Satellite-Based Weather Forecasting With Machine Learning
Carleton University
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Professor Luke Russell and Ms. Ashley Promislow
Carleton University
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Dear Professor Russell and Ms. Promislow:

I am submitting the attached report entitled Satellite-Based *Weather Forecasting With Machine Learning.*

This report underlines key topics of multispectral imaging sensors, Doppler weather radar, machine learning, spacecraft solar power systems, and satellite orbital mechanics for the use of weather forecasting. It will use these topics to understand the different methods used for cloud detection, imaging processes, and pattern recognition.

I hope this report is informative and underlines the importance of satellite-based weather forecasting.

Sincerely,

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Satellite-Based Weather Forecasting With Machine Learning

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Executive Summary

This report examines how different engineering technologies work together to support satellite-based weather forecasting with machine learning. The project focuses on five connected areas: satellite orbital mechanics, multispectral imaging sensors, Doppler weather radar, machine learning for pattern recognition, and spacecraft solar power systems.

The findings show that satellite orbits affect the coverage and quality of weather observations. Multispectral and thermal infrared sensors collect atmospheric information that can be used to identify clouds, while cloud masking helps reduce cloud obstruction in satellite images. Doppler weather radar provides information about severe weather conditions and can support the detection of events such as tornadoes. Machine-learning models process weather data to recognize patterns and support predictions, although missing data can reduce prediction performance. Spacecraft solar power systems provide the energy required to keep satellites and their equipment operating, while factors such as eclipse periods and long-term solar array degradation must also be considered.

Overall, effective satellite-based weather forecasting depends on these technologies working together to continuously collect, process, and analyze atmospheric data. Their integration can improve weather monitoring, forecasting, and public safety during severe weather events.

Contents

Introduction

In response to the CCDP 2100 project call, Group 7 is investigating "Satellite-Based Weather Forecasting with Machine Learning". Modern weather forecasting systems rely on a vast network of satellites that integrate orbital mechanics, imaging sensor technology, power generation, Doppler radar, and machine-learning algorithms to deliver continuous, high-resolution data. This project explores the engineering principles that enable these systems to operate efficiently and accurately in orbit. This project spans many fields and requires interdisciplinary collaboration between atmospheric scientists, engineers, and data analysts.

The project combines five interconnected subtopics, each addressing a critical subsystem within the weather satellite. Kevin Borde investigates *Satellite Orbital Mechanics,* focusing on how orbital configuration influences the effectiveness of weather observation. His research examines the trade-off between geostationary and polar-orbiting satellites, applying Kepler's Laws and principles of orbital mechanics. His second research question explores how atmospheric drag affects the operational lifespan of low-Earth-orbit satellites and how engineers use Hohmann transfer maneuvers and propulsion systems to counteract orbital decay.

Kalea investigated *Cloud Detection and Remote Satellite Imaging*, focusing on how satellites identify and classify cloud formations using multispectral sensors. Her research explains how blackbody radiation and Planck's Law allow satellites to measure thermal infrared emissions and determine cloud temperature and composition. She also explores how remote-sensing techniques overcome cloud obstruction through cloud-masking algorithms, enabling continuous and accurate surface observation for weather forecasting and environmental monitoring.

Laila studied *Doppler Radar Systems* and focused on how satellites and ground-based radars measure atmospheric motion to improve weather forecasting accuracy. Her research delves into the Doppler Effect, which allows waves to detect frequency changes caused by moving precipitation particles; this can reveal wind speed and storm detection. She also explores how radar data is integrated with satellite imaging and machine learning models to track weather patterns, enabling earlier warning and more precise predictions of extreme storms.

Bhavesh researched *Machine Learning for Pattern Recognition,* specifically how recurrent neural networks(RNNs) and long-short-term memory (LSTM) networks, a type of RNN, learn time-series patterns from sequential weather data. His research also addresses data-quality management, showing the handling of missing or incomplete datasets and how they impact prediction accuracy. These algorithms are the basis of modern forecasting systems that use machine learning and are used to transform raw satellite data into usable information.

Alexia examines *Spacecraft Solar Power Systems*, focusing on how satellites size their solar arrays and batteries to maintain operational power through eclipse periods. Her research applies the Shockley–Queisser limit to define photovoltaic efficiency and explores how thermal cycling and space radiation contribute to long-term material degradation. These findings highlight the importance of designing power systems that sustain functionality throughout the satellite's mission lifespan.

