Automation of Weather Forecast Data Summarization

Final Design Specification

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Executive Summary

The Meteorological Services of Canada (MSC) employs meteorologists, in the capacity of operational weather forecasters, to provide accurate and reliable weather information to audiences like the military, aviation and marine programs, media, and other weather information dissemination services. Operational forecasters use the MSC Weather Forecasting System (MWFS), a collection of tools and software applications, to facilitate the generation of weather forecast products. The forecast products consist of weather summaries for predefined geographical regions - called zones. As the zones vary in area, the weather summaries are not able to capture the complexity of the weather across the zone. As such, the Data Structure and Standards (DAS) team at the MSC, has ventured to solve this issue by employing the expertise of this capstone team.

Based on research and investigation of the current system, two major problems causing the inefficiency in MWFS have been identified: first the current system does not provide sufficient detail in the weather summaries, and second the meteorologists do not have flexibility to choose which level of detail they want to include in the summary. In the following report, the project requirements that have been developed as a result of this research are specified with objectives, constraints and metrics. The key design considerations include design for speed, scalability, modularity, flexibility, low additional data demand, solution interpretability and customizability. Throughout the Capstone project, the team integrated the design process with many design approaches and engineering methodologies to ensure the design would pass validation and verification. Many solution concepts were also generated and evaluated in order to find the best design solution.

The final design of this Capstone project is an automated and integrated solution that contains (1) a new operating model, which maximizes the scale of process automation while ensuring meteorologists' knowledge is still retained; (2) a machine learning model, which detects and aggregates spatial and temporal weather patterns regarding temperature, cloud coverage, precipitation, wind speed and direction, with adjustable sensitivity settings. Users no longer need to open all data and MWFS models in different applications. Everything is in one place and easy to access.

This solution was tested against the project requirements by the meteorologists. The evaluation results reassure that the final solution has outstanding performance when solving the two major problems. The solution summarizes weather data at various levels of granularity, provides more insights from the spatial and temporal data aggregation, and visualizes those insights to be easy to digest. All weather patterns are captured homogenous weather patterns in 100% of the cases provided. It reduced the task time by 19 minutes per forecast summary on average compared to the current MWFS.

Finally, the future direction of this work along with potential future work is discussed, including an interface that records meteorologists' interactions with the model for future training and improvement, and an advanced text generator that translates output data into forecast messages to downstream audiences.

1.0 Introduction

In this report, we will quickly introduce the background of Environment and Climate Change Canada (ECCC) and its weather forecasting system (MWFS). We would discuss the current problems within the MWFS and their impacts on ECCC and external organizations. The problem is defined with the problem statement and requirements. We will review the engineering approach and methodologies the team integrated through the entire design project, and discuss the final design solution and implementation. Results of the verification and validation are analysed to check if the system was designed correctly and the correct system was designed for the client. Finally, we would like to conclude the project with the major achievements and directions for future developments and improvements.

2.0 Background

Communicating weather information has become increasingly demanded as methods and technologies have evolved to enable weather forecasting. Governmental agencies, like Environment and Climate Change Canada (ECCC), employ meteorologists to issue weather forecasts and alerts to protect life, property, and economic interests across Canada [9]. In order for the meteorologists to perform their role as forecasters, the meteorologists at the Meteorological Services of Canada (MSC) use the MSC Weather Forecasting System (MWFS - a collection of rules-based expert systems that generate forecasts) [8].

Today, the MWFS uses NWP models and predefined geographical regions, called zones, as inputs. The gridded data (from the selected NWP models) is then summarized for the selected zone to produce a weather summary. The weather summary for all zones, regardless of zone size, contains the same level of detail. For instance, a single temperature value provided in a weather summary is used to represent the temperature of a zone that spans $40km^2$ or even $400km^2$.

3.0 Problem

3.1. Problem Statement

Over the past three decades, the existing weather forecasting system prioritizes satisfying redundant business rules over providing detailed weather forecasts. From our analysis of the current process, we identified two major problems:

- The current system does not provide sufficiently detailed weather summaries
- The meteorologists do not have flexibility to specify which level of detail they want to include in the summary

This is a significant issue as the audiences of the weather information (i.e. the audiences that are residing in or visiting the geographical region) may be presented with a weather summary that is not representative of the weather at their specific point of residence. Hence, from the perspective of the audiences, the weather summary provided to them is imprecise.

To resolve these two problems, the team needs to design a new solution that must satisfy the following goals: to recognize data patterns from weather and geographical data, and aggregate the data to summaries. It must also provide the weather summaries in various levels of details given the time and spatial range.

3.2. Problem Relevance

By overcoming the efficiencies in the current process, ECCC would be able to reduce meteorologists' workload, diminish the MSC's operational waste, provide more control to operating meteorologists, and produce more granular forecasts. This will result in more detailed weather forecast summaries that will benefit the interests of downstream audiences like the general public, aviation program, marine program, and the military.

Providing weather summaries that are insufficient in detail can also result in commercial and economic consequences for industries like tourism. For instance, the geographical region spanning from Port Dover in the west, Port Stanley in the east, Norwich in the north, and Long Point National Wildlife Area in the south is represented by a single geographical region (called "Zone A") for which a single weather summary is provided to forecast the weather - an area that spans nearly 200 km^2. The Long Point National Wildlife Area is an attractive tourist area that is visited by many campers, hikers, and outdoor enthusiasts in the warmer months of the year. A weather summary may suggest that the probability of precipitation (PoP) is 100% for the next 2 days in Zone A. This may only be the case for the 10 km^2 near the west end of Zone A - near Port Stanley. However, the weather summary does not contain sufficient detail to specify this information. As a result, visitors of the Long Point National Wildlife Area may decide against their visit due to the weather information provided to them - resulting in economic losses for the Wildlife Area.

3.3. Current Weather Forecast Production Process

In this section, the current system employed by ECCC to produce weather forecast information, would be discussed and analyzed.

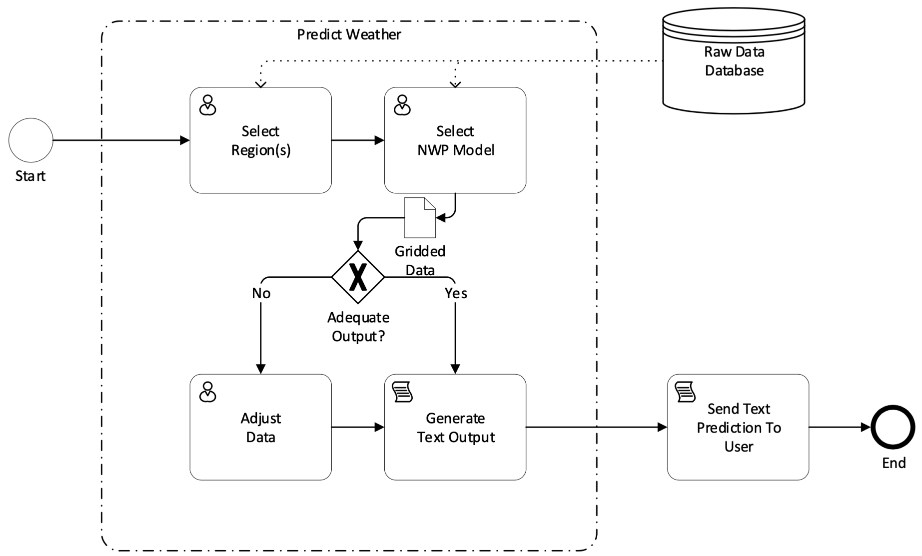


Figure 1: *Current Weather Forecast Prediction Business Process Diagram*

Weather information is measured and collected by ECCC through specialized weather equipment that is displaced across the country. These measurements are available in the MWFS where they can be used for weather forecasting and alerting.

An operational forecaster will initiate a forecast using Scribe (a weather forecasting software application in the MWFS) by selecting a geographical region and an NWP model [6]. The collected weather measurements are fed into the NWP Model to produce weather forecasts in a gridded format with a 2.5 km^2 resolution for the selected region. The gridded data are then aggregated to produce a weather summary for the selected geographical region. At this point, the forecaster must determine if the provided weather summary is adequate. If not, the forecaster can add only a single additional weather detail in the form of an exception using Scribe. The weather summary after the adjustment will then be fed into the Scribe text generator as a meteocode file (a proprietary information format) that will produce a final forecast product [7].

3.4. State-of-the-Art Review

In this section, many weather forecast prediction methods currently being employed in the industry will be briefly summarized. The most simple model is **Persistence & Trend prediction**, which assumes that the atmosphere changes extremely slowly such that it is equivalent to no change over a short period of time [1]. Hence, persistence models assume that the predicted weather is the same as the current weather. Another prediction method is **Analogue Forecasting** (AF) in which forecasters look for a point in history that closely matches the current state of the weather. This assumes that if two atmospheric states are very close initially, they will be relatively similar over the short-run [2]. The most successful weather prediction method so far is **Numerical Weather Prediction** (NWP), which uses sophisticated physical models and equations [1]. With the advancement of computational power and the emergence of artificial intelligence and machine learning, new methods of predicting weather became possible. The main three are **linear regression**, (fuzzy) **clustering**, and **neural networks** [3]. These methods require a large amount of data in order to train on and learn from.

Most successful models focus on very short-range forecast predictions (See Appendix A for range definitions). Almost all state-of-the-art models use combinations of the following inputs:

- Observational data sources
    - Weather towers
    - Weather sensors
    - Satellite
    - Radar
- Historical and climatological databases
- NWP model forecasts
- Operational forecaster/meteorologist expertise

AccuWeather, a successful commercial weather forecasting service, uses a Percentage-of-Precipitation (PoP) forecast model which uses many inputs such as current observational data sources, historical and climatological database sources, numerical model forecast sources, and direct input from operational forecast meteorologists to provide a percentage chance that a measurable amount of precipitation will fall at a specific location at a specific time [4].

Researchers have looked into improving the accuracy of weather prediction by investigating the spatial factor and restricting the scope of prediction to a very specific geographic area. They studied the effectiveness of predicting PoP using neural networks as opposed to other methods such as linear regression or nested grid models (NGMs). The consensus is that linear regression is better at predicting PoP at localized areas than other statistical and deep learning models [5].

4.0 Requirements

4.1. Stakeholders

In this section we will discuss the groups who are interested or affected by this problem. The primary stakeholders such as the clients, operators, users, along with other secondary stakeholders are identified. Their interest and involvement in the project are also analyzed.

