Hybrid Meteorological Forecasting: ML-driven Predictions of Lake Michigan's Lake-Effect Snow on Urban Preparedness

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Abstract of the Thesis

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Prof. Dino Konstantopoulos, Advisor

The phenomenon known as "lake-effect" refers to the weather pattern that occurs when cold air The occurrence of snow and associated precipitation events has had significant adverse effects on the socioeconomic progress of the regions surrounding the Great Lakes in North America. Traditional meteorological studies place significant emphasis on the utilization of fluid dynamic models for the purpose of conducting statistical modeling in order to create predictions. Nevertheless, despite their capacity to generate precise predictions regarding numerous climate variables, they encounter limitations in producing consistent and reliable forecasts over an extended temporal scope. Nevertheless, given the swift advancements in deep learning and time series forecasting, it is feasible to address the obstacles associated with statistical modeling by including spatial-temporal data on a broader scale.

In this study, machine learning techniques are employed to evaluate meteorological time series data for both classification and forecasting purposes. The research initiates by establishing a new data pipeline, designed specifically to extract the visible band data from the Lake Michigan region, as sourced from the Geostationary Operational Environmental Satellite under the aegis of the National Aeronautics and Space Administration. This aids in streamlining data assimilation and visualization. Subsequently, the study introduces a pioneering framework that amalgamates both 2-dimensional satellite imagery and 1-dimensional meteorological data, even when they differ in sampling frequencies and availability, to enhance time series classification and forecasting. Building upon the well-documented proficiency of deep learning in image classification, the study commences with a detailed review of the conventional Numerical Weather Prediction model. This paves the way for the proposal of a hybrid time series forecasting framework, geared towards precise mid-range precipitation predictions (spanning 2-3 days) with a special emphasis on severe weather events. By integrating the strengths of the Convolutional Neural Network and the Long Short-Term Memory Network, this framework not only ensures swift implementation and rapid training but also remains efficient in terms of computational expenses. Empirical evaluations corroborate the framework's outstanding accuracy in forecasting.

Furthermore, this enhanced understanding could act as a catalyst in the development of a hybrid model that possesses the capability to detect and forecast lake-effect precipitation

events. The efficacy of such a model would provide not only meteorological insights but also potentially serve to lessen the socio-economic impact on the communities residing in the proximity of the Great Lakes region. Hence, this research not only contributes to the existing scientific dialogue concerning lake-effect snow, but also paves the way for more innovative, interdisciplinary approaches to weather forecasting and climate change adaptation.

Chapter 1

Introduction

1.1 What is Lake-Effect Snow

Lake-effect snow constitutes a meteorological phenomenon of marked singularity that is typified by intense snowstorms. This occurrence bears immense relevance for the geographical locales encompassed by North America's Great Lakes. The term "lake-effect snow" is specifically attributed to the snowfall precipitated by atmospheric systems in transit across expanses of relatively warm water. During this process, the weather systems acquire heat and moisture, which subsequently materialize into snowfall on the leeward side. This phenomenon first received comprehensive academic scrutiny through the seminal research conducted by Niziol in 1987, who emphasized the profound hazards associated with these climatic events in the pertinent regions. The considerable ferocity of lake-effect snowstorms holds the capacity to introduce considerable disruption across a wide range of socio-economic activities. Such disturbances inherently engender a profound impact upon the life quality and daily operations of the inhabitants residing within the areas subjected to these weather phenomena.

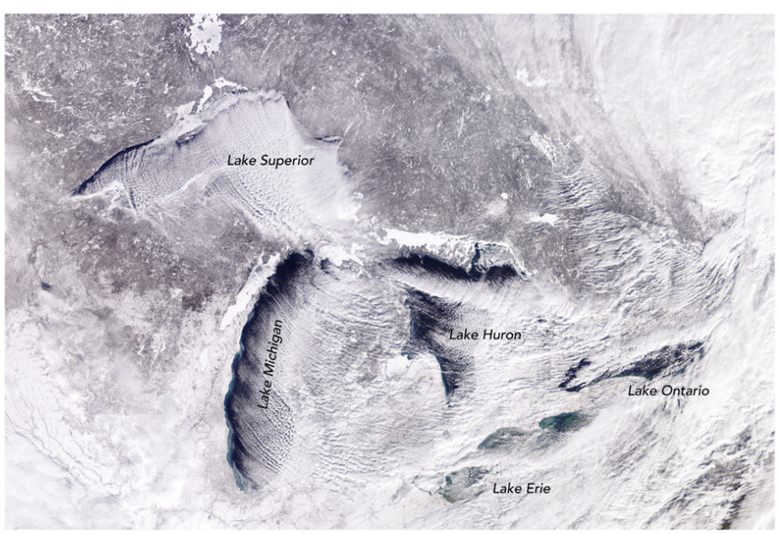

Figure 1.1: Example Lake Effect Snow Satellite Image

Building on Niziol's pioneering research, subsequent studies have solidified the understanding of the severe impacts of lake-effect snowstorms (Kristovich et al., 2003; Ayon, 2017). These events, while deeply rooted in meteorological phenomena, carry profound socio-economic implications. The repercussions are felt distinctly by communities living near the Great Lakes, as these severe weather occurrences can disrupt normal life and economic activities, thus reinforcing the importance of ongoing research and effective management of lake-effect snowstorms. Numerical Weather Prediction (NWP) models are widely utilized for the forecasting of lake-effect snow. These sophisticated tools incorporate various atmospheric parameters such as temperature, humidity, wind velocity and direction, as well as atmospheric pressure. Through manipulating the initial conditions of these models, meteorologists can make estimations about the likely occurrence and location of lake-effect snow.

Nevertheless, the specific nature of lake-effect snow generation - the phenomenon of cold air interacting with warmer lake surfaces - implies that conventional meteorological data collected from land-based weather stations are not fully equipped to offer critical insights into the cloud formation processes. Indeed, the conditions over large bodies of water that engender lake-effect snowfall fundamentally differ from those over land, thereby making the task of identifying and characterizing lake-effect snow events considerably challenging using terrestrial weather station data alone.

This underlines the necessity for more specialized approaches to capture the unique environmental interplay at the heart of lake-effect precipitation, and to enable more precise prediction and characterization of these impactful meteorological events. To forecast this kind of data, we need time series forecasting methods. Time series forecasting is a technique to predict future values over a period based on historical data with time order. Specifically, by assuming that the trends shown on the historical data will be like the future trends, time series forecasting estimates a sequence of future values by extrapolating necessary features from historical data such as trends, seasonal patterns, and irregular. Time series forecasting is widely used in many fields to help with decision-making, such as business, supply chain management, and production planning. In practice, we can utilize computer science techniques to analyze the time-related repeating change of the given data and then build mathematical models to predict future change.

1.2 What Are Meteorological Time Series Challenges?

Time series data is inherently collected in a sequential manner, indicating that the value of a particular observation is influenced by prior observations within the same series. The phenomenon of inherent interdependence is commonly referred to as autocorrelation or serial correlation. An illustration of this phenomenon can be discerned in the recurring temperature patterns of Lake Michigan, which display evident autocorrelation. Nevertheless, the acquisition of reliable meteorological data poses significant difficulties, particularly when dealing with datasets that involve satellite and radar measurements. Data collection interruptions may occur during nighttime for specific wavelength ranges, such as the visible light band. The presence of these data gaps poses challenges to the interpretation and prediction of time series, especially when attempting to extend forecasts to longer time periods.

In the quest to utilize diverse data sources capable of capturing the intricate spatial-temporal dynamics of atmospheric conditions, it's paramount to recognize the heterogeneity inherent in meteorological datasets. Such datasets can manifest in a myriad of dimensionalities, stemming from their disparate origins, collection methodologies, and intended applications. This heterogeneity poses a significant challenge when endeavoring to design a singular, unified model capable of assimilating and processing datasets of varying dimensional structures simultaneously. The integration of these diverse datasets, while ensuring the preservation of their inherent spatial and temporal nuances, requires careful consideration of model architecture and preprocessing strategies.