Together, these subtopics demonstrate how Satellite-Based Weather Forecasting with Machine Learning requires multidisciplinary engineering. The various systems required are all necessary in contributing to the functionality of the entire system and show how they combine to enhance the accuracy, reliability, and sustainability of modern weather-forecasting satellite

2.0 Satellite-Based Weather Forecasting With Machine Learning

2.2.1 Kalea - Distinguishing Cloud Types Using Thermal Infrared Radiation

Cloud detection is the process of identifying clouds by measuring the thermal infrared radiation they emit [1]. This process is based on the technical principles of Planck’s Law and blackbody radiation. A blackbody is a hypothetical object that absorbs all incoming radiation and emits the maximum possible energy at every wavelength. Real objects use the foundation of this principle; they will absorb incoming radiation and emit energy at different wavelengths; however, this emitted radiation depends on the temperature of the object [3]. The higher an object's temperature, the greater the amount of thermal radiation it emits. Conversely, as an object's temperature decreases, the amount of emitted radiation also decreases. Different wavelengths are represented at different points on the electromagnetic spectrum, and Planck’s Law describes the intensity of this emitted radiation at a given temperature [6]. This relationship between Planck’s Law and blackbody radiation presents the fundamental basis that gives the ability for thermal infrared remote satellite sensing to detect cloud types, heights, and locations.

Clouds at different altitudes have different temperatures, therefore emitting different quantities of radiation [1]. There are three classifications of cloud heights: low, medium, and high clouds. High altitude clouds are generally colder, such as cirrus clouds, while low altitude clouds are warmer, such as stratus clouds. The high altitude clouds emit a lower amount of radiation while the low altitude clouds emit a greater amount of radiation [4]. Satellites, in turn, measure this emitted radiation using thermal infrared sensors and apply Planck’s Law to convert it into an estimated temperature called brightness temperature. From there, the value will be compared to known temperature ranges depending on the location, which will allow the classification into low, medium, or high clouds.

One method of cloud detection is the Goldberg Cloud Detection Scheme, which determines whether each pixel in a satellite image contains a cloud. A pixel could be a cloud, ocean, snow, land, or ice, and this method determines whether it is a cloud by checking its characteristics. The main determinations are the temperature, reflected sunlight, or if it contains cloud-like characteristics. Clouds are generally cooler than Earth's surface because they remain high in the atmosphere; thus, based on the emitted thermal infrared radiation, the cloud will appear cooler than that of land. If the pixel is taken during the day, clouds will usually reflect more sunlight than land or water [7]. By comparing these measurements with the expected values for clouds, land, snow, and ice, the algorithm can accurately identify cloud-covered pixels and distinguish them from the surrounding environment.

The main limitation of the Goldberg Cloud Detection Scheme is the contamination of brightness temperature measurements caused by hazy atmospheric conditions or warm surface temperatures beneath the low clouds. These conditions can increase the estimated brightness temperature, leading to inaccurate estimates of cloud altitude and cloud height [7]. Despite these limitations, the combination of blackbody radiation, Planck’s Law, and cloud detection algorithms provides an effective method for satellites to distinguish cloud types and is a fundamental component in satellite weather forecasting.

2.2.2 Kalea - Remote Satellite Imaging with Cloud Obstruction

Remote satellite imaging is the collection of information about the Earth’s surface and atmosphere without making physical contact. This is done by using sensors that detect electromagnetic radiation that is reflected or emitted by objects [4]. One of the biggest challenges in satellite imaging is cloud obstruction, as clouds prevent satellites from obtaining clear images of the Earth's surface. Not only do clouds themselves block visible light, but the shadows they cast decrease the reflectance capability of the target object. Thick or hazy clouds can blur surface features or block the image entirely, in turn disrupting the measured emitted radiance captured by satellites [8].

One of the primary methods used to overcome this challenge is cloud masking; it is a key processing step before any further data analysis can be performed. Cloud masking identifies and filters out pixels that contain clouds or their shadows in the images obtained by satellites, ensuring only unobstructed observations are used for further analyses [8]. This process is important for applications such as weather forecasting, land monitoring, agriculture, and environmental assessment, where cloud-contaminated pixels could lead to incorrect conclusions. If the imagery is not time sensitive, another approach performed in cloud masking is to stack images of clear scenes versus the cloudy image, taken at different dates, to construct a full scene [5]. By stacking images containing clear regions with cloud-affected regions, a more complete representation of the observed area can be reconstructed.

Despite cloud masking's effectiveness, there are a few limitations. One of the most significant challenges is determining the difference between clouds and other bright surface features, particularly haze and snow [5]. Both clouds and snow appear as bright visible bands in the visible spectrum and cold in the thermal infrared spectrum, making it difficult for algorithms to differentiate the two. In regions that contain mountains, snow at high altitudes can resemble cirrus clouds while snow cover at ground level can produce patterns similar to cloud patterns [8]. These similarities can result in the cloud masking process incorrectly classifying snow as cloud or vice versa, reducing the accuracy of the processed image.

Overall, cloud masking improves the quality and reliability of satellite-acquired surface imagery by minimizing the effects of cloud obstruction. By identifying cloud-covered regions and removing or replacing contaminated pixels, remote satellite imaging systems provide more accurate observations for weather forecasting, environmental monitoring, disaster evaluation, and climate research by ensuring that surface analyses are based on unobstructed images.

2.3.1 Laila - How Does Doppler Radar Work?

Doppler radar is a radar tool that uses the Doppler effect to identify the location and velocity of particles within the atmosphere. A Doppler radar works by emitting energy in the form of electromagnetic radio waves. When the energy emitted collides with a precipitation particle, it scatters in different directions, and some of the energy reflects to the radar. The radar's computers then analyze the changes in these reflected signals, such as phase shifts, to generate important data about the particle, such as its position and its velocity, that is later used to track weather trends.