4.1.1. Primary Stakeholders

Table 1: *Table of primary stakeholders and their interests*

Stakeholder	Interests
Client - The Data Architecture and Standards (DAS) team	The DAS team at the MSC branch of ECCC consists of business analysts, system analysts, GIS specialists, data specialists, and computer scientists. The DAS team represents the needs of the current operational forecasters. The DAS team: - Are guiding the capstone project's direction - Are providing the capstone team with information and resources - Are providing the opportunity to elicit requirements - Are evaluating the requirements analysis - Are providing feedback on solution ideas - Are enabling the integration of the final solution into the MSC Weather Forecasting System (MWFS)
Operators and Users - Operational Forecasters	Forecasters are meteorologists who provide Canadians with real-time weather alerts and weather forecasts. Although they are not the primary point of contact for the capstone project, their needs are being addressed through the capstone project - as represented by the DAS team (introduced above). Task forces like the DAS team have been employed to address their needs and concerns. Operational forecasters: - Provide feedback regarding the project to the capstone team via the DAS team - Are interested in seeing this project succeed as it will address one of their many needs.
Users - Public Audiences	Public audiences are the receivers of the weather forecast information provided by operational weather forecasters. Public audiences consist of military, aviation and marine programs, media, and other weather information dissemination services,

	and the general Canadian population. These audiences receive weather forecasts and alerting information to protect their safety, economic, and commercial interests. Public audiences: - Are drivers of improvement at the MSC - Are interested in receiving accurate, reliable, and sufficiently complex weather forecast information. - Provide feedback to the MSC that has driven the change that this project hopes to address

4.1.2. Secondary Stakeholders

Table 2: *Table of secondary stakeholders and their interests*

Stakeholder	**Interests**
MSC Consultants	The current consulting team to MSC is identified as the process owner and had played a pioneering role in the development of the MSC Weather Forecasting System (MWFS). The MSC consultants: - Are invested in the improvement of the current forecasting system at MSC - Are invested in hearing the feedback of public audiences - Provide direction to the DAS team to navigate projects related to the MSC
The information management & information technology (IM/IT) branch	The IM/IT branch of the Government of Canada operates as enablers that perform the technological development, testing, integration, evaluation, and management of the tools required to address business needs as communicated to them by other branches of the government. The IM/IT branch: - Are interested to officiate and integrate the solution of this capstone project into MWFS

4.2. Functions

The primary function and its enablers capture what the design of the solution must do. The functions are problem-oriented and solution-independent. As such, they will allow for an exploration of multiple solution-oriented designs. The following table captures all the primary and secondary functions:

Table 3: *Table of primary and secondary functions*

Primary Function	The design of the solution must provide weather summaries[1] in varying levels of complexity across a specified spatial region (zone).

[1] A weather summary is a data aggregation over a specified area at a specific time

Secondary Functions (Enablers)	The design of the solution must recognize patterns in the weather data.
	The design of the solution must recognize patterns in the geographical data.
	The design of the solution must identify spatial regions (sub-zones) where patterns are observed.
	The design of the solution must aggregate weather data into weather summaries.
	The design of the solution must capture forecaster knowledge.

4.3. Objectives & Constraints

The objective defines what the design of the solution should be. The constraint is the maximal or minimal limit that must be achieved by the design solution.

Based on investigation and analysis conducted with the stakeholders, the team re-formatted the objectives and constraints from the Project Requirement document because not all objectives and constraints correspond to a one-to-one relationship. The team also revised the metrics to be more measurable and to better reflect the objectives.

Objectives

1. The design of the solution should perform aggregation quickly.
2. The design of the solution should be easy for users to set up.
3. The design of the solution should provide flexibility to select granularity of the summary.
4. The design of the solution should aggregate weather information in detail.
5. The design of the solution should capture the accurate weather patterns with precision.

Metrics

For each metric, the related objective is labelled in the brackets.

1. Average time spent on completing weather pattern identification and data aggregation (O1)

Unacceptable	Satisfactory	Good	Outstanding
> 10 min*	<= 10 min	<= 5 min	<= 3 min

*The average time for a meteorologist to complete pattern identification is 20 minutes. Therefore the constraint is set as a half of the time.

2. Average time reduced by the automated process compared to the human performance with the current MWFS applications (O1)

Unacceptable	Satisfactory	Good	Outstanding
Time reduced less than half of the original task performance time	Time reduced by the factor of 2 or more	Time reduced by the factor of 5 or more	Time reduced by the factor of 10 or more

3. Resources required to set up the solution (O2)

Unacceptable	Satisfactory	Good	Outstanding
Requires software/application(s) with commercial license to execute the solution	Does not require commercial license, and only uses public/open-source applications	Only uses public/open-source applications and common libraries, and can be set up in one hour	Solution only uses public/open-source applications and common libraries, and solution can be set up within 30 minutes

4. Flexibility in selecting summary granularity (O3)

Unacceptable	Satisfactory	Good	Outstanding
Meteorologists have not flexibility to choose the level of detail for the summary	N/A	Meteorologists have more than two detail level settings to choose from	Meteorologists can freely adjust sensibility of the summary based on their expertise and preference

5. Amount of additional weather insights captured (O4)

Unacceptable	Satisfactory	Good	Outstanding
No improvement compared to current MWFS applications	Able to summarize weather data spatially	Able to summarize weather data spatially and temporally	Able to visualize spatial & temporal summary

6. How frequent would the solution improve the details in the summary (O4)

Unacceptable	Satisfactory	Good	Outstanding
Less than 60% of the time	More information provided in more than 60% of the time	More information provided in more than 85% of the time	More information provided in more than 100% of the time

7. Percentage of patterns capturing only homogeneous weather over all patterns detected by the solution (O5)

Unacceptable	Satisfactory	Good	Outstanding
<60%	>= 60%	>= 85%	>= 95%

Constraints

1. Must generate a summary output for each zone selected.
2. Must provide a solution manual to guide the user execute the design.
3. Must provide comments in code outlining the purpose of each function.
4. The implementation of each function must be modifiable and/or replaceable without changing the entire structure of the design.

4.4. DFX Considerations

This section will discuss the key design considerations and why were they particularly important to the design of the solution. The DFX factors have also been integrated and changed since the Project Requirement, since the project scope has been refined with a clear definition. Usability related DFX is removed from the list because this project would focus on the design and implementation of pattern identification and data aggregation.

Table 4: *Table of Design for X's*

Design for X	Application to the problem
Speed	Weather pattern identification should be sufficiently quick
Scalability	Solution should perform well with massive increase in model size and complexity
Flexibility	Data aggregation could be done at different levels of granularity.
Low Data Demand	Solution could provide insightful summary with low quantity of additional data required aside from existing gridded data
Interpretability	Solution output could be understood and justified by humans.
Customizability	Aggregation should be applicable to historical weather data
Modularity	Functions should be replaceable and modifiable without changing the infrastructure

5.0 Design Approach And Methodologies

In this section, we will discuss how did the team approach the problem, and what engineering methodologies have been employed and iterated by the capstone team for this project at different design stages, including scoping, requirement gathering, data preparation, solution generation, and final testing and evaluation.

5.1. Scoping

Based on the problem statement and requirements, and given the time and workforce capacity of this project, the team chose to focus on pattern detection and summarization component of the forecasting system, as it was the cornerstone of ECCC's forecasting operation, and eliminating waste in this specific process would also amplify the positive impacts in the downstream processes.

The project scope was specified with three main silos: a weather pattern detection model, a data aggregation algorithm to describe the overall features of the pattern identified, and a visualization method to show the output data for model/algorithm evaluation. The silos were then broken down to subtasks outlined as follows:

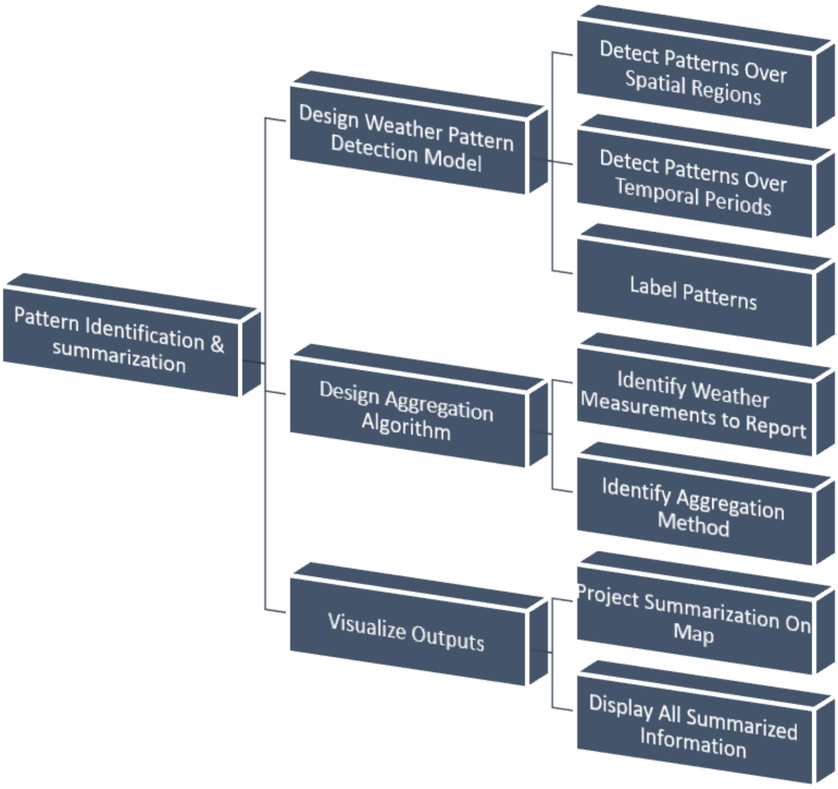


Figure 2: *Work breakdown structure of the capstone project*

Under each work silo, the team iterated the design process with the methods identified below. All methods mentioned were sourced from the book Designing Engineers: An Introductory Text [6].

5.2. Requirement Gathering

In order to understand the pain point and the root causes of the system inefficiencies in MWFS, the team Interviewed and shadowed the meteorologists to further investigate the weather forecasting process using business engineering methods, such as SIPOC, fishbone, and other Lean methodologies.