1.3 Research Questions

1.3.1 Observation and Output Time Duration for Lake-Effect Precipitation Forecast

The selection of an appropriate observation and prediction time window is crucial in the comprehensive examination of Lake-Effect climatic events, since it is essential for achieving precise forecasting. Lake-effect phenomena, which are known for their intrinsic unpredictability, arise from complex atmospheric mechanisms. The temporal uniformity of these processes, ranging from the initiation of distinct cloud formations above Lake Michigan to the subsequent precipitation in nearby areas, is not consistent. Regrettably, a comprehensive study that provides a thorough understanding of the average duration of lake-effect precipitation and the time interval between the initial formation of clouds over the lake and the onset of precipitation in neighboring regions has not been conducted by the scientific community. The presence of this noticeable deficiency within our meteorological knowledge repository poses challenges for academics and developers of models. The absence of essential temporal reference points complicates the development of a forecasting model that can reliably and precisely anticipate the occurrence, duration, and end of lake-effect precipitation events. These challenges highlight the necessity of doing thorough study with the objective of elucidating the temporal dynamics of these climatic phenomena.

The main focus of this study is to develop a reliable and reproducible methodology for identifying the optimal time periods for observing and predicting lake-effect precipitation events. The occurrence of these phenomena, which possess inherent complexity, initiates when distinct cloud forms manifest in the region of Lake Michigan. The prompt observation and analysis of precursor cloud formations significantly impact the forecast accuracy. Through the implementation of rigorous quantitative analysis on satellite imagery data, valuable insights can be derived, particularly with a focus on certain geographical regions where accurate prediction of upcoming precipitation events carries significant significance. This methodology not only improves our comprehension of the changing atmospheric dynamics over Lake Michigan but also assists in customizing forecast models to address the distinctive meteorological challenges of certain areas in close vicinity.

1.4 Structure of Thesis

In subsequent sections of this paper, we undertake a comprehensive examination of the current paradigms in forecasting methodologies. Specifically, Section 2 offers a thorough overview of the cutting-edge models and techniques that dominate the meteorological forecasting arena, elucidating the technicalities and methodologies underpinning each. This sets the stage for Section 3, wherein we delineate the intricacies of our dataset: its sources, characteristics, and the methodologies deployed in its acquisition. Following this, we embark on a rigorous numerical analysis, elucidating the systematic processes employed to determine optimal observation and prediction windows, whilst simultaneously benchmarking the effectiveness of our adopted strategies against contemporary methods. The section culminates with a summary, encapsulating the key findings and implications of our research.

A noteworthy mention is the consistency in the source of our datasets across all sections. These datasets, serving as the bedrock of our analyses, comprise satellite imagery coupled with meteorological data. This data, meticulously collated from federal weather stations, spans an extensive period from October 2006 to December 2017. To ensure seasonal relevance and robustness in our analyses, our datasets prioritize six-month intervals for each year, focused predominantly on the winter season.

Chapter 2

State-of-the-Art Practices in Meteorology

The field of meteorology, which can be traced back to ancient civilizations such as Mesopotamia, China, and Greece, has undergone substantial advancements from its early stages. The science of meteorology originated from the study of astrological patterns and fundamental literature such as Aristotle's "Meteorologica." Throughout the Medieval Ages, advancements in observational apparatus in the Arab world and the methodical documenting of weather in European monasteries contributed to the expansion of this field [5]. The Renaissance era saw a significant period of scientific advancements, exemplified by the introduction of Torricelli's barometer and Fahrenheit's thermometer, which enabled the systematic measurement and analysis of meteorological phenomena. The 19th century was a significant era characterized by notable advancements, particularly with the advent of the telegraph. This technological innovation played a pivotal role in enabling the development of synthetic weather maps and the subsequent realization of organized weather predictions [2].

Incorporating technology has accelerated meteorology's development during the 20th and 21st centuries. The utilization of radiosondes facilitated the collection of data pertaining to the upper atmosphere, while the integration of mathematical models with sophisticated computing systems revolutionized the field of weather forecasting [3]. In recent times, there has been a notable adoption of high-resolution atmospheric modeling in meteorological investigations, with a particular focus on localized forecasts. The increasing convergence between climatology and the incorporation of machine learning and AI techniques into conventional forecasting approaches underscores the field's forward-looking direction and its persistent pursuit of enhancing comprehension of atmospheric phenomena, mostly motivated by apprehensions over global climate change.

2.1 Numerical Weather Prediction (NWP) Models

The advent of the 20th century marked a pivotal transformation in the domain of computational capabilities. As the world stepped into the computer age, the magnitude of calculations that could be performed underwent a profound metamorphosis. What once took an arduous span of days to compute was now seamlessly executed in mere hours. This eruption of computational prowess unlocked the potential to analyze and interpret massive datasets related to the Earth's atmosphere at an unprecedented pace, laying the foundational stones for Numerical Weather Prediction (NWP).

NWP represented a radical departure from erstwhile forecasting methodologies which were primarily anchored in direct observations. Instead of being constricted to the confines of empirical data, NWP wove together observational datasets with sophisticated mathematical representations of atmospheric dynamics. This symbiotic amalgamation furnished forecasts of a distinctly objective nature, providing intricate details about myriad atmospheric variables. Where traditional techniques might offer generalized predictions, NWP delves into the granularity, bestowing meteorologists with the capacity to foretell specific metrics such as the exact volumes of impending precipitation, pinpoint wind velocities, or definitive temperature oscillations. This granular clarity conferred by NWP has been instrumental in revolutionizing multiple industries, spanning from the agricultural fields to the bustling corridors of aviation.

As we delve into the mechanics of NWP, we discern that these models commence by crafting a mathematical simulacrum of atmospheric and climatic patterns on a planetary scale. Over the decades, a multitude of these models has been meticulously refined, each designed to prognosticate distinct atmospheric states and climatic variables. The zenith of this modeling evolution is exemplified by formidable global NWP frameworks like the Integrated Forecast System, championed by the European Centre. This system boasts of rendering weather predictions on a vast grid canvas, each cell spanning approximately 10,000 square kilometers, situated around 5,500 meters above terrestrial or oceanic expanses, corresponding to a barometric pressure benchmark of 500 hPa. However, when the objective pivots towards more intricate, localized forecasts – delineating conditions on a minuscule 1 to 5 square kilometer grid scale hovering just 2 meters above terrestrial or marine surfaces, where the ambient temperature is benchmarked at 850 hPa – meteorologists employ specialized limited-area models. These models are contingent on the vast reservoir of data curated by their global counterparts to demarcate conditions at their peripheries. Such delineated boundary conditions are not mere ornamental add-ons; they are the linchpin ensuring the precision and veracity of the forecasts dispensed by these limited-area models.

2.1.1 Foundations of NWP Models

Numerical Weather Prediction (NWP) stands on the foundational bedrock of a set of governing atmospheric equations, with the Navier-Stokes equations taking center stage [1]. These pivotal equations provide an intricate mathematical portrayal of fluid dynamics and are deeply rooted in the core principles of conserving momentum, mass, energy, and various states of water.

1. **Continuity Equation**: Acting as the bastion for the principle of mass conservation, this equation delineates how mass is neither spontaneously created nor annihilated in the atmosphere.
2. **Momentum Equations**: As the guardians of momentum conservation, these equations meticulously define the conservation and propagation of momentum across three spatial dimensions.
3. **Thermodynamic Energy Equation**: Embodied within this equation is the sacrosanct principle of energy conservation, showcasing how energy transitions between different forms but remains conserved in totality.
4. **Water Substance Equations**: These equations serve as the sentinels for the conservation of water, detailing its intricate phase transitions among vapor, liquid, and solid (ice) states.

The tangible implementation of NWP necessitates compartmentalizing the expansive atmospheric canvas into a structured three-dimensional lattice or grid. The granularity of these individual grid cells is indicative of the model's resolution. Global Models, in their quest to canvas the entirety of our blue planet, inherently adopt a coarser resolution. However, when the forecasting lens narrows down to capture phenomena at a smaller scale, the baton is passed to Regional or Mesoscale Models. These models, with their heightened resolution, are adept at encapsulating and predicting localized atmospheric intricacies.

Embarking on a simulation voyage with NWP models mandates the infusion of accurate initial conditions, serving as the starting point for any forecast. These conditions are not conjured from thin air; they are meticulously distilled from a mélange of observational data. This alchemy, known as data assimilation, synergizes the essence of prior model forecasts with fresh observational inputs, ultimately crystallizing into the most accurate representation of the current atmospheric tableau.

Navigating deeper into the NWP paradigm, we encounter two distinct model types. Firstly, there are the deterministic models, which present a singular, definitive forecast for each meteorological parameter. These models are the stalwarts of short to medium-term weather predictions. In stark contrast, we have the ensemble prediction system (EPS) models. Eschewing the path of singular forecasts, EPS ventures into the realm of probabilities. By introducing minute variations in initial conditions or toggling with model physics, EPS germinates a bouquet of forecasts, often termed as ensemble members. This multitude of forecasts proffers a spectrum of potential atmospheric evolutions, bestowing meteorologists with a tool to gauge the inherent uncertainties lurking within their predictions.