The Doppler radar also tracks any changes in the radio wave’s phase, mainly any changes to its shape, position, and form. This is called the Doppler shift of the pulses. By measuring this change in phase from when the pulse is sent out to when it returns, the radar can determine the direction in which the precipitation is moving across (either towards or away from the radar). In other words, the phase change detected by the computer determines which direction the velocity of the precipitation is moving in. This information on the velocity of the precipitation is useful when estimating the speed of winds, as it can allow for the tracking of the development of thunderstorms or tornadoes.

The radar is primarily concerned with collecting these reflected signals, as “(the time the radar is actually transmitting), the radar is "on" for about 7 seconds each hour. The remaining 59 minutes and 53 seconds are spent listening for any returned signals”. [9]

2.3.2 Laila - How is Doppler Radar Beneficial?

Doppler radar is beneficial in providing real-time weather forecasting data. This data is valuable to meteorologists during active forecasting but also to engineers in developing and training machine-learning models. The Doppler radar data sets generate valuable information such as the properties of specific precipitation. These datasets are used to train machine-learning models. These models can learn patterns in the radar data and use those patterns to identify or predict different weather events before they occur.

Based on a study done by the National Natural Science Foundation of China [15], a machine learning model was developed to predict tornadoes based on Doppler radar datasets gathered from 2017-2023. The study “focused on three key variables: reflectivity, radial velocity, and spectrum width, to gain insight into tornado characteristics”. [15] The researchers trained the model by providing many examples of tornadoes detected by Doppler radar so that the model could learn to identify the trends associated with tornadoes. Once trained, the model can predict incoming tornadoes and identify areas that may contain tornadoes.

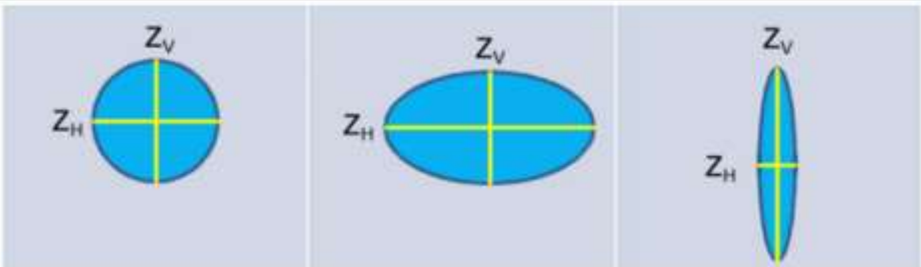
While the research focused on tornadoes, the idea of training machine-learning models can be applied to any type of precipitation detected by Doppler radar. The machine-learning model would need to be altered to identify another kind of precipitation, but the method of providing Doppler radar data sets to train the machine-learning models would still be the same.
This is why Doppler radar is so beneficial for weather forecasting systems. It provides detailed, real-time information about storms and weather forecasting, while also using that information to train machine learning models. This will make weather detection and forecasting systems faster, more accurate, and more capable of identifying dangerous climates before it reaches people.

2.3.3 Laila - How does Dual Polarization Work

Dual polarization radar employs Doppler radar in both the horizontal and vertical direction. Doppler radar transmits and receives electromagnetic waves in the horizontal plane. These waves get reflected off precipitation particles and back to the radar dome, determining the location and velocity of these particles. When Doppler radar is employed in both the vertical and horizontal planes, it allows for further analysis of the particles, helping obtain information such as the shape and size of the particle, precipitation type, and intensity of the precipitation. This further analysis allows for improved accuracy in weather forecasting and faster data collection. This newfound speed and accuracy allow for more protection and less uncertainty during severe climate disasters such as thunderstorms, hurricanes, and tornadoes.

2.3.4 Laila - The Differential Reflectivity (ZDR)

A way in which dual polarization allows for further analysis of precipitation is through The Differential Reflectivity (ZDR). The Base Reflectivity (Z) measures the strength of the radar signal reflected from the precipitation in both the horizontal and vertical plane. The Differential Reflectivity (ZDR) measures the difference between the two signals, revealing the shape of the precipitation, helping better identify what type of precipitation is active. Using the formula "ZDR = ZH – ZV" [2], and the units of ZDR being in decibels (dB), the difference is categorized in three ways. As shown in Figure 1, if the ZDR is close to zero dB, the precipitation is round "similar to a sleet pellet, small piece of hail, or small water droplet" [2]. If the ZDR is less than zero dB, the precipitation is elongated, indicating falling ice crystals or elongated snowflakes. If the ZDR is greater than zero dB, the precipitation is flattened, indicating large raindrops. Having a clear image of the shape of the precipitation can help distinguish what kind of precipitation is at hand, providing more precise weather data.