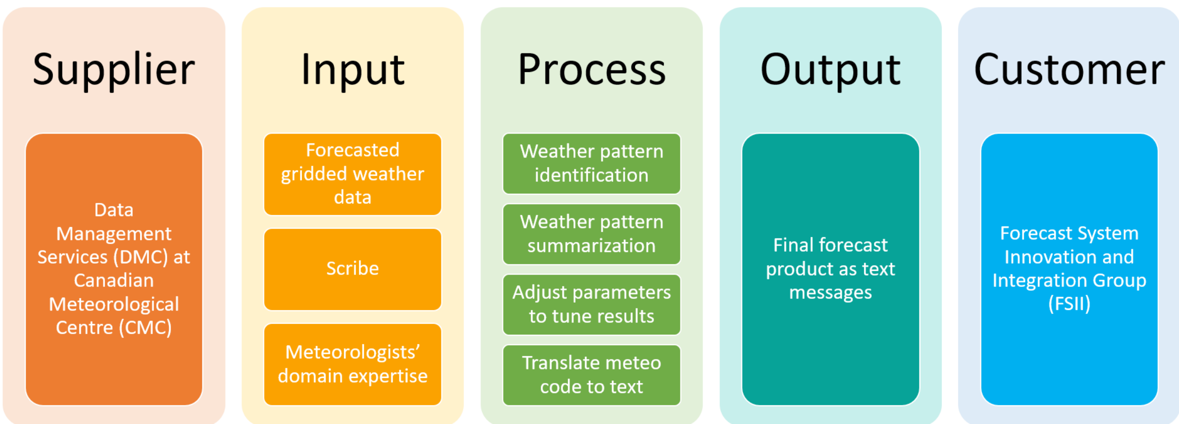


Figure 3: *SIPOC Analysis of the entire weather forecast summarization process*

For better comprehension of the overall business context, the team reviewed ECCC documentations of the current process/system to understand the operating environment and constraints regarding data structures. Reviewed documents included but was not limited to: Canadian Meteorological Centre (CMC) wiki for WEoG and on WxO for the HRDPS, GRIB2 data format official guide [5][7], HRDPS data official guide [8], Meteocode Coding Standard v3.9.1. The team then applied the Black box methodology to generate functions while how-why trees and objective trees were used to formalize the objectives and constraints.

5.3. Data Request and Preparation

One major challenge the team experienced during the project is the delayed delivery of the input data from the Data Management Services (DMC) at CMC. In order to avoid the entire project falling behind schedule, the team leveraged the public HRDPS data sample [9] to study the data format, test the data engineering processes, and implement the structure of the machine learning model solution. Once the requested data was received, it was used for model evaluation and further improvement, and the team was able to use the requested data to test solution performance on larger and more complicated dataset. Detailed implementation would be discussed in Section 6.

5.4. Solution Generation

The team conducted continuous research on existing industry solutions of weather forecasting and geographic data aggregation, explored and identified design concepts relevant to spatial weather data aggregation. In order to discover fresh thoughts and innovative design ideas/concepts of weather forecasting, blue sky thinking and SCAMPER (Substitute, Combine, Adapt, Modify, Put To Another Use, Eliminate, Reverse) were applied to explore potential design alternatives. Pairwise comparison was also used to evaluate the design alternatives with respect to solution efficiency, scalability, interpretability, customizability, additional data demand, flexibility, and modularity as per Section 4.4.

Throughout the project design, there were many subproblems to solve, and the major solution decision was the weather pattern detection model. The reasoning and decision making process would be briefly discussed below, as an example of how the team applied engineering methodologies to iterate through solution generations.

5.4.1. Design Solution Concepts

Expert System

A rule-based artificial intelligence produces pre-defined outcomes that are based on a set of certain rules manually implemented. This expert system solution involves designing a rule-based system that accounts for all possible weather element combinations and classifies them. Cases like “heavy rain, high wind, sub-zero temperatures” corresponding to a snowstorm will need to be identified and manually entered to produce an effective system.

A model like this would be highly interpretable and customizable to reflect known knowledge, but only at relatively small scales. As the clients have mentioned, the current system in place has thousands of business rules which include redundancies and inefficiencies, and trying to find and fix a rule that is causing a problem can be troublesome. Furthermore, the model would be static in the sense that it would not be able to account for a different set of weather elements than the ones it was designed for without major changes and additions.

Supervised Machine Learning

The second concept is supervised learning. This method involves training a machine learning model such as a deep neural network or simply fitting a regression model to a labelled dataset. Machine learning models are probabilistic and can account for data patterns which haven't been seen before. The model is dynamic in the sense that it gets better with time as more and more data becomes available. However, the model's accuracy will heavily rely on the quality of the data it trains on. The problem with this approach is that it requires a large amount of labelled data which is currently unavailable and would require many hours of manual labelling. This, coupled with the low interpretability associated with machine learning models makes this solution less favorable at the moment.

Unsupervised Machine Learning

This unsupervised learning solution involves using unsupervised machine learning methods (such as clustering) to identify and classify weather patterns, and separate them into zones. The weather features of each zone can then be summarized and reported. Based on the flexible sensitivity setting, each zone can be broken down into smaller subzones of insightful patterns within the zone that are detected. This allows the forecaster to control the granularity of the summaries provided. It could respond to the dynamic weather change, can easily capture more complex patterns, and it is very flexible.

However, the main drawback is that the model will be purely trained on the gridded data, which means it would not take meteorologists knowledge for consideration, and it'd be difficult to assess how accurate are the identified patterns.

5.4.2. Evaluation of Solution Concepts

In order to compare the design concepts, the team recalled the DFX requirements to assess the potential solutions. Modularity was excluded from the assessment as it applied to the overall structure of a solution, and each above-mentioned concept is a replaceable component of the same function. All three solution concepts could output insightful information with a significant time reduction compared to human performance when completing pattern identification activity.

Table 5: *Decision matrix to determine which solution method to proceed for the development phase*

	Speed	Scalability	Flexibility	Low Data Demand	Interpretability	Customizability
Expert System	✔				✔	✔
Supervised Learning	✔	✔				✔
Unsupervised Learning	✔	✔	✔	✔		

The expert system solution concept is easy to interpret as the rules that dictate how the system works is visible and understood. Both the expert system solution concept and the supervised learning solution concept can be customized to reflect the meteorologist's knowledge. However both methods require a great amount of additional data to represent meteorologist's knowledge which is not yet available.

The two unsupervised and supervised learning solution concepts are both scalable that will allow the system to perform regardless of a massive increase in model size. However, the unsupervised learning solution concept outwits the other due to its flexible nature. The flexible sensitivity setting allows it to provide various levels of detailed information based on meteorologists preferences. Hence, the unsupervised learning solution concept is the final design which we will proceed with developing.

5.5. Testing and Evaluation

5.5.1. Verification of the Design

The team performed the verification of the design from two fronts:

1. The operation of the design was evaluated against the requirements that were procured in the requirements phase of the project
2. The task support verification was completed to evaluate if the necessary features are in place to support the operation of the design

Table 8 in Section 7 outlines the results of the completed verification.

5.5.2. Validation of the Design

The validation was performed by the team to ensure that the correct system was designed and that it operates as expected in the intended environment. The team first designed the operating model that was requested by the client. Following this, the team then developed the (machine learning model that is responsible for identifying weather patterns, aggregating weather data for the selected regions, and producing a data based output).

Development of the Validation Plan

The validation plan was developed carefully to ensure that the design was being judged in the correct manner to see if it will satisfy the client's needs. Initially, the team proposed to evaluate the output of a developed use case from our solution against the output of the system currently in place at the MSC. However, this plan was not feasible as the solution developed by the team does not replicate every function of the current system at the MSC. In a certain way, many of the highlight features of the developed design were novel for the forecasting system at the MSC.

1. The current system at the MSC does not have the capability to detect weather patterns
2. The current system at the MSC does not overlay weather patterns on the relevant geography
3. The current system at the MSC does not provide the output in the manner generated by our solution

Due to the aforementioned differences, it was difficult to evaluate the solution against anything that the MSC employed. As such, the team decided to take a more qualitative approach to develop the validation plan.

The next iteration of the development of the validation plan involved developing scenarios and finding criteria upon which the solution could be evaluated. After consulting with professor Fox, the team's supervisor, and the client, the team developed the following validation plan upon which to base the evaluation.

System Representation Validity

The most important consideration for the design of the validation procedure was to ensure that the developed scenarios best represent real world conditions under which meteorologists utilize the forecasting system. The following considerations were made to ensure that the system representation validity was maintained:

1. Adequate model fidelity: participants should operate with the design as they would on the forecasting desk. Hence, the participants were asked to work within the Toronto policy zone, Weather Radio zone, and the CHUM Radio zone that they would forecast for on a regular basis.
2. Adequate participant fidelity: participants should be representative of the users of the forecasting system. Hence, the participants of the validation test were selected to be operational forecasters.
3. Adequate scenario fidelity: scenario should not be oversimplified. The workload of the scenario was created to represent the workload that the operational forecaster undergoes in an hour.

Therefore, the test was to be performed by three subject matter experts (operational forecasters) where they would be presented with scenarios (to be completed within an hour) that represent a real life situation for forecasters on duty at the operating desk.

The operational forecasters (participants) were to be presented with six scenarios and asked to identify the weather patterns and summarize the weather information around Toronto, ON, based on key weather measurements and geographical regions, first using any available forecasting tools used in their daily work, and then presented with the capstone project solution. The following six cases represented the tasks performed in a regular hour of forecasting at the forecasting desk on a typical day:

Table 6. *Use cases developed to capture a variety of real-life forecasting scenarios*

	Forecasting region	Time	Season	Time Length	Weather elements used in the Capstone solution
1	Around Toronto, ON	December 27, 2019 from 6AM to 6PM	Winter	12 hours	Temperature, Wind Speed, Wind Direction
2	Around Toronto, ON	December 27, 2019 from 6AM to 12PM	Winter	6 hours	Temperature, Wind Speed, Wind Direction
3	Around Toronto, ON	December 27, 2019 from 12PM to 6PM	Winter	6 hours	Temperature, Wind Speed, Wind Direction
4	Around Toronto, ON	July 19, 2020 from 6AM to 6PM	Summer	12 hours	Temperature, Wind Speed, Wind Direction
5	Around Toronto, ON	July 19, 2020 from 6AM to 12PM	Summer	6 hours	Temperature, Wind Speed, Wind Direction
6	Around Toronto, ON	July 19, 2020 from 12PM to 6PM	Summer	6 hours	Temperature, Wind Speed, Wind Direction

Test Design Validity

The next few considerations for the design of the validation procedure are the development of the test procedures, training of the participants, and assigning of the participants to the scenarios. We considered the following sources of bias:

1. Test procedure bias: clear instructions were provided on the test document to the participants. The start and stop scenarios were provided and the participants were briefed via the instructions on the document.
2. Tester bias: to remove this source of bias, the testers were not present during the hour in which the forecasters were presented with the scenarios. The participants were asked to message the team if they had any questions. This would prevent the participants from obtaining cues from the participants during the test.
3. Test environment bias: The participants were asked to work on the scenarios as they would on the forecasting desk. The participants chose to work together as this is how they would operate as forecaster. Since we did not impose the test to be performed independently, we removed this source of bias.