2.2.2 Challenges and Limitations of NWP Models

The proficiency of Numerical Weather Prediction (NWP) models, be it global or limited-area, is unequivocally acknowledged in the meteorological realm. Their prowess in churning out forecasts with commendable accuracy is a testament to the intricate mathematical and physical underpinnings these models are built upon. However, this prowess isn't a monolithic entity; it's malleable, influenced and often swayed by a myriad of factors [7].

1. **Forecast Horizon**: The adage, "The devil is in the details," encapsulates the challenges faced by NWP models, particularly the acclaimed Integrated Forecast System, when peering deeper into the future. Their clairvoyance, while potent in the short-term forecast window (1-3 days ahead, boasting an impressive 75% accuracy ballpark), starts to wane as they tread into the realms of medium-range (3-10 days, averaging around a 60% accuracy) and extended-range forecasts. It's a manifestation of the inherent chaotic nature of the atmosphere, where minuscule perturbations can spawn significant variations over extended periods.
2. **Weather Parameter**: NWP models, while holistic in approach, often exhibit variable competencies when predicting distinct climatic parameters. The terrain of accuracy isn't uniform. For instance, the tapestry of factors influencing temperature may render its

predictions more precise compared to the intricate dance of variables governing precipitation, especially under certain regional or atmospheric contexts.

3. **Geographical Region**: The planet's topography isn't a uniform expanse, and these geographical undulations often throw unique challenges to NWP models. Predictive tasks in areas adorned with complex terrains, be it the rugged mountains or the dynamic coastal zones, present a higher degree of intricacy compared to their counterparts set in flatter landscapes. The intertwining of local wind patterns, temperature inversions, and microclimates in these terrains often puts the model's prowess to a stringent test.
4. **Seasonality**: Just as a musician's performance might vary with the composition, NWP models too exhibit seasonal oscillations in their forecasting acumen [8]. The atmosphere's intrinsic predictability isn't a constant entity; it ebbs and flows with the seasons. Certain atmospheric configurations in specific seasons may either enhance the model's foresight or cloak the future in layers of uncertainty.

2.2 Machine Learning Methods

In contemporary meteorological research and applications, Numerical Weather Prediction (NWP) models have stood out as the cornerstone. Rooted in the foundational principles of physics and continually augmented by the leaps in computational capabilities, these models present a state-of-the-art approach to understanding and predicting the dynamics of the atmosphere. Their prowess in simulating the temporal evolution of the atmospheric state is unmatched, although they are not without their set of challenges and limitations [3].

In recent years, the meteorological realm has witnessed an unprecedented influx of data, stemming from advanced observational instruments, satellites, and ground-based sensors. Coupled with significant computational advancements, this data avalanche has paved the way for the emergence and adoption of machine learning (ML) models. These models, characterized by their ability to sift through vast datasets and discern patterns, promise heightened forecast accuracy and a streamlined efficiency in weather prediction endeavors.

Diving deeper into the machine learning applications tailored for meteorological predictions, two paradigms prominently surface: regression and classification [10]. Regression models, encompassing methodologies such as linear regression, support vector regression, and decision trees, are fine-tuned to predict continuous variables. These models excel in tasks like forecasting nuanced temperature gradients or dissecting the patterns of precipitation intensities. In juxtaposition, classification models utilize a suite of algorithms, notably logistic regression, random forests, and neural networks, aiming to predict discrete outcomes. They are particularly adept at identifying and categorizing distinct weather phenomena or events.

However, a critical assessment reveals that many conventional models, despite their methodological soundness, occasionally grapple with achieving the desired forecast accuracy. A contributing factor to this limitation is the inherent simplicity of some models, which may not fully encapsulate the multi-layered complexities and interactions within the atmospheric system. Another challenge lies in their constrained ability to seamlessly integrate diverse measurements from a myriad of data sources populating the atmospheric landscape.

Notably, the frontier of modern ML in meteorology has been invigorated by methodologies originally sculpted for the realm of Computer Vision. Deep learning architectures, with their multi-layered neural networks, and reinforcement learning paradigms, where models iteratively learn from their past actions, are being repurposed and fine-tuned for meteorological applications, ushering in an era of enhanced predictive capabilities and novel insights.

2.2.1 Foundations of ML Models

Around the commencement of the 2010s, an era marked by the ascendancy of graphic processing unit (GPU)-driven computations, the fields of deep learning and reinforcement learning began to conspicuously mark their footprints in the domain of meteorological research [6]. This was not merely a dalliance with new methodologies but an evolution driven by the intrinsic benefits of these techniques. With deep learning, for instance, came the unparalleled ability to scale the number of trainable parameters and to holistically encompass diverse data streams within the neural network architectures. Such advantages precipitated a perceptible shift in the research paradigm, with a growing cohort of scientists ardently embedding deep learning methodologies into their investigative pursuits.

In this milieu, Convolutional Neural Networks (CNNs) emerged as potent tools, especially when trained on satellite and radar images. Their prowess in discerning intricate patterns made them especially suited for tasks such as identifying telltale signs associated with phenomena like lake-effect snow. On the other hand, Recurrent Neural Networks (RNNs) and their sophisticated counterparts, Long Short-Term Memory (LSTM) networks, with their design tailored to capture the ebb and flow of temporal sequences, became invaluable in predicting the chronology of events like snowfall evolution.

Indeed, machine learning thrives in environments awash with data, and meteorology, with its myriad data sources, serves as a veritable playground for these techniques. Satellite imagery, with its panoramic vantage, offers continuous snapshots of cloud morphologies and sea surface temperatures. In tandem, terrestrial weather stations serve as meticulous chroniclers, documenting a suite of atmospheric metrics ranging from temperature and humidity to wind dynamics. Radar installations, with their keen focus, paint a detailed tableau of precipitation – its genesis, intensity, and trajectory. Ascending higher, weather balloons, like sentinels of the skies, offer a stratified glimpse into atmospheric conditions, capturing vertical nuances often overlooked by other instruments [11].

In the mosaic of deep learning applications tailored for meteorological pursuits, two research trajectories have gained prominence. The first orbits around leveraging cutting-edge deep learning architectures for remote sensing applications. Venerable models such as TITAN and NEXRAD, with their radar-centric focus, have pioneered video analytic techniques, particularly for identifying and tracing the tempestuous dance of thunderstorms. TITAN [4], for instance, stands out as a beacon in this space, consistently showcasing its mettle in storm cell detection and monitoring. It's worth noting that the precision of such tools is tethered to the fidelity and granularity of the radar data they assimilate. Given high-resolution radar feeds, TITAN manifests a commendable consistency in storm detection, tracking their trajectories and evolution in real-time. Predictive radar imaging, a byproduct of these models, offers forecasts on cloud drifts. While the prediction accuracy remains sterling for immediate short-term windows (spanning 1-2 hours), it wanes as the forecasting horizon extends [13]. In a similar vein, the Rapid Refresh model, with its focus on short-term predictions, has mirrored comparable accuracy metrics, underscoring the dynamism and potential of deep learning in reshaping the meteorological landscape.

2.2.2 Challenges and Limitations of ML Models

In the vast expanse of meteorological data that today's technology provides, it is somewhat paradoxical to observe that the majority of Deep Learning (DL) frameworks largely tether their predictions to short-term horizons, typically spanning no more than 24 hours. Furthermore, these systems, despite the plethora of available data, often draw upon only a modest subset of this reservoir, arguably not maximizing their predictive potential.

Nowcasting [9], a significant facet of these DL models, primarily focuses on foretelling the imminent trajectories and dynamism of storm cells. A characteristic feature of nowcasting, akin to most predictive systems, is its inversely proportional relationship between forecasting duration and accuracy. For instance, a tool like TITAN [4] or RainNet [2] exhibits commendable precision when tasked with predictions on an imminent scale, say, for the upcoming 30 minutes to an hour. Yet, when the model ventures to predict meteorological patterns 2-3 hours into the future, its accuracy exhibits a discernible decline. This attenuation in predictive power can be attributed to the inherent capriciousness of thunderstorms, which often resist deterministic predictions over such brief time scales.