(Left) Round precipitation: Vertical and horizontal about the same, ZDR near 0 dB.
(Center) Flattened precipitation: Vertical shorter than horizontal, ZDR > 0 dB.
(Right) Elongated precipitation: Vertical longer than horizontal, ZDR < 0 dB.

Figure 1: Different shapes of precipitation particles indicate different ZDR values. [2]

2.3.5 Laila - The Correlation Coefficient (CC)

Another way in which dual polarization provides more accurate data is through the Correlation Coefficient (CC). This is the most used by-product of dual polarization, often displayed on TVs during weather forecasting. The correlation coefficient is a unitless measure that determines if the precipitation is uniform across the area. If the returned radar signals are similar in both the horizontal and vertical planes, the correlation coefficient will be high, and if the signals are different in both planes, then the correlation coefficient will be low. The correlation coefficient is useful because it helps provide accurate weather forecasting for areas that have mixed precipitation, such as rain and snow mix.

2.4.1 Bhavesh - Recurrent Neural Networks and LSTM

A Recurrent Neural Network (RNN) is a type of neural network that is designed to work with data that comes in a sequence. Instead of looking at each piece of information separately, an RNN uses information from previous inputs when processing new information. This gives the model a form of memory and allows it to recognize patterns that happen over time [16].

This is useful for weather data because weather conditions are connected over time. For example, the temperature or humidity at one point in the day can be related to the conditions that came before it. An RNN can process these measurements in order and use information from earlier time steps when looking at the next measurement [16].

However, a standard RNN can have difficulty remembering information from much earlier in a sequence. This can be a problem when a pattern depends on information that happened many steps earlier. RNNs can therefore be useful for sequential information, but they can have limitations when longer relationships need to be learned [17].

A Long Short-Term Memory (LSTM) network is a special type of RNN that is designed to handle longer relationships in sequential data. LSTMs use memory cells and gates to control the information that moves through the network. The gates help decide which information should be kept and which information can be forgotten. This gives the model more control over its memory [17].

As shown in Figure 1, information moves through different parts of an LSTM cell before being passed to the next time step. This allows an LSTM to keep useful information for longer periods than a standard RNN [17]. Because weather patterns can develop over many hours or days, this longer memory can be useful when working with weather data.

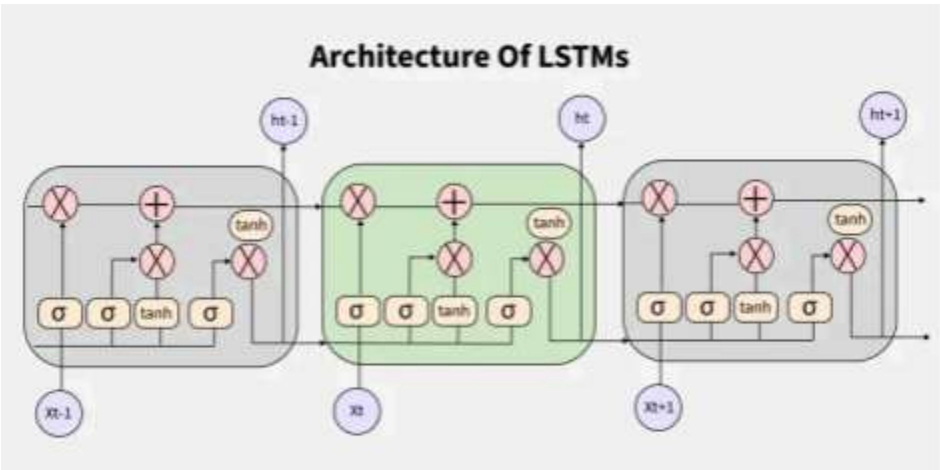


Figure 1. Architecture of an LSTM showing how information is processed across sequential time steps. Source: GeeksforGeeks [2].

2.4.2 Bhavesh - Learning Weather Patterns

Time-series data is information recorded in time order. Weather data is a good example because measurements are collected at different times throughout the day. These measurements can include temperature, humidity, rainfall, wind speed, and air pressure. Before weather information is given to a model, it usually needs to be prepared. This process is known as data preprocessing. The data may need to be organized, checked for missing information, and placed in the correct time order. Preparing the data is important because the model learns from the information that it receives [18].

An RNN processes the prepared weather data one time step at a time. When it processes a new measurement, it also uses information that was passed forward from an earlier time step. This allows the network to connect earlier conditions with newer conditions instead of treating every measurement as unrelated [16].

During training, the model makes predictions and compares them with the correct values. The model then adjusts its internal values to reduce its prediction errors. By repeating this process across many examples, it can learn relationships within sequential data [16].

For example, a model could receive previous temperature, humidity, wind speed, and air pressure measurements. It could learn how changes in these measurements are connected over time and then use those patterns to help predict a future value.

LSTMs follow the same general idea but can keep useful information for longer periods. This can help when older weather information is still important to a future prediction [17]. The memory cells and gates in an LSTM allow the network to control which information continues through the sequence and which information is no longer needed [17].