Therefore, the team was not directly observing the participants during the test so as to remove any source of tester bias. The participants were provided with clear instructions in writing and were asked to work on the scenarios as they would work on the forecasting desk. This way, test procedure and test environment bias were removed from the validation.

Performance Representation Validity

Another important consideration for the validation was to select reliable measurement characteristics and define the criteria for the selected metrics. This is also the basis on which the first iteration of the validation was not followed through with. As such, for this iteration of the validation, the team decided that time would be a good metric to evaluate the design. The forecasters were asked to develop forecasting models for the two days provided in the six scenarios using the tools that they usually would. They were given two minutes of time (as the criteria) for each scenario and then were asked how much time they would deem sufficient to develop a mental model of the weather pattern for each scenario. The participants were also asked to evaluate whether the boundaries provided by the solution capture a homogeneous weather pattern. This metric was developed to evaluate the efficacy of the zone detection algorithm and could only be evaluated by the subject matter experts.

In addition to the more quantitative performance metrics, the team also created inquiries more qualitative in nature. The team considered that these inquiries were appropriate given the nature of the design. The following queries were considered in the design of the validation tests:

1. Does this system provide you with information that you can use in forecasting?
2. Does this system provide new information that you did not have access to previously or information in a new manner? How so?
3. Does this system provide you with the ability to derive more insight about the weather?

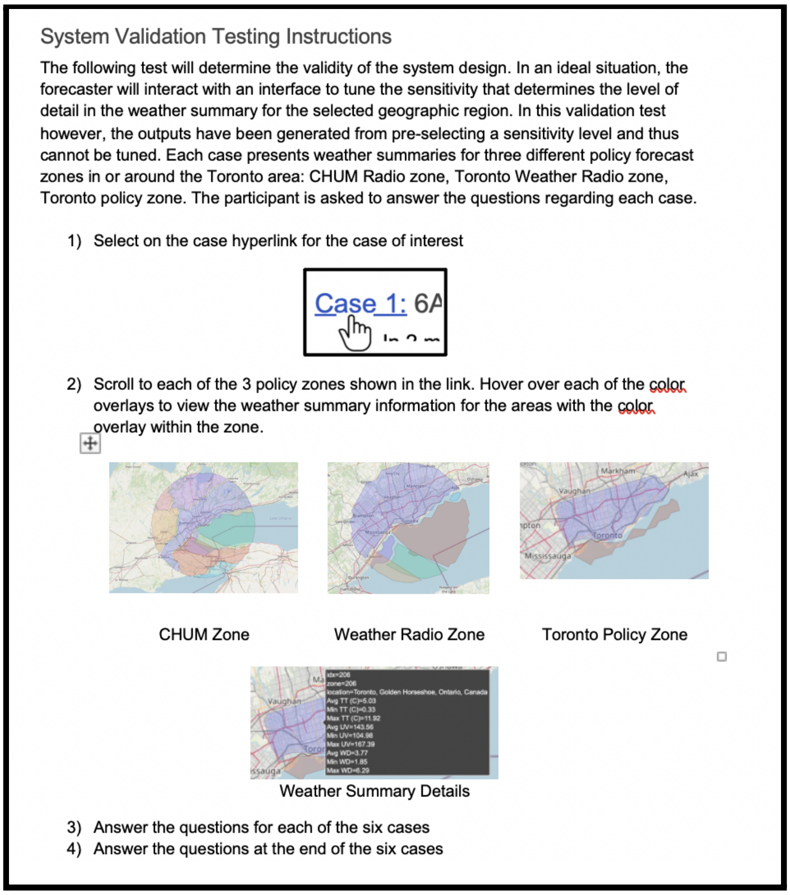
We believe that the combination of the quantitative time and precision metrics along with the more qualitative inquiries provide a good basis for a validation evaluation which assess whether the users' needs are met.

Statistical Conclusion Validity

The final consideration for the design of the validation procedure was to determine how to analyse the results of the tests with respect to the defined performance measurements and criteria. Some of the concerns we have are the low sample size and the possibility of obtaining increased variation in the results of the tests. We understand that the low sample size is a limitation of this validation as we were only to perform validation on subject matter experts, of which there are only a very few at the MSC. Hence, we were able to obtain the participation of three operational forecasters currently employed by the MSC. Regarding the increased variance in the results, this source of threat to the statistical validity was eliminated as we were told that in the real world, forecasters tend to work together to develop an understanding of the weather and so the conclusions they will derive in the test will more likely converge than not.

5.5.3. Test Procedure

The participants (3 operational forecasters) were notified and gathered by the client for an hour long meeting on Tuesday March 30th, 2021 to perform the validation tests. The participants were given access to the raw data immediately before the validation test began. They were then briefed regarding the validation test and provided with instructions regarding the test.


System Validation Testing Instructions

The following test will determine the validity of the system design. In an ideal situation, the forecaster will interact with an interface to tune the sensitivity that determines the level of detail in the weather summary for the selected geographic region. In this validation test however, the outputs have been generated from pre-selecting a sensitivity level and thus cannot be tuned. Each case presents weather summaries for three different policy forecast zones in or around the Toronto area: CHUM Radio zone, Toronto Weather Radio zone, Toronto policy zone. The participant is asked to answer the questions regarding each case.

1) Select on the case hyperlink for the case of interest
2) Scroll to each of the 3 policy zones shown in the link. Hover over each of the color overlays to view the weather summary information for the areas with the color overlay within the zone.

3) Answer the questions for each of the six cases
4) Answer the questions at the end of the six cases

__Figure 4:__ Validation test brief and instructions provided to participants

An interface was designed specifically to perform this validation procedure. Three policy zones were overlaid on the geography near Toronto, ON that are representative of the policy zones that the participants work with (refer to section 5.5.2 for considerations of system representation validity). The participants were asked the following four questions for each case:

1. In 2 minutes, please identify the weather summary for the region around the Toronto, ON region. Then, please rate the difficulty of this task (from 1-5) by highlighting the number.
2. If sufficient time was not provided to complete the task, how much time would you estimate is required to appropriately identify a temperature summary for this scenario (this includes time to access visualization tools to view weather data)?
3. Do the boundaries presented in this case precisely capture areas where the weather is homogenous/uniform?
4. Is sufficient detail present in this case to create weather forecast summary text (for temperature and wind only)?

Following the completion of all six provided scenarios, the participants were then asked the following four questions:

1. Does this system provide you with information that you can use in forecasting?
2. Does this system provide new information that you did not have access to previously or information in a new manner? How so?
3. Does this system provide you with the ability to derive more insight about the weather?
4. Do you have any other comments or questions or concerns regarding the system?

6.0 Solution: Design & Implementation

6.1. New Operational Model

After research and investigation, the team approached the opportunity from a systematic perspective, and undertook the design of an overall restructuring of the current MSC Weather Forecasting System (MWFS). The team proposed a new operating model to maximize the scale of process automation while ensuring meteorologists' knowledge is still retained. Our design includes the following:

- An automated forecast summarization process powered by a machine learning model that considers multiple weather elements and identifies data patterns spatially and temporally
- An interface that records meteorologists' interactions with the model, and captures their subject matter expertise for sustainable model training and improvement
- An advanced text generator that translates weather summaries into forecast messages to downstream audiences

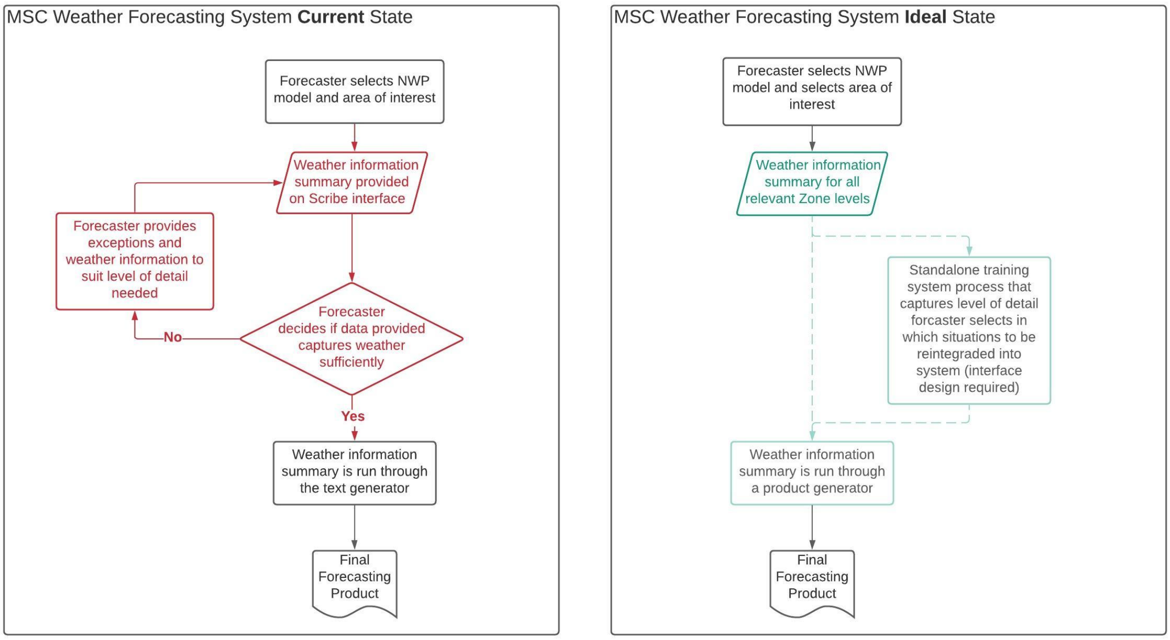


Figure 5: *The forecasting system as it exists is on the left and the ideal implementation of an autonomous system is on the right. The green polygon intends to replace the functions of the red processes on the left.*

As discussed in Section 5.1, this project scope focused on delivering a solution of the first component of MSC's weather forecasting system. Figure 5 above demonstrates current processes on the left hand side (in red to highlight the processes we expect to replace with the green highlight). The processes in grey on the right hand side in Figure 5 are hypothesized next steps outside the scope of this capstone that will deliver a complete and autonomous standalone weather forecasting system. The final weather pattern detection and summarization solution, as highlighted in the green polygon in Figure 5, would be discussed further in the next section.