A notable lacuna in the current modeling landscape is the limited emphasis on adaptability [11]. Few, if any, models have ventured into the realm of designing frameworks that can seamlessly transfer knowledge from one region to another. Such "transfer learning" capabilities would allow a model trained in one geographic region to be repurposed for another, potentially reducing computational costs and expediting deployment.

Moreover, while the models excel in general forecasting, there's a marked dearth of specialized tools that cater to particular meteorological phenomena [12]. For instance, events like lake-effect snows, which can have profound climatic and societal implications, often do not find prominent representation in most DL models. This underscores a broader need to diversify and specialize our modeling arsenal to cater to the myriad complexities that our atmosphere presents.

2.3 Summary

In the subsequent sections of this chapter, we undertake a thorough examination of the current state-of-the-art approaches utilized in weather forecasting. The discourse is initiated by providing an overview of the fundamental ideas, algorithms, and technological intricacies that form the basis of each of these well-established forecasting methodologies. Nevertheless, despite the notable progress in meteorological modeling, it is important to acknowledge the inherent limits associated with these methodologies. As the study advances, a thorough evaluation is conducted to discover inherent limitations within each approach, thereby illuminating areas that could benefit from further enhancement and refinement. The reoccurring difficulty highlighted in our critical review pertains to the authenticity and accuracy of forecasts, specifically in the context of a mid-range temporal window. The creation of our model is based on the recognition of this highlighted gap, with a specific emphasis on improving the accuracy of predictions throughout crucial time intervals.

Chapter 3

Data Assimilation and Model Evaluation

In the pursuit of deciphering the complexities associated with lake-effect snow, it becomes paramount to possess a detailed understanding of the prevailing meteorological conditions over and around the lake region [1]. Historically, researchers have leaned heavily on satellite imagery of the Great Lakes coupled with comprehensive meteorological data gleaned from locations ranging from the immediate lake shores to regions as far as 150 miles inland. Such an expansive data range is justified by the realization that peak snowfall, as a result of the lake-effect, predominantly manifests within approximately 10 to 40 miles (16 to 64 km) from the shoreline [2]. Yet, the true extent of this phenomenon is malleable, often influenced by the vastness of the lake in question and the direction and intensity of the winds at play.

For instance, vast water bodies like Lake Superior and Lake Michigan possess the ability to generate lake-effect snow bands which then travel and exert influence over remarkably distant inland areas. To provide perspective, specific atmospheric conditions can empower snow bands originating from Lake Superior to extend their influence over areas situated more than 100 miles (160 km) inland [3].

Instrumental in this research journey are satellites such as the Geostationary Operational Environmental Satellite (GOES) [4]. These sophisticated celestial observers proffer high-definition imagery pivotal in identifying and studying the morphologies of cloud configurations specifically linked to lake-effect snow. Ground-truthing these satellite observations is an ensemble of data sources: airports that register snowfall metrics, meticulously placed weather stations capturing a gamut of climatic conditions, and astute observations from trained meteorological spotters who document snowfall intensities and patterns. All these data, in tandem, equip researchers with the tools and insights necessary to unravel the phenomenon of lake-effect snow.

3.1 GOES Imagery Data

3.1.1 Data Summary

The Geostationary Operational Environmental Satellite (GOES) service, an initiative championed by the National Oceanic and Atmospheric Administration (NOAA) [5], serves as a beacon in this endeavor. This pioneering satellite platform has been instrumental in casting a detailed gaze over continental climates, archiving a decade's worth of precise atmospheric data that is generously available for public consumption.

At the heart of our computational methodology is the raw meteorological imagery curated by the NOAA GOES Weather Toolkit [6]. This state-of-the-art toolkit is not just a mere repository of weather data; it stands as a holistic suite equipped to render rich background maps, facilitate intricate animations, and conduct surgical filtering across selected spectral bands, thereby empowering researchers with the tools to derive actionable insights.

The workflow necessitates an initial stage of data procurement post toolkit extraction. Users are mandated to tap into the vast databanks housed on NOAA's FTP server. It's crucial to appreciate the depth and breadth of this data - the GOES weather satellite, armed with an array of sophisticated camera sensor modules, continuously surveils Earth's atmosphere. Depending on the specific operational timeline, users will find a palette of either 13 or 16 distinct spectral bands at their disposal. This spectrum spans two visible channels, four that operate in the near-infrared spectrum, and a robust set of ten infrared channels. Each of these channels plays a pivotal role in piecing together the holistic climate tableau, paving the way for a nuanced understanding of phenomena like lake-effect snow.

Here is a quick reference on all the available bands for selections shown in Table 3.1.

ABI Band Number	Central Wavelength (μm)	Notation	Band Type	Available Year
1	0.47	Blue	Visible	2007
2	0.64	Red	Visible	2007
3	0.86	Veggie	Near-IR	2007

ABI Band Number	Central Wavelength (µm)	Notation	Band Type	Available Year
4	1.37	Cirrus	Near-IR	2007
5	1.6	Snow/Ice	Near-IR	2007
6	2.2	Cloud Particle	Near-IR	2007
7	3.9	Shortwave Window	IR	2007
8	6.2	Upper-Level Tropospheric Water Vapor	IR	2007
9	6.9	Mid-Level Tropospheric Water Vapor	IR	2007
10	7.3	Lower-level Water Vapor	IR	2007
11	8.4	Cloud-Top Phase	IR	2007
12	9.6	Ozone	IR	2007
13	10.3	"Clean" IR Longwave Window	IR	2013
14	11.2	IR Longwave Window	IR	2013
15	12.3	"Dirty" Longwave Window	IR	2013
16	13.3	"CO_2" longwave infrared	IR	2013

Table 3.1: Band Description for GOES System

In the development of our project, meticulous emphasis was placed on leveraging data derived from the Band 1 sensor. This strategic decision emanated from extensive academic investigations undertaken by distinguished scholars across various reputable universities. Band 1 sensor stands out due to its unique characteristic of possessing the lowest central wavelength. Such a feature empowers it with the capability to continuously monitor and register a diverse array of atmospheric components, from intricate cloud formations right down to minuscule dust particles.

One of the quintessential features of the Band 1 sensor is its encompassing spectral coverage of all naturally occurring visible true colors – encapsulating the Red, Green, and Blue spectrum. Owing to this comprehensive spectral range, the Band 1 sensor showcases exemplary performance during daylight hours, capturing vivid and detailed imagery that proves invaluable for our analytical processes. This band's ability to vividly represent these true colors ensures that the data acquired is both accurate and meaningful, making it an ideal choice for our project's objectives [8].

3.1.2 2-D Lake Imagery Data

Within the ambit of our research, we have meticulously devised a robust data pipeline tailored explicitly for the analytical dissection of the Lake Michigan zone, distinctively segregating it from the expansive terrains of the Great Lakes region. Central to our investigative framework is the rigorous examination of quarter-hourly cloud density indices that span a dedicated temporal window from October 1, 2006, through to March 31, 2007—a considerable period of 11 years. This longitudinal perspective affords us unparalleled granularity into the intricacies of region-specific meteorological patterns, with an acute emphasis on phenomena such as lake-effect snow.

To enhance the precision of our analytical endeavors, we have harnessed a curated table encapsulating both longitude and latitude values pertinent to the shores of Lake Michigan. This targeted approach enabled the isolation of data specific to Lake Michigan, thereby mitigating the noise and variability that might be inherent in larger regional datasets. As we navigate through these indices, it is imperative to underscore their range—oscillating between values of 0 and 1—which serve as a lucid metric of the cloud cover intensity prevailing in the designated region.

In a subsequent phase of data transformation, we have judiciously marshaled this information into an organized 2D array construct. Within this matrix, each individual row embodies a specific latitude, while each column encapsulates a corresponding longitude. Embedded within this array is the pivotal cloud density index, a linchpin in our analytical framework. Such an arrangement not only streamlines our computational processes but also fosters an intuitive understanding of the data. Through this methodical configuration, we have engendered a platform that facilitates rapid identification and nuanced evaluation of distinct cloud concentration pockets native to the Lake Michigan territory.

After successfully converting our meteorological data into a two-dimensional array with dimensions 106 by 79, we proceeded with a comprehensive data refinement process to improve the clarity and specificity of our study. One of the primary processes involved in this process was the allocation of a numerical value of '0' to pixels that are situated outside the specified zone of Lake Michigan. The absence of intensity, when represented visually, corresponds to the color black. The necessity for such a differentiation was determined based on multiple factors.