Together, this answers the first research question. RNNs learn time-series weather patterns by processing observations in order and using information from earlier time steps when processing newer information [16]. LSTMs add a stronger memory system that helps the networks keep important information across longer sequences [17].

2.4.3 Bhavesh - Impact of Missing Weather Data

Weather datasets do not always contain every measurement that is expected. Values may be missing because of operational problems or equipment failures at weather stations [19]. This creates gaps in the weather information available to a prediction model.

Missing values are especially important for time-series models because the order and relationship between observations matters. If a model is supposed to receive a sequence of weather measurements but some of those measurements are missing, the sequence is no longer complete.

This can affect how well a model learns. Neural networks depend on their training data to recognize useful relationships. Research has shown that incomplete datasets often require missing values to be replaced before neural-network training. The method used to replace those values can also affect the prediction performance of the model [20].

There is also evidence of this problem specifically with weather information. A study on solar power forecasting examined the effect of missing weather information on prediction. The researchers found that missing weather values could reduce forecasting performance and that the effect changed depending on the amount of missing data [21].

For an RNN or LSTM weather model, this means data quality is an important part of the prediction process. Missing temperature, humidity, wind speed, or pressure values can leave the model with an incomplete picture of what happened over time. If these gaps are not handled properly, the model may have more difficulty learning useful patterns from the data. The amount of missing data is also important. A small number of missing measurements may have less of an effect than larger gaps in the dataset. Research on weather forecasting found that prediction performance generally became worse as the amount of missing weather information increased [21].

Overall, missing values can lower the quality of the information available to a neural network. This can make it harder for the model to learn patterns and can result in less reliable predictions [20], [21].

2.4.4 Bhavesh - Handling Missing Weather Data

One common way of dealing with missing information is called imputation. Imputation means replacing a missing value with a reasonable estimate instead of leaving the space empty. This allows the dataset to remain usable while giving the model a more complete sequence to work with [19].

There are several ways to estimate missing values. The correct choice depends on the dataset and the amount of information that is missing. This is important because the method used to replace missing values can affect the final performance of a neural network [20].

Li, Ren, and Zhao tested 20 machine-learning methods for filling missing values in meteorological data. Their research used ten years of hourly observations from 124 weather stations across six climate regions [19]. The study included weather measurements such as temperature, wind speed, solar radiation, air pressure, and humidity [19].

The researchers found that Random Forest, bidirectional LSTM, and Temporal Convolutional Networks were some of the stronger methods for filling missing weather information. Random Forest performed best overall for many of the weather variables that were tested [19].

This shows that LSTM-based methods can work well for missing weather data, but one method may not always be the best choice for every dataset.

Another study compared different methods for replacing missing weather information before solar power forecasting. The methods included linear interpolation, mode imputation, k-nearest neighbours, also known as KNN, and multivariate imputation [21]. The researchers found that the choice of method affected forecasting performance. Under the conditions tested in the study, KNN produced results that were closest to the original complete dataset [21].

These results show why weather data should be checked before a prediction model is trained. Missing values should not simply be ignored. Instead, a suitable imputation method should be chosen based on the dataset and the type of information that is missing [19], [21].

Overall, missing weather values can reduce forecasting performance because the model has less complete information available to learn from [21]. Checking the dataset and using a suitable imputation method can reduce this problem and provide the model with more complete information [21], [21]. This answers the second research question by showing that missing weather values can make neural-network predictions less reliable, while properly handling those values can help reduce their effect.

2.5.1 Alexia - Efficiency over Eclipse Periods

This section examines how satellites size their solar arrays and batteries to remain powered through orbital eclipses while also accounting for the satellite's efficiency. The *Shockley–Queisser* limit defines the theoretical maximum efficiency (~33% for single-junction cells), meaning only one-third of sunlight can be converted into usable electricity. This value represents the upper boundary of photovoltaic conversion efficiency, or how effectively sunlight is turned into electricity [23]. As Zanatta explains, "the maximum theoretical efficiency of solar cells made of crystalline Si is ~33%," which has become the accepted benchmark for photovoltaic design [23].

During *eclipse periods*, solar input drops to zero, meaning the power needed to ensure the satellite still functions in Earth's shadow comes entirely from stored battery energy. NASA notes that "solar energy is not always available during spacecraft operations due to orbital dynamics… so spacecraft require onboard energy storage, usually via batteries" [22]. Engineers therefore determine how much to scale up the arrays to generate the necessary excess power before entering the shadow. Orientation also plays a role. NASA's State-of-the-Art of Small Spacecraft Technology report highlights that "power generation is predicated primarily by the angle of incidence to the sun. Perpendicular orientation provides maximum generation, which then drops off by the cosine of the angle as the solar array is tilted away" [22]. This cosine loss means satellites rarely operate at full efficiency, requiring additional array area to compensate for off-angle illumination.

In short, photovoltaic conversion efficiency and the Shockley–Queisser limit define how much energy can be captured, while eclipse planning determines how much energy must be stored. Together, these principles guide how satellites size their power systems to ensure continuous operation. While array sizing defines how satellites maintain power through eclipse periods, the long-term ability to meet those power demands depends on how well the solar cells withstand their environment. Over time, exposure to radiation and extreme temperature cycling reduces photovoltaic efficiency and structural integrity. These degradation effects ultimately determine how much of the designed power capacity remains available at end-of-life and are further discussed in section 2.2.