6.2. Weather Pattern Detection & Summarization

6.2.1. Technical Specifications Overview

The solution was implemented on Google Colaboratory for ease of collaboration and quick prototyping. The final working prototype uses Python 3.7.10 with the python libraries outlined in table 7 below.

***Table** 7: Python libraries used in the final working prototype*

Library	**Use**
Numpy	Efficient array computations by using vectorized mathematical functions
Pandas	Storing data in formats recognized by other libraries that use Pandas
SciPy	Labelling function to efficiently label features in an array using a convolution kernel
Scikit-learn	Advanced clustering algorithms implemented based on NumPy and SciPy
Plotly	Interactive map plotting and zone visualization for the Proof-of-Concept & Testing
MatPlotLib	Debugging data visualization
Shapely	Storing data in formats recognized by Plotly
GeoPy	Access to Nominatim; a tool to reverse search OSM data by longitude and latitude
GeoJson	Loading and reading GeoJson geometry files
PyGrib	Loading and reading GRIB data files

6.2.2. Input Data Overview

The inputs to the design solution are in the form of .grib2 files. GRIB (General Regularly-distributed Information in Binary form) is a file format for the storage and transport of gridded meteorological data [10]. These files consist of gridded weather data that is one step removed from the raw Numerical Weather Prediction (NWP) model output. These files contain the following information:

1. Qualitative nature of the data (field, level, date of production, forecast valid time, etc)
2. Header information (meta-information on header length, header byte usage, presence of optional sub-headers)
3. Method and parameters to be used to decode the packed data
4. Layout and geographical characteristics of the grid the data is to be plotted on (e.g. Latitude/Longitude)

Each .grib2 file consists of gridded weather data for a single weather characteristic (ex. temperature, precipitation amount, precipitation type, etc.) point in time for a large geographical region.

The solution produced was prototyped and tested on grib data from ECCC's HRDPS (High Resolution Deterministic Prediction System), which produces a "2.5 km horizontal grid spacing for the inner domain over one main Pan-Canadian region and a northern region over the Arctic archipelago and Greenland" [8]. The output of this model is essentially forecasted data across Canada, with a data point every 2.5 km.

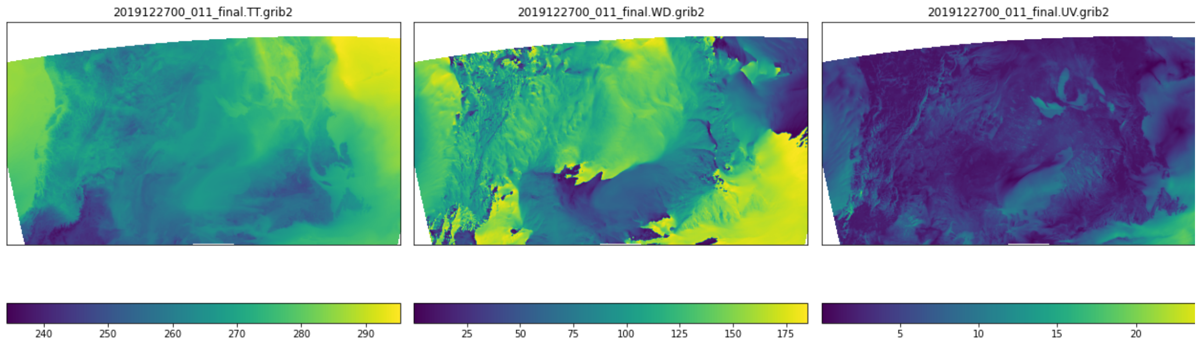


Figure 6: *HRDPS GRIB Files from December 27th, 2019 at 12pm UTC. Left to right: temperature (in Kelvin), wind direction (in degrees), wind speed (in km/h)*

Once HRDPS is run, it outputs 48 folders, one for every hour in the next 48 hour forecast period. Each folder contains a .grib2 file for each weather element tracked by ECCC. This solution focused on (but is not limited to) six weather elements; temperature, wind speed, wind direction, cloud coverage, precipitation amount, precipitation type.

6.2.3. Data Preprocessing and Structure

File Combining

Each .grib2 file used contained a (W x H) masked array representing a specified weather element at the start of a specified hour, where W and H are the width and height of the matrix, respectively. For a given hour, the data was stacked depth-wise, forming an "element stack" (W x H x E) masked array, where E is the number of elements used. For a given time range, each element stack was stacked depth-wise, forming a (W x H x E x T) masked array, where T is the number of hours the solution summarizes. For example, a temperature and cloud coverage summary over the weekend across the entire region would take an input matrix with shape (1456 x 2576 x 2 x 48). See Figure 8 for a simple visual diagram showing the matrix dimensionality.

Relevant Data Crop

The solution accepts two tuples, a lower-left point and an upper-right point in Latitude/Longitude), which represents a bounding box around an area of interest. To maximize computational efficiency, the masked arrays are cropped to this bounding box before any further computations. This crop forms a matrix with shape (W' x H' x E x T), where W' and H' are the cropped width and height, respectively.

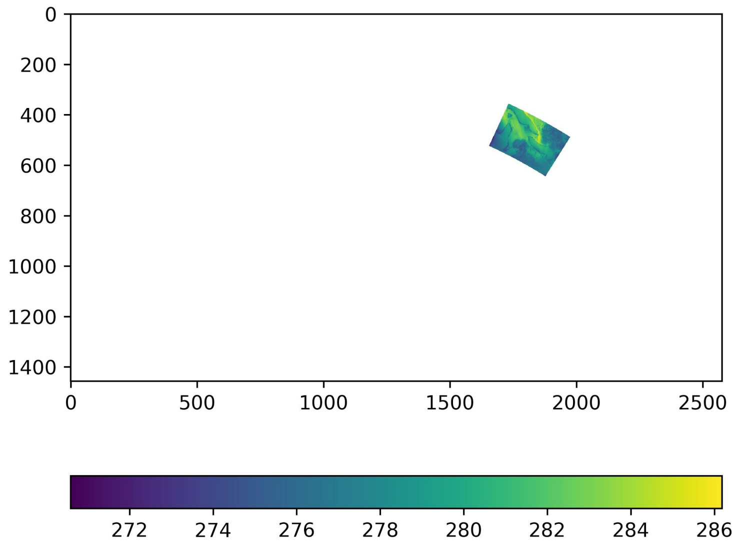


Figure 7: *Sample HRDPS GRIB File cropped to GTA (Greater Toronto Area) region*

6.2.4. Pattern Identification/Zone Detection/Clustering Algorithm

Clustering Algorithm

Using Sklearn's clustering algorithm implementations, the team added a clustering function that accepts (W' x H' x E x T) input matrix and produces a label matrix with shape (W' x H'), assigning each point in the matrix to a cluster. The clustering algorithm accepts a sensitivity parameter in the form of the number of centroids to generate. All points assigned to the same cluster should exhibit the same weather pattern (e.g. heavy rain, sunny skies). The final solution used Mini Batch K Means as it worked best in terms of finding relevant clusters in a reasonable amount of time. Other algorithms such as Birch and K Means also performed well, but only on smaller sample sizes. On larger sample sizes (>6 hour time period over 3 elements across a province-sized region), Birch and K means regularly caused crashes after consuming all the memory capacity available for this project. However, in order to better understand the performance of other clustering algorithms, testing on a system with a larger memory capacity (high-performance GPUs) may be necessary in the future.

Cluster Separation

Since the same weather pattern can occur in different areas, all the points exhibiting the same weather pattern will be assigned to the same cluster. Thus, to separate the clusters spatially, the contour lines were found and clusters that contained two or more non-adjacent groups of data points were separated into smaller clusters called "zones" and given unique zone IDs.

6.2.5. Zone Labelling and Statistics

Data Statistics, Aggregation, and Labelling

Depending on the weather element's data type, various statistics can be reported. By default, the solution calculates the average, minimum, and maximum of non-categorical weather elements and the most frequent entry in categorical weather elements. Each zone's data is summarized by reporting the statistics across the entire time period the solution is used on. In the future, more complex element-specific statististics can be reported, such as the time when temperature is at its highest/lowest.

Each zone is also given a descriptive name by reverse geocoding a point (represented by a latitude and longitude) to an address. This is done using Nominatim, which is a geocoder for OpenStreetMap data [11]. The solution currently reverses the average latitude and longitude of all the points in a zone, but this is sometimes inaccurate. A better solution would require a paid service to reverse geocode many points randomly sampled from a zone, with the most frequent address(es) representing the zone. The best solution is to query by bounding box, which ECCC already has a service for [12] and would just require access to the service's API.

6.2.6. Solution Output and Visualization

Output

Once all the zones are summarized, the final output is stored in a JSON (dictionary-like) structure with zone IDs as keys, and their corresponding statistics as values.

Visualization

A visual interface is developed to validate the solution. Although the ultimate goal is to automate the entire summarization process, at this point human interaction was still required to evaluate the identified pattern and aggregated weather information. The visualized data could be leveraged to capture meteorologists expertise and improve the machine learning models and the automated process. However, the usability of the visual interface was not considered as a key factor in the final solution evaluation.

In order to assess the solution's performance, the team visualized the zones and their statistics on an interactive map. Zones were represented by GeoJSON polygons with statistics as GeoJSON features. Polygon vertices were found by converting the zone's masked array into a binary masked array, where masked data is represented as 0 and unmasked data is represented as 1. Then, the union of the discrete difference along the horizontal axis and vertical axis was calculated. This was a crude but effective way to find the vertices of all the polygons, including concave ones. Other methods exist to get a more accurate representation of the zone's shape such as curvature-constrained shortest paths, but this problem has been shown to be NP-Hard [13]. Another method that can be used is slicing concave polygons into smaller concave polygons, for which vertices can more easily be found.

Once the vertices are found, the library Plotly allows for plotting interactive maps with tile-based geographical maps as the base layer on which the polygons can be rendered.