The Lake Michigan region exhibits distinctive geographical and climatic characteristics that can result in occasional snowfall or the presence of reflective surfaces in inland locations. The occurrence of this phenomena might lead to interference in the interpretation of satellite pictures due to its reflecting nature. In particular, the presence of sunlight on terrestrial surfaces poses considerable difficulties in distinguishing between landforms and atmospheric cloud cover, just based on imaging observations.

In light of these inherent restrictions and the potential distortions they may cause, we have taken proactive measures to refine our dataset, ensuring that it only represents the domain of Lake Michigan. The utilization of this discerning methodology permitted the production of visuals that exclusively encompass the geographical region of Lake Michigan, thereby avoiding the aforementioned uncertainties in interpretation.

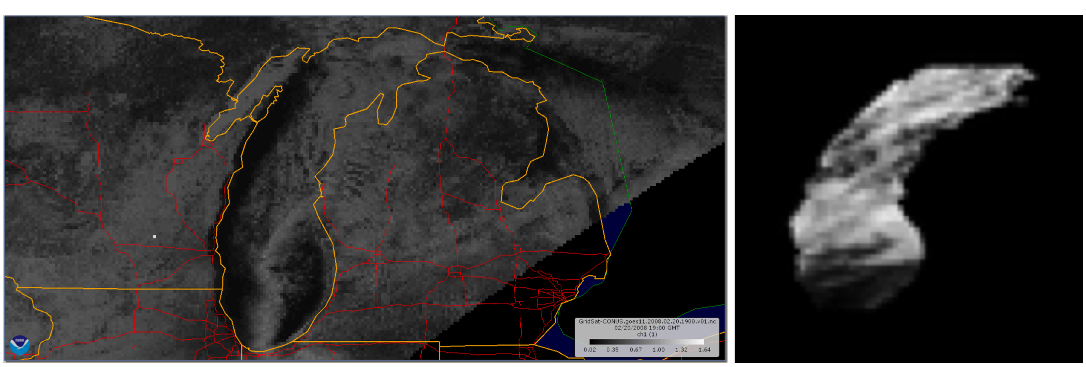

Figure 3.1: Pre- and Post-processed Sample of Satellite Images

Nevertheless, our efforts in data transformation did not cease at that point. The image was further enhanced through the removal of extraneous peripheral data, resulting in a downsizing of the matrix to a more practical dimension of 48 by 48 pixels. The prudent reduction described here serves to significantly decrease the amount of extraneous data designated for future training and validation. Importantly, this reduction preserves the overall morphological integrity of Lake Michigan. Therefore, notwithstanding its diminished size, the altered image remains a correct depiction of the unique contour of the lake, guaranteeing that our machine learning models have access to precise and efficient input datasets.

3.2 NWS Meteorological Data

3.2.1 Data Summary

In our research endeavor, we have profoundly depended on meteorological datasets assiduously gathered by federal weather stations, operating under the esteemed umbrella of the National Weather Service network [1]. With data recorded at hourly junctures, these collections are emblematic of a vast spectrum of parameters. Each of these meticulously documented parameters offers a profound window into the intricate meteorological intricacies that play a pivotal role in the genesis and dynamics of lake-effect snow.

The roster of directly procured parameters [9] is exhaustive and includes:

- **Temperature**: Articulated in Fahrenheit, this gives insights into the ambient atmospheric conditions.
- **Relative Humidity**: Expressed as a percentage, it gauges the moisture content in the atmosphere.
- **Dew Point Temperature**: Also articulated in Fahrenheit, this signifies the temperature at which the air becomes saturated.
- **Wind Speed and Gust**: Denoted in miles per hour, they offer a perspective on the force and occasional surges of wind.
- **Wind Direction**: Measured in degrees and recorded at ten-degree intervals, it provides information about the orientation of prevailing winds.
- **Cloud Heights**: Denoted in feet, it provides an understanding of the vertical distribution of clouds.
- **Visibility**: Tracked in miles, it gauges the clarity of the atmosphere.

- **Atmospheric, Altimeter, and Sea Level Pressure**: All expressed in hecto-Pascals, these parameters provide invaluable information about atmospheric conditions at different altitudes and pressures.
- **Precipitation**: Quantified in inches, it records the amount of moisture deposition, be it in the form of rain, sleet, or snow.

To further bolster our analytical depth, two derivative metrics have been incorporated into our dataset:

- **Wind Chill**: Articulated in Fahrenheit, it encapsulates the perceived temperature drop induced by wind effects.
- **Heat Index**: Also expressed in Fahrenheit, this metric amalgamates actual temperature readings with relative humidity levels to project the perceived warmth.

The depth and precision of this meteorological data treasure trove provide us with a granular lens to dissect the environmental tapestry enveloping Lake Michigan. This, in turn, fortifies our comprehension of the lake-effect snow mechanisms and their multifarious manifestations.

3.2.2 Correlation Analysis Observations

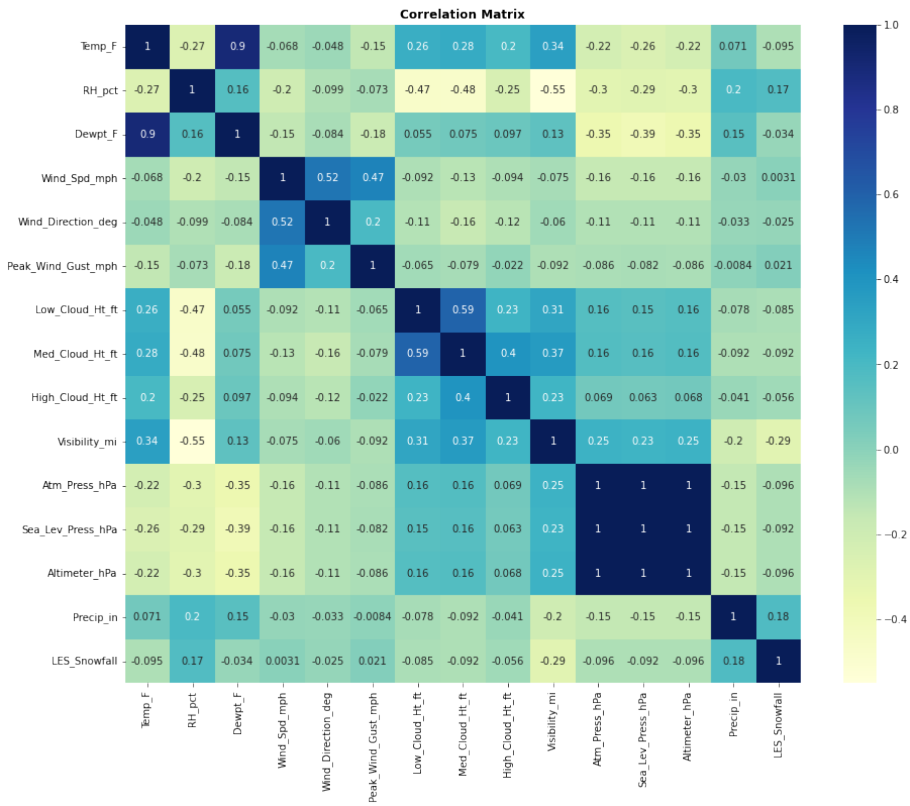

Figure 3.2: Correlation Matrix of Meteorological Data

Upon thorough examination of the provided correlation plots, several insightful patterns emerged:

1. **Prominent Correlations:** A cluster of features exhibited remarkably strong correlations with one another, registering a score of 0.50 or more.
    - The **Temp_F** variable showcased a pronounced correlation with **Dewpt_F**.
    - There's a tangible link between **Wind_Spd_mph** and **Wind_Direction_deg**.
    - A trinity of metrics, namely **Atm_Press_hPa**, **Sea_Lev_Press_hPa**, and **Altimeter_hPa**, were interrelated with profound intensity.
2. **Negative Correlations:** Although some strong negative correlations were discernible, none descended below the -0.5 mark. Given their magnitude, we deemed it unnecessary to eliminate these features from our dataset.

3. **Feature Redundancy:** In light of the aforementioned correlations, certain columns seemingly relay redundant information. Retaining such overlapping features would unnecessarily inflate our model, potentially compromising efficiency.