2.5.2 Alexia - Radiation and Thermal Degradation in Orbit

Solar-cell degradation in low-Earth orbit is driven primarily by radiation-generated defects and thermal-cycling stress. These mechanisms decrease overall power output. Efficiency further declines under high temperatures and radiation exposure, so engineers must account for these losses when oversizing arrays to maintain required power until end-of-life. This connects directly to RQ1 and TP1 since material degradation and exposure affect long-term efficiency.

Peer-reviewed sources describe how energetic particles create defects that reduce electrical performance [22]. This mechanism aligns with findings, which show that "radiation-induced degradation links optical, thermal, and electrical responses within the solar-array system through a progressive photo-thermal-electrical interaction pathway" [24]. Radiation exposure causes displacement damage in semiconductor lattices, creating defect states that trap charge carriers and reduce conversion efficiency. Over time, this leads to measurable decreases in maximum power output. Data shows that silicon cells lose 12.5% power at 300 km altitude, while triple-junction cells, which are solar cells composed of three semiconductor layers, lose only 3–4% under the same conditions [23]. Meaning that regardless of material, power loss is unavoidable; however, these values are consistent with published displacement-damage studies and demonstrate how material choice is incredibly important, as it directly affects the degradation rate.

Silicon (Si) cells exhibit higher susceptibility to radiation-induced degradation, while Gallium Arsenide (GaAs) and multi-junction cells show improved tolerance due to stronger lattice bonding [24]. The comparative data table below reinforces this, showing that triple-junction coatings maintain higher power output across all altitudes. This finding is critical for weather satellites, which require predictable power generation to support continuous data collection.

Table 2. Power loss comparison (%).

Altitude of An Orbit (km)	Si Coated	GaAs	TJ	CIGS
300	12.5	7.0	3.0	9.0
400	10.7	6.0	2.3	7.7
500	9.0	5.0	1.8	6.5
600	8.2	4.7	1.6	6.0
700	7.8	4.5	1.5	5.5

Figure 2: Data showing power loss in relation to material & Altitude

Another thing to note from this table is that altitude also has a substantial effect on the percent of power lost in orbit. This is important to take into account given that most weather satellites are LEO(Low Earth Orbit) satellites and, according to the table, as orbit altitude is lower, the power loss is higher.

As for *thermal cycling*, which is the repeated heating and cooling as a satellite moves between sunlight and shadow, weather satellites experience transitions causing temperature swings of up to 150 °C. These cycles induce mechanical stress in the solar-cell structure, accelerating microcrack formation and delamination. Xie and Li describe that “cyclic temperature fluctuations disturb the heat balance and further induce expansion-contraction stresses, interfacial fatigue, and delamination” [24]. These mechanical effects compound radiation damage, resulting in accelerated degradation.

For weather satellites, degradation reduces available power for sensors and communication systems. This directly affects data-collection reliability and the performance of machine-learning forecasting models that depend on consistent power availability. As reported in Logbook 1, “within a few months of launch, the output power had decreased to a level at which the batteries could no longer fully recharge, thereby limiting the satellite’s functionality” [22]. This demonstrates how degradation can compromise mission objectives if not properly modeled during design.

2.5.3 Alexia - How Efficiency and Thermal Degradation Matter Together

The findings across both research questions reveal that solar-array sizing and degradation modeling must be treated as a combined design problem. Engineers cannot simply size arrays for nominal efficiency; they must anticipate radiation and thermal losses throughout the mission lifetime. The Xie and Li model emphasizes that solar arrays in space are “exposed to complex multi-physics stressors, including intense radiation, temperature fluctuations, and long-term thermal cycling” [24]. These stressors interact rather than act independently; radiation weakens materials, and thermal cycling worsens those weaknesses.

This is incorporated in designs by recommending oversizing arrays to meet end-of-life power requirements. This ensures that even after years of degradation, the spacecraft can still meet operational demands during eclipse periods. Degradation modeling, such as the photo-thermal-electrical coupling approach, allows engineers to predict how optical and electrical properties evolve under combined stressors.

In practice, this means selecting materials with high radiation tolerance (e.g., GaAs or multi-junction cells), applying protective coatings against atomic oxygen erosion, and integrating thermal-control systems to minimize temperature extremes. These strategies extend array lifespan and maintain power reliability for critical missions like weather forecasting.

3.0 Conclusion

In conclusion, this report brought forth research conducted by Team 7's engineers on how satellite-based weather forecasting systems with machine learning depend on the quality of the data collected and the ability to process this data efficiently. The research conducted in subtopics 1,2,3 and 5 highlights the importance of determining when, where, and what type of weather data can be collected through satellite imaging and sensors, and the feasibility of maintaining the reliability of these satellites over long-term operation. The research in subtopic 4 connects how these systems use these large amounts of weather data produced as inputs for machine learning models.

