL031936                17                   15.558104
109     AL031854                26                   53.884409
110     AL101958                 4                   51.518403
111     AL081906                 3                   52.004914
112     AL092022                14                   36.466052

[113 rows x 3 columns]
```

(b)

```
Mean deviation per point (km): 48.86
Median deviation per point (km): 42.46

Number of test hurricanes assigned to each cluster:
Assigned_Cluster
0      1
1      5
2      6
3      4
4      8
5      2
6      8
7      4
8      9
9      2
10     1
11     1
12     6
13     5
14     4
15    10
16     4
17    10
18     4
21     4
24     6
26     5
27     2
29     2
Name: count, dtype: int64
```

Figure 4. Model validation results for test hurricanes: (a) assignment of test hurricanes to clusters with average per-point trajectory deviation, and (b) summary statistics including mean and median per-point deviation and the distribution of test hurricanes across clusters.

6. Conclusion
This study presents a data-driven framework for probabilistic hurricane trajectory forecasting that integrates K-means clustering with sequential spatial filtering to generate realistic trajectory scenarios and associated likelihoods. By leveraging historical hurricane track data recorded at six-hour intervals, the proposed approach captures dominant movement patterns and dynamically updates scenario probabilities as a storm progresses, the results show that the framework effectively represents early-stage trajectory uncertainty and progressively narrows the set of possible paths as new position data becomes available, improving forecast accuracy over time. A key finding is that the model should not be interpreted as a replacement for operational meteorological forecasts, but as a complementary decision-support tool that converts historical path behavior into multiple probability-weighted scenarios for planning purposes. This distinction is important because disaster response decisions are often made before the final track is certain.

Model validation using generalized testing confirms that cluster average trajectories provide accurate and interpretable representations of unseen hurricane paths. The observed deviations between historical trajectories and their assigned cluster centroids remain small relative to the spatial scale of hurricane impacts, indicating strong generalizability and robustness of the proposed method. These findings support the suitability of the framework for operational, scenario-based forecasting rather than deterministic track prediction.

Beyond trajectory forecasting, the framework supports disaster preparedness by linking probabilistic hurricane scenarios with disruption estimation and pre-hurricane resource allocation models. By providing scenario-specific trajectories, probabilities, and impact estimates, the approach helps emergency planners prepare for multiple plausible landfall outcomes instead of depending on a single forecast line. This supports more balanced staging of supplies, personnel, shelters, and transportation resources across alternative impact zones under uncertainty.

Future work will focus on incorporating additional storm characteristics such as intensity evolution and environmental factors, extending the framework to multi-basin applications, and embedding the probability outputs directly into stochastic or robust resource-allocation models. This integration would allow emergency assets to be distributed according to both path likelihood and expected disruption severity, strengthening the framework's value for pre-landfall emergency logistics, infrastructure resilience, and decision-making under uncertainty.

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Biographies

Rudra Brahmbhatt is currently pursuing a Master of Science in Engineering and Operations Management at the University of New Haven. His research interests include data-driven modeling, hurricane forecasting, scenario analysis, optimization, and resource planning for disaster preparedness and emergency management. His work focuses on developing analytical and decision-support frameworks that enhance preparedness and improve resource allocation under uncertainty. He applies quantitative and systems-based approaches to address complex problems in risk assessment, predictive analytics, and resilient decision-making. His research integrates data analysis and operations management techniques to support effective planning and response strategies in disaster and uncertainty-driven environments.

Dr. Marzieh Soltanolkottabi is an assistant professor of Industrial Engineering at the University of New Haven whose research focuses on data-driven decision-making, humanitarian logistics, healthcare analytics, and complex systems modeling. She integrates methods such as agent-based simulation, stochastic optimization, and machine learning to address real-world challenges in supply chains and disaster response. She teaches courses in optimization, decision-making under uncertainty, and computing for engineering systems, and is passionate about bridging theory and practice to equip students and organizations with tools for smarter, more resilient decisions.

Dr. Ali Tolooie is a tenure-track Assistant Professor of Supply Chain Management at the Stetson-Hatcher School of Business, Mercer University, USA, where he also serves as Program Director for the BBA program and the Supply Chain Management major. His research focuses on humanitarian and disaster relief supply chains, stochastic optimization, decomposition algorithms for large-scale decision problems, and drone-enabled last-mile logistics under uncertainty. At Mercer, he teaches courses in operations management, logistics management, project management, and supply chain analytics, and is actively involved in program and curriculum development.