Before committing to any feature elimination, a closer inspection of **Atm_Press_hPa**, **Sea_Lev_Press_hPa**, and **Altimeter_hPa** was undertaken to discern their intrinsic dynamics. While not identical in composition, their inherent nature suggested a near-inevitable high degree of correlation. Subsequent to this examination, we resolved to remove:

- **Dewpt_F**
- Both **Sea_Lev_Press_hPa** and **Altimeter_hPa**

Our current approach errs on the side of caution. It's worth noting that perceptions of what qualifies as "high" correlation can be contingent on the specific analytical context and the peculiarities of the dataset under scrutiny. Often, correlation coefficients exceeding 0.8 or 0.9 are flagged as being of high magnitude. However, this isn't a universal benchmark, and distinct projects might warrant alternate thresholds. It's paramount that researchers remain attuned to the idiosyncratic demands of their study, ensuring that correlation thresholds are not only empirically sound but also contextually appropriate.

3.3 Observation and Forecast Duration Analysis

Clouds can form at any time, regardless of day or night. However, there are specific mechanisms during the daytime that enhance cloud formation. Here's why clouds commonly form during the day:

1. **Solar Heating and Convection:** During daylight hours, the sun provides thermal energy to the Earth's surface, resulting in an increase in temperature. As solar radiation is absorbed by the earth, it undergoes an increase in temperature. The phenomenon of warm air at the Earth's surface becoming less dense and subsequently ascending is referred to as convection. As the warm and moist air ascends, it undergoes a cooling process and expands due to the reduced atmospheric pressure at higher elevations. The atmospheric moisture undergoes condensation, resulting in the formation of minuscule water droplets or ice crystals. These droplets or crystals subsequently combine to create cloud formations.
2. **Thermal Currents:** In diurnal periods, specific regions on the Earth's surface may experience differential rates of thermal absorption, resulting in varying degrees of heating. The phenomenon of differential heating, such as the contrast between a paved road and

a grassy field, can give rise to the development of localized upward-moving air currents referred to as "thermals." The upward movement of these thermals facilitates the ascent of humid air, which, upon undergoing cooling, might result in the development of clouds.

3. **Topography-Induced Lift:** In regions characterized by the presence of mountains or hills, the diurnal heating process can induce wind patterns that result in the ascent of air down the slopes. The phenomenon of orographic lift can also result in the process of condensation and subsequent creation of clouds.
4. **Land-Sea Interactions:** In coastal areas, the differential heating between land and ocean during the afternoon can lead to the formation of a sea breeze. This phenomenon induces the inland movement of colder air originating from the sea, thereby displacing the warm air present over the land in an upward direction. The upward movement of warm air has the potential to give rise to the formation of clouds.
5. **Human Activity:** The diurnal period, also known as daytime, is characterized by the culmination of human activities, resulting in heightened levels of pollution and particulate matter within the Earth's atmosphere. These particles have the ability to function as cloud condensation nuclei, serving as sites for the condensation of water vapor and subsequent formation of cloud droplets.
6. **Increased Visibility:** Additionally, it is important to acknowledge that our impression of clouds can be altered by the varying levels of lighting. Cloud formation is indeed influenced by the aforementioned elements. However, the visibility and perceptibility of clouds are enhanced in the presence of sunlight, in contrast to the diminished visibility seen during darkness.

In the course of our study, we provide a specific definition for the term "lake-effect precipitation event." We designate such an event as the onset of cloud formation over Lake Michigan during daylight hours. This delineation is grounded in the empirical understanding that the evaporation rate from the lake's surface is markedly enhanced during the period between sunrise and sunset. The underlying reason for this phenomenon is the pronounced rise in temperature due to solar radiation, which accelerates water vaporization. Given this premise, a central focus of our analysis is the tracking of the temporal interval between the initial emergence of clouds over Lake Michigan and the onset of precipitation over the adjoining terrestrial regions.

To ensure a comprehensive analysis, our data sampling incorporated weather stations strategically situated at varying proximities from the Lake Michigan shoreline, ranging from 10 to

100 miles inland. These stations facilitated a rigorous monitoring of the aforementioned temporal intervals. For a visual representation of the distribution of these intervals, readers are referred to Figure 3.3, which showcases a histogram detailing the relevant data.

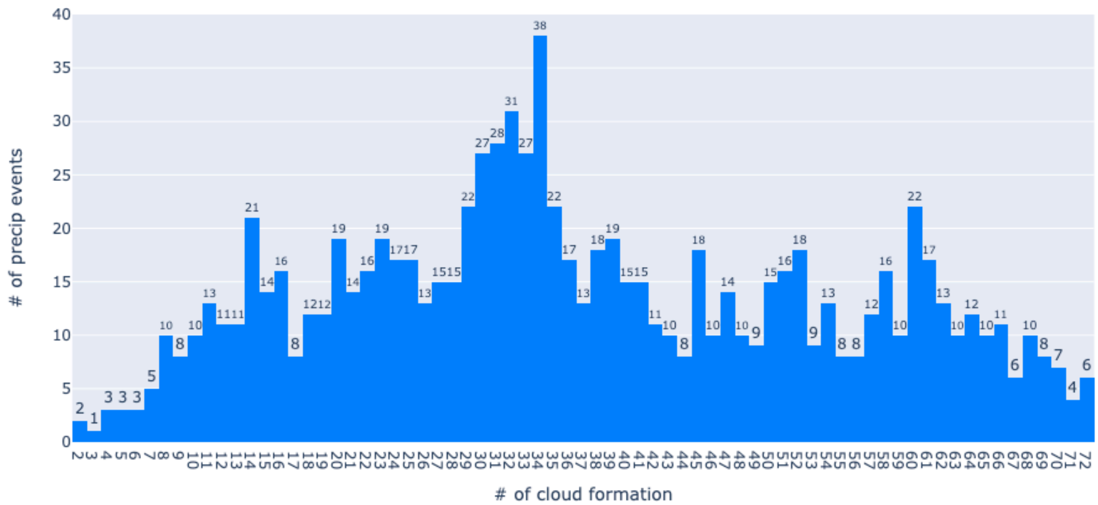

Figure 3.3: Overall Duration of Cloud Formation Before All Precipitation

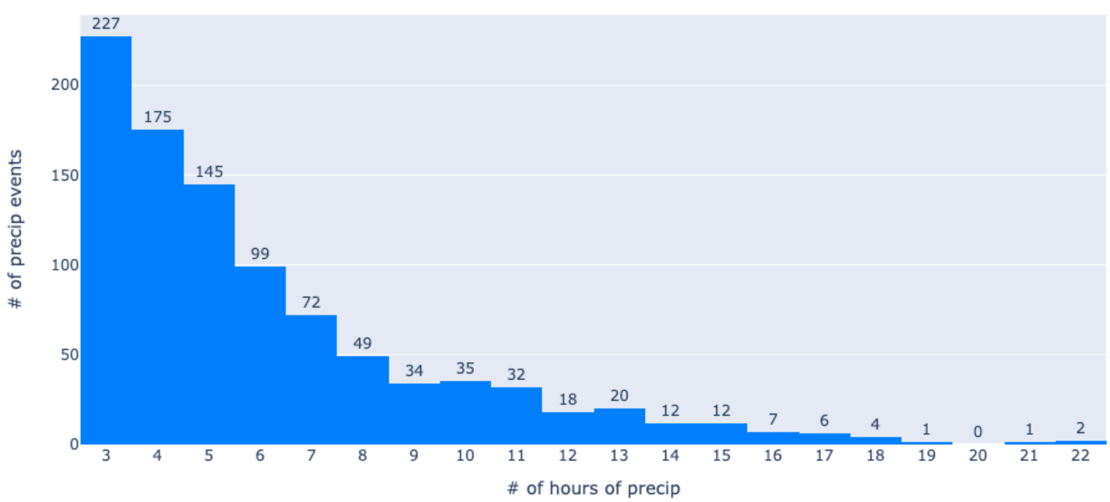

Figure 3.4: Overall Duration of Precipitation Events

In an extension of our investigation, we embarked on an exhaustive assessment of the durations of lake-effect precipitation events as recorded by the potentially impacted weather stations. The compilation of these durations, presented in a structured manner, can be visually inspected in Figure 3.4. Drawing insights from this assembled data, certain critical conclusions emerge regarding optimal observation and prediction windows for our forecasting model.

Upon analysis, it becomes evident that an observation window spanning 72 hours encapsulates the most relevant and significant data, thus maximizing the informational input crucial for accurate forecasting. When turning our attention to the prediction time window, we discern that a baseline of 24 hours is indispensable. This duration ensures the model's capability to comprehensively detect and represent the majority of lake-effect associated precipitation events.