The integration of machine learning with these weather forecasting systems provides an opportunity to adopt faster and more reliable weather forecasting. Models such as RNN's and MTI-Net can be trained on the sequential weather data provided to learn patterns and trends in different climates, and use them to predict future weather conditions. Ultimately, the research shows that machine learning is not a replacement for traditional satellite and radar weather forecasting systems, but rather a tool that can be used to build upon and improve the use of the data these systems provide. As weather forecasting continues to aim for greater accuracy, speed, and reliability, combining advanced observation technologies with machine learning has the potential to make weather forecasting more efficient and better equipped to respond to rapidly changing weather conditions.

Glossary

Albedo: Fraction of reflected radiation to incoming radiation, how bright or reflective a surface is [1].
Blackbody Radiation: Emission of radiation based on the temperature of the object [3].
Data Preprocessing: The process of cleaning and preparing data before it is used to train a machine-learning model [3].
Doppler Effect: "The change in frequency of a wave when either the source or an observer moves became known as the Doppler effect" [3].
Doppler Radar: Doppler radar is a radar system that employs the Doppler effect to measure the frequency shift of radio waves to determine velocity and position [4].
Dual Polarization: Employing Doppler radar in both the horizontal and vertical directions [3].
Eclipse Period: The portion of a satellite's orbit when it passes through Earth's shadow and receives no sunlight [14].
Imputation: The process of estimating and filling values that are missing from a dataset [4].
Long Short-Term Memory (LSTM): A type of RNN that uses memory cells and gates to keep useful information for longer periods [2].
Machine Learning: Machine learning, in the context of Satellite-Based Weather Forecasting, refers specifically to AI that is trained to recognize patterns through data, to later self-operate through experience rather than through prewritten code [6].
Meteorologists: Scientists who study meteorology [5].
Meteorology: The study of Earth's atmosphere and the climate affecting events that occur in it, to provide short-term weather forecasting [5].
Multispectral Satellite Imaging: Data obtained from multiple wavelengths and bands for analysis of Earth features and environmental conditions [1].
Planck's Law: Intensity and spectral distribution of blackbody radiation based on the object's temperature [2].
Recurrent Neural Network (RNN): A neural network that processes sequential data, using previous information to process new information [1].
Remote Sensing: Acquisition of data from satellites of varying Earth orbits.
Sequential Data: Information that is arranged in an order, such as weather measurements recorded over time [1].
Shockley-Queisser Limit: A theoretical maximum efficiency (~33% for single-junction cells) that defines the upper boundary of how much sunlight a traditional solar cell can convert into electricity [13].

Thermal Cycling: Repeated heating and cooling as a satellite moves between sunlight and shadow. These temperature swings stress solar-cell materials and can lead to microcracks or reduced efficiency [10].

Thermal Infrared Satellite Sensors: Unique pattern of infrared radiation emitted by an object [4].

Time-Series Data: Data that is recorded in time order, such as temperature measurements taken every hour [1].

Triple-Junction Solar Cell: A high-efficiency solar cell composed of three semiconductor layers tuned to different wavelengths of sunlight. (More effective than single-junction designs) [10].

References

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Appendix A: AI-Use Statements

I used Microsoft Copilot, ChatGPT, Claude, and Grammarly to support my work on this report in the following ways: clarifying concepts related to my subtopic to ensure I had an accurate understanding before writing; finding and evaluating specific sources, including narrowing down sources that described particular concepts using photos; assisting with IEEE formatting, including citation structure and reference section formatting; improving sentence structure, grammar, organization, and conciseness; explaining technical concepts related to recurrent neural networks (RNNs), long short-term memory (LSTM) architectures, and data preprocessing in a simpler way that matched the intended audience of the report; and assisting with glossary definitions and making complicated topics easier to understand.

Grammarly is connected as an add-on to my Google account and makes suggestions on sentence format as well as spelling. AI was also used in Section 1.0 to assist in re-wording sentences to be more concise. This was done after all the information was written and was fact-checked again with my notes to ensure all the information was correct.

All AI-generated content was carefully reviewed before being included in the final report. The technical information and definitions were checked against the sources to make sure they were accurate and relevant. The references, citations, and figure sources were also verified before submission.

The research question, analysis, source selection, and final wording of the report were reviewed and edited by the author. All ideas, analysis, and final writing decisions were my own. Responsibility for the accuracy and quality of the submitted work remains with the author.

Appendix B: Engineers' Statement

Appendix B -2 Kalea Lebenhagen's Engineers Statement

Author: Kalea Lebenhagen

Submission: A5 Individual Final Report

Subtopic: Remote Satellite Imaging for Cloud Detection

Date: August 12, 2026

This statement follows my Individual Final Report on remote satellite imaging for cloud detection. I am writing it to formally document what I have verified, what I could not verify, and what I would want a domain expert to check before this work is used in a non-academic context.