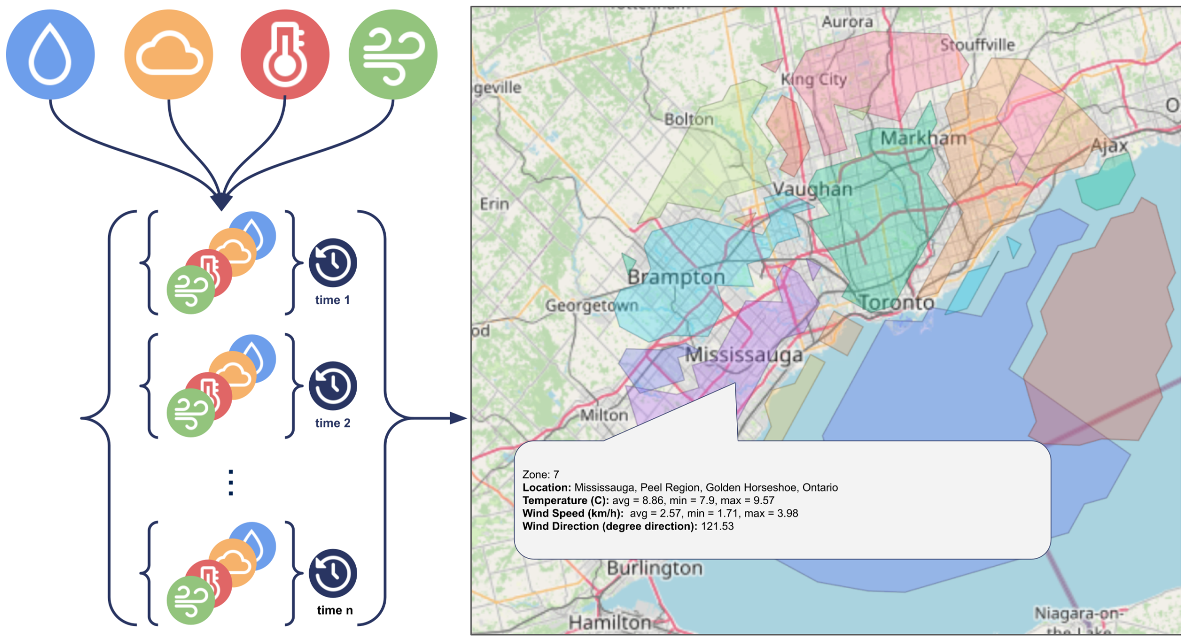


Figure 8: *Diagram showing data input and visualized output on an interactive map*

7.0 Results & Analysis

The final design of this Capstone project is an automated and integrated solution. Users no longer need to open all data and MWFS models in different applications. Everything is in one place and easy to access.

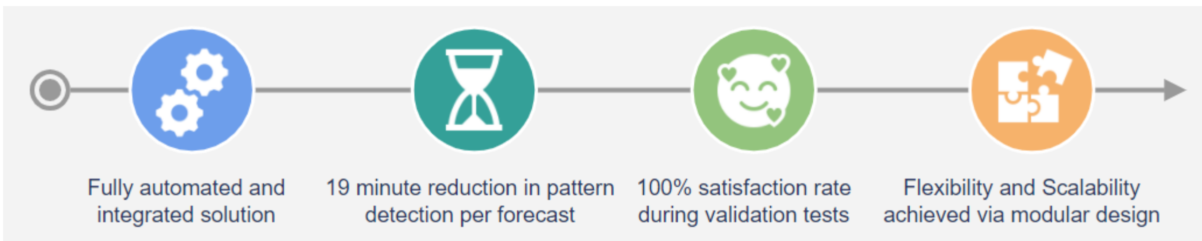


Figure 9: *Overview of the key results achieved by the final solution*

7.1. Results of Verification

The verification was done by evaluating the test results against the criteria developed for the objectives we had defined and refined in the problem requirements and design review phases of the design. The following are the objectives that were previously developed:

O1. The design of the solution should perform aggregation quickly.
O2. The design of the solution should be easy for users to set up.
O3. The design of the solution should provide flexibility to select granularity of the summary.
O4. The design of the solution should aggregate weather information in detail.
O5. The design of the solution should capture the accurate weather patterns with precision.

Table 8: *Outline of the verification results evaluated against defined criteria for the selected performance measure*

Metrics	Result	Score
Average time spent on completing weather pattern identification and data aggregation (O1)	58 seconds	Outstanding
Average time reduced by the automated process compared to the human performance with the current MWFS applications (O1)	19 minutes	Outstanding
Resources required to set up the solution (O2)	Used python and public libraries commonly used in the industry, can be set up in 10-15 minutes	Outstanding
Flexibility in selecting summary granularity (O3)	Meteorologists can tune the sensitivity of the machine learning model, unlimited granularity levels to test to choose	Outstanding
Amount of additional weather insights captured (O4)	Summarization over spatial and temporal perspectives and visualized on an interactive map	Outstanding
How frequent would the solution improve the details in the summary (O4)	100%	Outstanding
Percentage of patterns capturing only homogeneous weather over all patterns detected by the solution (O5)	100%	Outstanding

As outlined in table 8 above, the results of the verification are outstanding for each of the measured objectives. Therefore we can conclude from the analysis of the verification that the features designed for the solution were indeed designed correctly.

7.2. Results of Validation

7.2.1. The Time Advantage

The average time for the solution algorithm to detect weather patterns and generate weather summaries was 58 seconds (for the six provided scenarios). The participants were unable to complete the weather pattern recognition task in two minutes for the provided scenarios. They instead provided an estimated time for each scenario (refer to table 9 below).

In summary, the solution reduced weather pattern identification and summarization time by 9-28.5 minutes, with an average time reduction of 19 minutes per forecast task. The average time the participants estimated was 20 minutes for each scenario. This means the solution provides nearly a 20 fold time advantage to the users.

Table 9: *Participant time to develop a mental model of weather for each scenario vs. time for the algorithm to generate the weather patterns and aggregate weather data.*

Scenario	Time forecasters estimated it would take to compute manually	Time for zone detection algorithm to compute (using free Google Colab w/2vCPU@2.2GHz, 13GB RAM)
December 27, 2019 from 6AM to 6PM	30 min	1 min 48 sec
December 27, 2019 from 6AM to 12PM	10 min	57 sec
December 27, 2019 from 12PM to 6PM	15 min	48 sec
July 19, 2020 from 6AM to 6PM	30 min	1 min 34 sec
July 19, 2020 from 6AM to 12PM	15 min	39 sec
July 19, 2020 from 12PM to 6PM	20 min	50 sec

7.2.2. Homogeneity of Captured Weather Patterns

In all, the participants agreed that for each of the provided scenarios, the boundaries capture areas of common temperature and wind patterns. This is a great result as the algorithm clustered on temperature and wind data to detect the patterns in the first place. However, the participants did point out some areas of concern outlined in table 10 below. However, this could be a result of providing the participants with a preselected sensitivity whereas they would ideally select the sensitivity in the algorithm themselves.

Table 10: *Participant answers regarding provided weather patterns capturing homogeneous weather*

Scenario	Is Pattern Capturing Homogenous Weather?	Comments made by participants
December 27, 2019 from 6AM to 6PM	Yes	"the differences between a couple of the reference zones are quite small. Perhaps the algorithm would have captured fewer categories, if the sensitivity had been lower."
December 27, 2019 from 6AM to 12PM	Yes	"the differences between reference zones are very small. Ideally, the algorithm should have captured fewer categories, with a lower sensitivity applied.

		In this case the reference zones created did capture the Oak Ridges Moraine, as previously expected.”
December 27, 2019 from 12PM to 6PM	Yes	“the differences between reference zones are very small. Ideally, the algorithm should have captured fewer categories, with a lower sensitivity applied. The cold frontal passage was obviously captured by the Capstone algorithm.”
July 19, 2020 from 6AM to 6PM	Yes	“the differences between a couple of the reference zones are quite small. Perhaps the algorithm would have captured fewer categories, if the sensitivity had been lower.”
July 19, 2020 from 6AM to 12PM	Yes	“some of the summarized values for wind speed seem inaccurate. For example, at 1600Z, the max wind was 16.5 m/s compared to 11.0 m/s on the map (northwest quadrant) provided by the students for visualization. Again, the differences between the reference zones are quite small. Perhaps the algorithm would have captured fewer categories, if the sensitivity had been lower.”
July 19, 2020 from 12PM to 6PM	Yes	“the differences between a couple of the reference zones are quite small. Perhaps the algorithm would have captured fewer categories, if the sensitivity had been lower.”

7.2.3. Sufficiency of Detail to Create Weather Summary

The participants unanimously agreed for all given scenarios that sufficient data was presented by the algorithmic solution to warrant the production of a superior forecasting product. This is primarily due to the detection of over one weather pattern over the forecasted region.

Table 11: *participant response to whether sufficient detail is provided in the output of the algorithm that would allow for the generation of a forecast product.*

Scenario	Is sufficient detail present to create weather forecast summary text?
December 27, 2019 from 6AM to 6PM	Yes
December 27, 2019 from 6AM to 12PM	Yes
December 27, 2019 from 12PM to 6PM	Yes
July 19, 2020 from 6AM to 6PM	Yes
July 19, 2020 from 6AM to 12PM	Yes

July 19, 2020 from 12PM to 6PM	Yes

7.2.4. Usage in Weather Forecasting

Regarding the usage outcomes of the design solutions, the participants indicated that the automation of finding weather forecast patterns within the data will lead to better performance and outcomes. To elaborate, they mentioned that the methodology (of the target operating model in figure 10) in addition to the zone detection and pattern recognition algorithm will add rigor to help standardize the analysis, diagnosis, and prognosis for weather forecasting.

7.2.5. Novelty of Solution

The participants mentioned that the "classified map provides an artefact that, to this day, is only represented as a mental map in the minds of forecasters". As such, the solution presents information such that it forms a basis upon which the source of variance between forecasters can be analysed and removed. As of now, the expertise of the meteorologist is heavily relied upon to develop models of weather patterns. This varies from forecaster to forecaster depending on many factors such as experience and seniority. This system can provide a basis upon which forecasters can evaluate the accuracy of their mental model leading to a more standardized way of detecting and assessing weather patterns.

7.2.6. Driver of New Insights

The solution allows the forecaster to adjust the sensitivity of the algorithm and identify the weather pattern in as much detail as they would like. It reduces the need for the forecaster to rely entirely on their mental model of the weather patterns to develop a forecasting product. As such, this tool will help forecasters to work in a different way than they currently do using the weather forecasting suite of tools at the MSC.

8.0 Conclusion & Future Work

The capstone team has investigated and created the design of the new forecast system operating model and has developed the unsupervised machine learning model to facilitate the automation of weather pattern detection and weather data aggregation.

The final unsupervised Machine Learning solution allows flexibility in data summarization at different levels of granularity, provides more insights from the spatial and temporal data aggregation, and visualizes those insights to be easy to digest. The model is also able to capture the accurate weather pattern with precision and fast speed. With a modular design feature, this capstone design solution demonstrates the potential of a fully automated weather forecasting system at ECCC using Big Data analytics methods.