Proceeding from these insights, the subsequent phase of our research involves empirical testing. We intend to methodically experiment with various combinations of observation and prediction time windows. The primary objective of these trials is to ascertain the precision with which our model identifies lake-effect precipitation events at specified locations.

3.4 Model Summary

3.4.1 Goal of This Study

In the pursuit of advancing meteorological forecasting, the primary objective of this research is to conceptualize and develop a predictive model that seamlessly integrates both satellite imagery and meteorological datasets. To achieve this, our architectural design adopts a bifurcated approach. Specifically, two distinct subnetworks are constructed - one dedicated to processing satellite imagery and the other to assimilating meteorological data.

The ingenuity of the model lies in its final stages. After independent processing within their respective subnetworks, the outputs are then concatenated using a dense layer. This methodological fusion ensures that the model imbibes comprehensive spatial-temporal information from both sources. Consequently, this enriched information repository augments the model's capability, enabling it to adeptly forecast lake-effect precipitation events within defined observation and prediction time windows. The overall structure of the model can be seen in Figure 3.5.

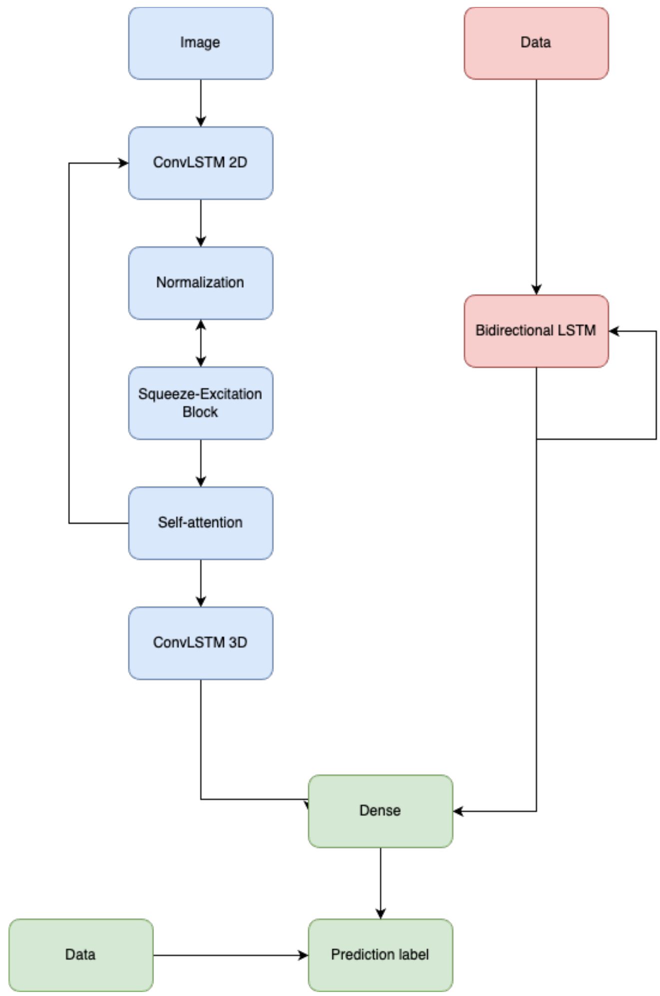

Figure 3.5: Structural Presentation of Established Model

3.4.2 Imagery Subnetwork

Within the realm of imagery data for this study, our selection criteria honed in on a specific temporal sequence. We strategically chose a contiguous set of 8 images spanning each day, with the time frame demarcated between 14:00 and 21:00 Coordinated Universal Time, which represent the daytime in the local state. This decision was predicated on the rationale that this window encapsulated significant meteorological patterns vital for our analysis.

For the associated label of each time-series frame, we adopted a forward-looking approach. Instead of relying on concurrent precipitation values, the label was designed to reflect the cumulative precipitation metric for the succeeding day. To ensure continuity and non-overlapping data samples, we employed a systematic approach to data extraction: with each subsequent sample being gleaned by translocating the original 24-hour window by an equivalent interval, thereby achieving a rolling window effect for our dataset.

In this study, the image data fed into our model bears a resolution of 48x48 pixels, which is particularly chosen to retain the essential spatial characteristics while being computationally efficient. Our methodology involves harnessing the capabilities of ConvLSTM2D, a sophisticated neural network architecture. This architecture amalgamates the spatial feature extraction prowess of Convolutional Neural Networks (CNN) with the sequential data processing strength of Long Short-Term Memory (LSTM) networks.

The ConvLSTM2D is specifically designed to manage spatial sequences [14], wherein each frame in the sequence has spatial correlations. By adopting this architecture, we are poised to perform image classification across a series of frames rather than on isolated instances. This enables the model to discern patterns that unfold both spatially within each image and temporally across the sequence, thereby bolstering its predictive accuracy and relevance in the context of meteorological data. The output of the imagery subnetwork has a length that matches with the number of input images.

In our quest to elevate the performance of the imagery subnetwork, we introduce advanced architectural augmentations—specifically, the integration of squeeze-excitation (SE) blocks [12] and self-attention mechanisms interposed amidst ConvLSTM2D layers. These inclusions are precisely orchestrated to augment the model's discriminative learning capabilities, which we detail below:

1. **Squeeze-Excitation (SE) Block**:
    - **Purpose**: Neural networks, despite their capacity to model complex functions, may not always exhibit optimal channel-wise feature recalibration, potentially leading to suboptimal representations.
    - **Mechanism**: The SE block is tailored to execute explicit channel-wise feature recalibration. It adaptively adjusts channel-wise feature responses by explicitly modeling the interdependencies between channels.
    - **Process**: The block consists of two distinct stages, namely "Squeeze" and "Excitation". During the "Squeeze" step, the process of aggregating global geographical information is employed to generate channel-wise statistics. Subsequently, the "Excitation" phase utilizes the aforementioned information to calculate recalibration weights specific to each channel. The weights are employed for the purpose of rescaling the initial feature maps, thereby emphasizing more pertinent features and diminishing superfluous ones.
2. **Self-Attention Mechanism**:
    - **Purpose**: Within the realm of imagery, it is important to acknowledge that various parts of a picture do not possess equal significance in terms of their contribution to the portrayal of an item or scene. Certain geographical areas may possess a higher degree of informational content, whereas others may have a lower level of informativeness. The objective is to enhance the network's ability to prioritize regions of significance.

- **Mechanism**: The self-attention mechanism equips the network with the capability to weigh the importance of different regions in the image in a dynamic manner.
- **Process**: At its core, the self-attention mechanism calculates a weighted sum of features, wherein the weights are based on the compatibility of features with other features in the image. In other words, it captures the global dependencies of features, regardless of their spatial proximity. This provides the network a more global perspective, allowing it to discern and prioritize regions in the image that are crucial for the task at hand.

The combined utilization of SE blocks and self-attention processes within the network augments its overall efficacy. The SE block is responsible for fine-tuning the dynamics of channel-wise features [10], whereas the self-attention mechanism is responsible for refining spatial dependencies. The inclusion of ConvLSTM2D layers within the model enhances its capacity to incorporate temporal and spatial relationships. This results in improved feature representations and, subsequently, higher predictive accuracy.

In conclusion, the integration of these sophisticated modules seeks to improve the model's ability to identify complex patterns, which is essential for meteorological forecasting jobs. This is achieved by optimizing both channel-wise and spatial feature recalibrations.

3.4.3 Meteorological LSTM Network

In contrast to the imagery-centric subnetwork, the meteorological subnetwork is devised to process temporal sequences of atmospheric parameters. This intricacy in its data structure and inherent patterns necessitates a divergent architectural approach. Herein, we elucidate the details of this subnetwork.

- **Data Input:** The meteorological subnetwork is fed with a multi-dimensional dataset comprising 11 distinctive meteorological features. This dataset encapsulates the entirety of a day, capturing variations across all 24 hours. A day-long granularity is deliberately chosen to ensure the network is privy to the complete diurnal variations inherent in the meteorological parameters. Such comprehensive data ingestion is pivotal for discerning subtle nuances and patterns which could be influential in forecasting.
- **Bidirectional LSTM (Bi-LSTM) Network:** While traditional LSTMs process data from the start to the end of a sequence, in many meteorological scenarios, the future state might provide valuable context to understand the past. The Bidirectional

paradigm allows the model to access information from both past (backward direction) and future (forward direction) states simultaneously. The Bi-LSTM layers consist of two LSTMs: one processes the sequence from start to end (forward LSTM) while the other processes it from end to start (backward LSTM). By doing this, at any point in time, the model has information about what happened before and after a particular event. This bidirectional processing endows the network with a more comprehensive understanding of the sequence, making it adept at capturing patterns that might be missed by traditional unidirectional LSTMs.