One key advantage of unsupervised machine learning models is that the model can perform tasks in real-time without resources used on labelling data. This feature, combined with the modular design, makes the current machine learning model able to be easily scaled to improve weather services in other areas, such as weather alerting.

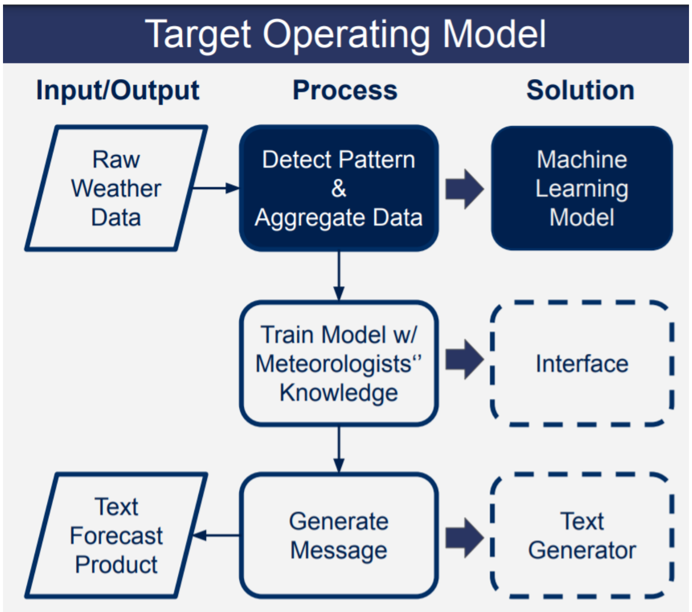


Figure 10: *Target operating model of the forecasting system developed for the MSC*

8.1. Interface Design and Semi-Supervised Learning

The next step in the design process of the target operating model we've developed in this capstone is the design and development of an interface, through which the forecasters can interact with the system with ease. Once an interface is developed, it can record meteorologists interactions with the machine learning model outputs, capture their domain-specific knowledge and expertise, and eventually find a way to label the weather data, move from a purely unsupervised learning to semi-supervised learning, with improvement in solution's interpretability and customizability in a continuous and sustainable way.

Additionally, historical weather data could also be used to train the machine learning model in the future. It could be a very powerful feature when identifying the weather pattern. The identified zones could be labelled both by their locations and the meteorological names of the weather, such as freezing rain, blizzard, and thunderstorm.

8.2. Text Generator Design

The end product of the entire weather forecasting process is the text messages that can be comprehend by people without deep meteorological knowledge. Therefore text generators at the MSC are utilized to develop products for different dissemination channels. For instance, weather radio, weather office, and twitter are different dissemination channels for which different forecasting products are created. However, the input to create each of these products is the metnote file type that contains all of the summarized weather data.

The unsupervised machine learning algorithm developed in this capstone project also generates an alternative data file type that was created with the purpose of being used in the development of forecasting products. Hence, a future task would be the creation of product generators that are able to utilize the data output of the developed model in this capstone project. A Natural Language Processing solution might be a good design candidate for a fully automated text generation process.

9.0 Credits

We are very thankful to the DAS team (specifically Isabel and Patrick) for the opportunity to work on this fascinating project and for generously providing us with your time and help. We would also like to thank Atoosa Nasiri, our communication instructor for the help she provided in formulating the problem requirements and the design of the poster. Finally, we would also like to thank professor Fox for providing us insight and guidance when we needed it the most.

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Appendix

A. User Guide

Please follow this link to access the User Guide hosted on Google Colab. This guide includes libraries used, all (commented) code written, and two examples which showcase how to use the script.
The GRIB data used in this report is at this link, hosted on Google Drive. The GeoJSON geometry used to visualize the data in the second example is at this link, hosted on Google Drive.

The project is also uploaded to GitHub and is found at this link.

User Guide Link URL:
https://colab.research.google.com/drive/1k4WV6T2SuGB_i55CehuoNoxefok_LUXw?usp=sharing

GRIB Data Link URL:
https://drive.google.com/drive/folders/116oQVBnjSUI0Js80oV6Ed0iuzOmM8c78?usp=sharing

GeoJSON Geometry Link URL:
https://drive.google.com/file/d/1Gx6KGLp0DIRSND6hDdlkpPBf9ljtGcDw/view?usp=sharing

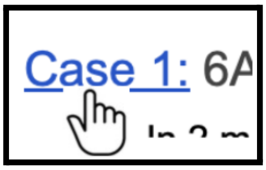
Github Project Link URL:
https://github.com/MIE-Capstone-2020/Automation-of-Weather-Forecast-Data-Summarization

B. Testing Plan & Questionnaire

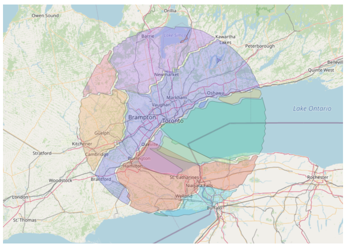
System Validation Testing Instructions

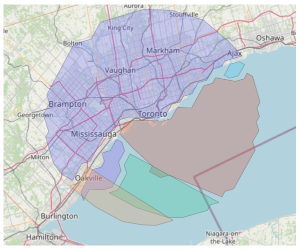
The following test will determine the validity of the system design. In an ideal situation, the forecaster will interact with an interface to tune the sensitivity that determines the level of detail in the weather summary for the selected geographic region. In this validation test however, the outputs have been generated from pre-selecting a sensitivity level and thus cannot be tuned. Each case presents weather summaries for three different policy forecast zones in or around the Toronto area: CHUM Radio zone, Toronto Weather Radio zone, Toronto policy zone. The participant is asked to answer the questions regarding each case.

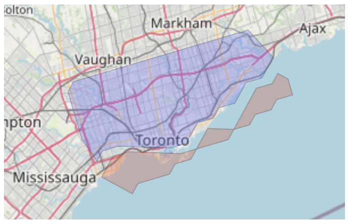
1) Select on the case hyperlink for the case of interest



2) Scroll to each of the 3 policy zones shown in the link. Hover over each of the color overlays to view the weather summary information for the areas with the color overlay within the zone.


CHUM Zone


Weather Radio Zone



Toronto Policy Zone

Weather Summary Details

3) Answer the questions for each of the six cases
4) Answer the questions at the end of the six cases

Case 1: 6AM Dec 27, 2019 to 6AM Dec 28, 2019

1) In 2 minutes, please identify the weather summary for the region around the Toronto, ON region. Then, please rate the difficulty of this task (from 1-5) by highlighting the number.
2) If sufficient time was not provided to complete the task, how much time would you estimate is required to appropriately identify a temperature summary for this scenario using all

available resources you currently have at work (this includes time to access visualization tools to view weather data)?

3) Do the boundaries presented in the new map interface precisely capture areas where the weather is homogenous/uniform?
4) Is sufficient detail present in the new map interface to create weather forecast summary text (for temperature and wind only)?

Case 2: 6AM Dec 27, 2019 to 12PM Dec 27, 2019

5) In 2 minutes, please identify the weather summary for the region around the Toronto, ON region. Then, please rate the difficulty of this task (from 1-5) by highlighting the number.
6) If sufficient time was not provided to complete the task, how much time would you estimate is required to appropriately identify a temperature summary for this scenario using all available resources you currently have at work (this includes time to access visualization tools to view weather data)?
7) Do the boundaries presented in the new map interface precisely capture areas where the weather is homogenous/uniform?
8) Is sufficient detail present in the new map interface to create weather forecast summary text (for temperature and wind only)?

Case 3: 12PM Dec 27, 2019 to 6PM Dec 27, 2019

9) In 2 minutes, please identify the weather summary for the region around the Toronto, ON region. Then, please rate the difficulty of this task (from 1-5) by highlighting the number.
10) If sufficient time was not provided to complete the task, how much time would you estimate is required to appropriately identify a temperature summary for this scenario using all available resources you currently have at work (this includes time to access visualization tools to view weather data)?
11) Do the boundaries presented in the new map interface precisely capture areas where the weather is homogenous/uniform?
12) Is sufficient detail present in the new map interface to create weather forecast summary text (for temperature and wind only)?

Case 4: 6AM July 19, 2020 to 6AM July 20, 2020

13) In 2 minutes, please identify the weather summary for the region around the Toronto, ON region. Then, please rate the difficulty of this task (from 1-5) by highlighting the number.
14) If sufficient time was not provided to complete the task, how much time would you estimate is required to appropriately identify a temperature summary for this scenario using all available resources you currently have at work (this includes time to access visualization tools to view weather data)?
15) Do the boundaries presented in the new map interface precisely capture areas where the weather is homogenous/uniform?
16) Is sufficient detail present in the new map interface to create weather forecast summary text (for temperature and wind only)?

Case 5: 6AM July 19, 2020 to 12PM July 19, 2020

17) In 2 minutes, please identify the weather summary for the region around the Toronto, ON region. Then, please rate the difficulty of this task (from 1-5) by highlighting the number.
18) If sufficient time was not provided to complete the task, how much time would you estimate is required to appropriately identify a temperature summary for this scenario using all

available resources you currently have at work (this includes time to access visualization tools to view weather data)?

19) Do the boundaries presented in the new map interface precisely capture areas where the weather is homogenous/uniform?
20) Is sufficient detail present in the new map interface to create weather forecast summary text (for temperature and wind only)?

Case 6: 12PM July 19, 2020 to 6PM July 19, 2020

21) In 2 minutes, please identify the weather summary for the region around the Toronto, ON region. Then, please rate the difficulty of this task (from 1-5) by highlighting the number.
22) If sufficient time was not provided to complete the task, how much time would you estimate is required to appropriately identify a temperature summary for this scenario using all available resources you currently have at work (this includes time to access visualization tools to view weather data)?
23) Do the boundaries presented in the new map interface precisely capture areas where the weather is homogenous/uniform?
24) Is sufficient detail present in the new map interface to create weather forecast summary text (for temperature and wind only)?

Final Questions

1) Does this system provide you with information that you can use in forecasting?

2) Does this system provide new information that you did not have access to previously or information in a new manner? How so?

3) Does this system provide you with the ability to derive more insight about the weather?

4) Do you have any other comments or questions or concerns regarding the system?

C. Testing Results

Case 1: 6AM Dec 27, 2019 to 6AM Dec 28, 2019

1) In 2 minutes, please identify the temperature summary for the region around the Toronto, ON region. Then, please rate the difficulty of this task (from 1-5) by highlighting the number.

1	2	3	4	5

Insert answer/comments here: It was not possible to create a detailed temperature summary for any of the reference zones. Within 2 minutes, we were able to find only 4 distinct, weather pattern, geographic areas, but it was not a thorough job (not with any spatial precision). It took nearly 2 minutes to simply view and process the data in our minds. A previous knowledge of topographical features was employed, in trying to do this quickly.

2) If sufficient time was not provided to complete the task, how much time would you estimate is required to appropriately identify a temperature summary for this scenario using all available resources you currently have at work (this includes time to access visualization tools to view weather data)?

Insert answer/comments here: To come up with an analysis that is as detailed as what was generated by the CapStone algorithm, it would have taken approximately 30 minutes to do a detailed job, with precise spatial edges for each reference zone, and a high degree of confidence in the summary. Each of the two forecasters that performed this task created different interpretations of the information.

3) Do the boundaries presented in the new map interface precisely capture areas where the weather is homogenous/uniform?

Insert answer/comments here: Yes, they seem to capture areas of common temperature and wind patterns. However, the differences between a couple of the reference zones are quite small. Perhaps the algorithm would have captured fewer categories, if the sensitivity had been lower. We were surprised to find that the reference zones created did not follow the Oak Ridges Moraine, as closely as we would have expected. Using topography to summarize temperature is a method currently used by forecasters. Model forecast precision and/or an overuse of topography as a predictor could be factors to explain this difference. This would require further analysis. From this process, we were also able to determine the next steps that we would want to take following this initial analysis.

4) Is sufficient detail present in the new map interface to create weather forecast summary text (for temperature and wind only)?

Insert answer/comments here: Yes.

Case 2: 6AM Dec 27, 2019 to 12PM Dec 27, 2019

1) In 2 minutes, please identify the temperature summary for the region around the Toronto, ON region. Then, please rate the difficulty of this task (from 1-5) by highlighting the number.

1	2	3	4	5

Insert answer/comments here: It was not possible to create a detailed temperature summary for any of the reference zones. Within 2 minutes, we were able to find only 4 distinct, weather pattern, geographic areas, but it was not a thorough job (not with any spatial precision). It took nearly 2 minutes to simply view and process the data in our minds. A previous knowledge of topographical features was employed, in trying to do this quickly. In addition, the previous exercise biased our analysis of the reference zones.

2) If sufficient time was not provided to complete the task, how much time would you estimate is required to appropriately identify a temperature summary for this scenario using all available resources you currently have at work (this includes time to access visualization tools to view weather data)?

Insert answer/comments here: To come up with an analysis that is as detailed as what was generated by the CapStone algorithm, it would have taken approximately 10 minutes to do a detailed job, with precise spatial edges for each reference zone, and a high degree of confidence in the summary. This analysis was shorter because it followed the previous knowledge. We learned from the previous exercise.

3) Do the boundaries presented in the new map interface precisely capture areas where the weather is homogenous/uniform?

Insert answer/comments here: Yes, areas of common temperature and wind patterns are captured. However, the differences between reference zones are very small. Ideally, the algorithm should have captured fewer categories, with a lower sensitivity applied. In this case the reference zones created did capture the Oak Ridges Moraine, as previously expected.

4) Is sufficient detail present in the new map interface to create weather forecast summary text (for temperature and wind only)?

Insert answer/comments here:

Yes.

Case 3: 12PM Dec 27, 2019 to 6PM Dec 27, 2019

1) In 2 minutes, please identify the temperature summary for the region around the Toronto, ON region. Then, please rate the difficulty of this task (from 1-5) by highlighting the number.

1	2	3	4	5

Insert answer/comments here: It was not possible to create a detailed temperature summary for any of the reference zones. Within 2 minutes, we were able to find only 6 distinct, weather pattern, geographic areas, but it was not a thorough job (not with any spatial precision). It took nearly 2 minutes to simply view and process the data in our minds. A previous knowledge of topographical features was employed, in trying to do this quickly. In addition, the previous exercises biased our analysis of the reference zones.

2) If sufficient time was not provided to complete the task, how much time would you estimate is required to appropriately identify a temperature summary for this scenario using all available resources you currently have at work (this includes time to access visualization tools to view weather data)?

Insert answer/comments here: To come up with an analysis that is as detailed as what was generated by the CapStone algorithm, it would have taken approximately 15 minutes to do a detailed job, with precise spatial edges for each reference zone, and a high degree of confidence in the summary. This analysis was shorter because it followed the previous knowledge. We learned from the previous exercise.

3) Do the boundaries presented in the new map interface precisely capture areas where the weather is homogenous/uniform?

Insert answer/comments here: Yes, areas of common temperature and wind patterns are captured. However, the differences between reference zones are very small. Ideally, the algorithm should have captured fewer categories, with a lower sensitivity applied. The cold frontal passage was obviously captured by the CapStone algorithm.

4) Is sufficient detail present in the new map interface to create weather forecast summary text (for temperature and wind only)?

Insert answer/comments here:

Yes.

Case 4: 6AM July 19, 2020 to 6AM July 20, 2020

1) In 2 minutes, please identify the temperature summary for the region around the Toronto, ON region. Then, please rate the difficulty of this task (from 1-5) by highlighting the number.

1	2	3	4	5

Insert answer/comments here:

It was not possible to create a detailed temperature summary for any of the reference zones. Within 2 minutes, we were able to find only 3 distinct, weather pattern, geographic areas, but it was not a thorough job (not with any spatial precision).

2) If sufficient time was not provided to complete the task, how much time would you estimate is required to appropriately identify a temperature summary for this scenario using all available resources you currently have at work (this includes time to access visualization tools to view weather data)?

Insert answer/comments here:

To come up with an analysis that is as detailed as what was generated by the CapStone algorithm, it would have taken approximately 30 minutes to do a detailed job, with precise spatial edges for each reference zone, and a high degree of confidence in the summary. Each of the two forecasters that performed this task created different interpretations of the information.

3) Do the boundaries presented in the new map interface precisely capture areas where the weather is homogenous/uniform?

Insert answer/comments here:

Yes, they seem to capture areas of common temperature and wind patterns. However, the differences between a couple of the reference zones are quite small. Perhaps the algorithm would have captured fewer categories, if the sensitivity had been lower.

Note that, after having looked at the wind pattern, it took another 5 minutes to simply view, interpret this more complicated weather pattern, and process the data in our minds. We determined that there was a band of showers and thunderstorms would have swept across this area that drove the changes in the temperature and wind patterns.

4) Is sufficient detail present in the new map interface to create weather forecast summary text (for temperature and wind only)?

Insert answer/comments here:

Yes.

Case 5: 6AM July 19, 2020 to 12PM July 19, 2020

1) In 2 minutes, please identify the temperature summary for the region around the London, ON region. Then, please rate the difficulty of this task (from 1-5) by highlighting the number.

1	2	3	4	5

Insert answer/comments here: It was not possible to create a detailed temperature summary for any of the reference zones. Within 2 minutes, we were able to find only 3 distinct, weather pattern, geographic areas, but it was not a thorough job (not with any spatial precision).

2) If sufficient time was not provided to complete the task, how much time would you estimate is required to appropriately identify a temperature summary for this scenario using all available resources you currently have at work (this includes time to access visualization tools to view weather data)?

Insert answer/comments here: To come up with an analysis that is as detailed as what was generated by the CapStone algorithm, it would have taken approximately 15 minutes to do a detailed job, with precise spatial edges for each reference zone, and a high degree of confidence in the summary. Each of the two forecasters that performed this task created different interpretations of the information.

3) Do the boundaries presented in the new map interface precisely capture areas where the weather is homogenous/uniform?

Insert answer/comments here: Yes, they seem to capture areas of common temperature and wind patterns. However, some of the summarized values for wind speed seem inaccurate. For example, at 1600Z, the max wind was 16.5 m/s compared to 11.0 m/s on the map (northwest quadrant) provided by the students for visualization. Again, the differences between the reference zones are quite small. Perhaps the algorithm would have captured fewer categories, if the sensitivity had been lower.

4) Is sufficient detail present in the new map interface to create weather forecast summary text (for temperature and wind only)?

Insert answer/comments here:

Yes

Case 6: 12PM July 19, 2020 to 6PM July 19, 2020

1) In 2 minutes, please identify the temperature summary for the region around the London, ON region. Then, please rate the difficulty of this task (from 1-5) by highlighting the number.

1	2	3	4	5

Insert answer/comments here: It was not possible to create a detailed temperature summary for any of the reference zones. Within 2 minutes, we were able to find only 3 distinct, weather pattern, geographic areas, but it was not a thorough job (not with any spatial precision).

2) If sufficient time was not provided to complete the task, how much time would you estimate is required to appropriately identify a temperature summary for this scenario using all available resources you currently have at work (this includes time to access visualization tools to view weather data)?

Insert answer/comments here: To come up with an analysis that is as detailed as what was generated by the CapStone algorithm, it would have taken approximately 20 minutes to do a detailed job, with precise spatial edges for each reference zone, and a high degree of confidence in the summary.

3) Do the boundaries presented in the new map interface precisely capture areas where the weather is homogenous/uniform?

Insert answer/comments here: Yes, they seem to capture areas of common temperature and wind patterns. Again, the differences between the reference zones are quite small. Perhaps the algorithm would have captured fewer categories, if the sensitivity had been lower.

4) Is sufficient detail present in the new map interface to create weather forecast summary text (for temperature and wind only)?

Insert answer/comments here: Yes

Final Questions

5) Does this system provide you with information that you can use in forecasting?

Insert answer/comments here:

Yes, the ability to automate the process of finding patterns within forecast weather data will lead to better performance and outcomes. Also, it is anticipated that the methodology developed will add rigor and help standardize the Analysis, Diagnosis, and Prognosis outcomes from forecaster to forecaster. To be made operational, work is required to learn from forecasters what the optimal sensitivity (i.e. number of classifications) is for various geographic regions and extents, however this was out of scope of the current project.

6) Does this system provide new information that you did not have access to previously or information in a new manner? How so?

Insert answer/comments here:

Yes. The classified map provides an artefact that, to this day, is only represented as a mental map in the minds of forecasters. These mental maps may vary substantially from forecaster to forecaster based on knowledge and experience. Having this artefact is crucial to the standardization mentioned above.

7) Does this system provide you with the ability to derive more insight about the weather?

Insert answer/comments here:

No more mental maps…captured in detail, adjustable..
Greatly speeds up analysis.

8) Do you have any other comments or questions or concerns regarding the system?

Insert answer/comments here:

We remain very impressed by the work completed, in a very short period of time, by Omar, Khaled, and Suri. It has provided a tangible example of an automated process that has been hard to articulate here at MSC.