3.4.4 Output Harmonization

A salient feature of this architecture is the congruence in the output dimensionality of both subnetworks. The meteorological subnetwork's output is designed to mirror the number of images employed in each input sequence of the imagery subnetwork. This design choice facilitates seamless integration when outputs from both subnetworks converge. By ensuring matching dimensions, we sidestep potential bottlenecks during data fusion, allowing for a smooth and efficient concatenation process in subsequent stages.

3.4.5 Result

In our endeavor to ascertain the optimal temporal window for predicting lake-effect precipitation events, we embarked on a systematic exploration, assessing varying observation durations against their corresponding forecast periods. Specifically, our study gravitated around three primary combinations:

1. 24-hour Observation vs. 24-hour Forecast: We commenced by delving into the most immediate window. Here, we furnished the model with meteorological data from a 24-hour span and tasked it with forecasting the meteorological conditions for the subsequent 24 hours. This short window sought to gauge the model's efficacy in near-term predictions.
2. 48-hour Observation vs. 48-hour Forecast: Our observational horizon was expanded to two days, with the model entrusted with predicting the succeeding 48 hours. This intermediate window tested the model's robustness in maintaining predictive accuracy over a slightly extended timeframe.
3. 72-hour Observation vs. 72-hour Forecast: The final and the most extended observational window spanned three days. The model, armed with 72 hours of historical data, was directed to prognosticate the weather patterns for the following three days. This long window aimed to assess the limits of the model's predictive capability.

For the purpose of this analysis, we posited a benchmark criterion. Any total precipitation within either the observation or forecast window that surpasses 0.10 inch is classified as a severe lake-effect precipitation event. This threshold was instrumental in distinguishing ordinary from extraordinary precipitation episodes, thus aiding the models in discerning patterns germane to significant lake-effect events.

The locale for this analytical exercise was not arbitrarily selected. Traverse City, situated approximately 35 miles to the east of Lake Michigan, is in the direct trajectory of lake-effect influence, rendering it particularly susceptible to lake-effect precipitation. Such a location is emblematic, and its meteorological patterns provide rich insights into the dynamics of lake-effect events. The results are shown in Table 3.2.

Model	NOT Harsh LES Precipitation	Harsh LES Precipitation	Overall Accuracy
24 -> 24	93.893 %	27.083 %	87.419 %
48 -> 48	83.028 %	50.538 %	73.312 %
72 -> 72	84.091 %	77.612 %	81.290 %

Table 3.2: Systematic Prediction Summary

Model	NOT Harsh LES Precipitation	Harsh LES Precipitation	Overall Accuracy
72 -> 24	98.473 %	27.083 %	87.419 %
72 -> 48	93.689 %	62.500 %	83.226 %
72 -> 72	84.091 %	77.612 %	81.290 %

Table 3.3: Validation Accuracy for Using 72 Hours Observation to Predict 24, 48, and 72 Hours

Observation Time Window	NOT Harsh LES Precipitation	Harsh LES Precipitation	Overall # of Cases
24	262	48	310
48	206	104	310
72	176	134	310

Table 3.4: Number of Cases 24, 48, and 72 Hours in Validation Data

Following our initial analyses, we refined our approach to further probe the predictive capabilities of the model over varying forecast windows, while maintaining a fixed observational period. Specifically, we harnessed 72 hours of historical observation data and gauged its efficacy in forecasting lake-effect precipitation events over three distinct future intervals:

1. Next 24 hours
2. Subsequent 48 hours
3. Ensuing 72 hours

The outcomes of this focused study are systematically tabulated in Table 3.3, presenting a lucid juxtaposition of the 72-hour observational data against its predictive accuracy over the three forecast horizons.

Through this systematic and graded approach, we sought to discern the optimal observation-prediction window combination that yields the highest accuracy in forecasting severe lake-effect precipitation events. Furthermore, to offer readers a granular insight into the composition of our test set and the inherent challenges in forecasting, Table 3.4 enumerates the total number of instances encountered within each distinct label category. This enumeration aids in contextualizing the model's performance, offering a holistic view of both its successes and areas warranting further refinement.

In a detailed review of the outcomes from our initial experimental set, several patterns and insights emerge:

1. **Accuracy Paradox with 24-hour Observations**: At a first glance, the pronounced accuracy attained when deploying a 24-hour observation window to predict the subsequent 24-hour interval might suggest superior model performance. However, a deeper analysis reveals that this ostensibly high accuracy is predominantly a consequence of class imbalance in the prediction phase. Essentially, the accuracy metric was skewed due to the disproportionate representation of the two prediction classes.

2. **Shortcomings of Limited Observation Windows**: The constrained, 24-hour observation window evidently curtails the model's ability to grasp comprehensive atmospheric dynamics, especially in the context of severe lake-effect precipitation events. While it might offer a snapshot of meteorological conditions, this timeframe is seemingly insufficient to capture the nuanced lead-up to significant climatic occurrences.

3. **Validation of the 72-hour Observation Hypothesis**: On the other end of the spectrum, the marked success achieved with the 72-hour observation window in predicting future events aligns well with our preliminary hypothesis. The extended observation span evidently equips the model with a richer contextual backdrop, enhancing its capacity to discern and predict severe lake-effect precipitations. This not only validates our initial postulations but also underscores the inherent value in adopting a comprehensive observation strategy for optimal training and forecasting outcomes.

In delving deeper into the findings from our second experimental suite, several critical observations surface:

1. **A Shift in Prediction Accuracy**: One of the more salient observations from this experiment is the model's contrasting performance dynamics across varying precipitation events. While the model manifests a drop in predictive accuracy for non-severe lake-effect precipitation events, its performance notably escalates for more extended prediction durations.

2. **Model Sensitivity to Prediction Window**: A significant contributing factor to this observed trend is the model's heightened sensitivity to the length of the prediction window. As this window expands, the model seems to leverage the accumulating meteorological data more effectively, facilitating more precise forecasts for impending weather anomalies.

3. **Balancing the Dataset Imbalance**: A noteworthy aspect underpinning this phenomenon is the progressive rectification of the dataset's inherent imbalance as the prediction duration extends. The longer prediction horizons essentially offer a more balanced representation of meteorological events, diminishing the skewness present in shorter windows. This balanced view, in turn, appears to enhance the model's proficiency in distinguishing and forecasting severe lake-effect precipitation events, even as it slightly underperforms in predicting milder weather conditions.

Overall, these insights underscore the importance of carefully calibrating the prediction window in weather forecasting models, particularly when working with datasets that may exhibit class imbalances or other inherent biases.

3.5 Summary and Future Works

In this study, we have robustly navigated towards our primary objective of attaining elevated predictive accuracy, especially when forecasting intense lake-effect precipitation events over mid-duration time frames. This research not only shines a light on the optimal observation and prediction windows pivotal for reliable meteorological forecasting but also paves the way for subsequent investigative endeavors.

1. **Reassessing Model Thresholds**: While the achievements of this study are palpable, there remains a significant opportunity space around our model's further refinement. A key aspect worth deliberating upon is the class-separation threshold. By recalibrating this threshold, the model's proficiency in anticipating severe meteorological phenomena – such as high-velocity lake-effect snowstorms that pose substantial socioeconomic challenges for Lake Michigan's peripheries – can be notably bolstered.
2. **Geolocation Transferability of the Model**: An intriguing avenue for further exploration is assessing the geographical transferability of our model. Understanding whether a model, primed on data from one specific location, can be seamlessly applied to proximate areas without significant retraining will be seminal in gauging its adaptability and potential for broader deployment.
3. **Computational Efficiency and Accessibility**: While the model's computational performance throughout the training phase has been commendable, it's imperative to acknowledge the infrastructural heft underpinning it – particularly the reliance on high-caliber hardware configurations like NVIDIA A100 SXM-80GB and H100 SXM-80GB. Looking ahead, it would be propitious to scout avenues for refining the model's architecture. The aspiration would be to retain, or even enhance, its predictive prowess but achieve it on more economical hardware platforms. Such advancements would significantly democratize access, making high-fidelity weather prediction more accessible and feasible across a wider spectrum of computational setups.

In summation, while the current milestones of this research are both significant and promising, the horizon ahead beckons with myriad opportunities for enhancement, expansion, and deeper exploration.

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