I have personally verified all of the blackbody radiation and Planck's Law facts listed in Section 2.1 by reading cloud detection methods for optical satellite imagery and cross-referencing it with source [3]. I read in full each of the 7 IEEE papers cited in Section 2 ([1], [3], [4], [5], [6], [7], [8]) and checked every statement with a specific page in the papers.

I could not verify how snow and haze are differentiated at different altitudes as referenced in Section 2.2 with the process of cloud masking cited by [5].

Before this work went to a client, I would want a meteorological engineer to verify my area usage of the Goldberg Cloud Detection Scheme. I am relying on a simplified model of it, and a more advanced review might identify where this detection scheme is more useful depending on the location of needed detection.

All other content in this report is my own work. I take professional responsibility for the claims, citations, and analysis presented.

Signed:

Kalea Lebenhagen

Printed Name:

Kalea Lebenhagen

Date:

August 12, 2026

Appendix B -3 Laila Bedir’s Engineer's Statement

Laila Bedir

A5 Individual Final Report

Doppler Radar

August 12, 2026

This statement accompanies my A5 Individual Final Report on Doppler Radar. This statement is to document what I was able to verify, what I wasn’t able to verify in my research, as well as to state which areas of my research I would want a domain expert to check before execution takes place.

I can verify that section 2.1 on how Doppler radar works is accurate, because I cross-referenced it with multiple accredited sources, all agreeing on the same fundamental principles of how Doppler radar works. I can verify that in section 2.4, the mathematical equation used for the Differential Reflectivity is accurate. This is based on cross-referencing multiple sources that identify the ZDR formula works in identifying precipitation with a ZDR value close to zero as being round, small raindrops; a ZDR value greater than zero indicating flat big raindrops, and finally a ZDR value less than zero indicating elongated precipitation.

I cannot verify that the results from the MTI-Net machine-learning model are accurate or unaltered, as I did not conduct the experiment myself. I cannot verify that the data used to train the machine-learning models from 2017-2023 were accurate, as I did not retrieve these data sets myself. Those results were based on research conducted by accredited sources rather than personal experiments or calculations.

Before this research can be used in the field of meteorology, I would want a computer systems engineer and a software engineer to verify that the MTI-Net model is correctly designed to process and interpret the radar datasets and that the results reported from the model are accurate. This is to ensure whether the machine-learning model can be useful to meteorologists in reliably contributing to faster and more accurate weather forecasting.

I, Laila Bedir, take responsibility for the research gathered in this report.

Laila Bedir

August 12, 2026

Appendix B -4 Bhavesh Bhatia's Engineer's Statement

Author: Bhavesh Bhatia

Submission: A5 Individual Final Report

Subtopic: Learning Weather Patterns Using Recurrent Neural Networks and LSTM

Date: August 8, 2026

This statement explains what I personally verified in my report, what I was not able to independently verify, and what I would want a domain expert to check before the information in this report was used outside of an academic setting.

I personally reviewed the sources used in my report and checked that they supported the main ideas presented in Section 2. For Sections 2.1 and 2.2, I checked the information about recurrent neural networks and LSTMs against sources [1] and [2], including how RNNs process sequential data and how LSTMs use memory cells and gates. I also checked the information about data preprocessing against source [3]. For Sections 2.3 and 2.4, I reviewed sources [4], [5], and [6] to check my claims about missing weather data and imputation. I also checked that Figure 1 matched the LSTM information provided by source [2].

I was not able to independently reproduce the experiments described in sources [4], [5], and [6]. These studies used their own datasets, models, and testing methods to measure the effects of missing data and different imputation methods. I therefore relied on the results reported by the researchers instead of testing these results myself.

Before this information was used for a real weather prediction system, I would want a machine-learning expert to review my explanation of RNN and LSTM models and confirm that the technical details are complete. I would also want a weather-data expert to review the missing-data section and determine which imputation methods would be most appropriate for real weather datasets.

I take responsibility for the claims, citations, and analysis presented in my report.
Signed: Bhavesh Bhatia, August 8th, 2026

Appendix B -5 Alexia Savage's Engineers Statement

As an aspiring engineer, my approach to this research emphasizes the integration of theoretical efficiency limits with real-world degradation modeling to inform spacecraft power-system design. The findings demonstrate that solar-array sizing and material selection cannot be treated independently; both are governed by the same physical constraints that define photovoltaic performance in orbit.

The Shockley–Queisser limit establishes the upper boundary of conversion efficiency, but operational conditions, such as orbital eclipses, temperature fluctuations, and radiation exposure, reduce performance well below that theoretical maximum. Recognizing this, engineers must design arrays and batteries to meet end-of-life power requirements rather than beginning-of-life estimates. This ensures that even after years of radiation damage and thermal fatigue, the spacecraft can sustain critical operations through eclipse periods.

Radiation and thermal cycling emerge as dominant degradation mechanisms. The data show that silicon cells experience significant carrier-lifetime reduction and structural fatigue, while multi-junction and GaAs cells maintain higher efficiency due to stronger lattice bonding and better radiation tolerance. These insights guide material selection for long-duration missions, where reliability is one of the most important factors. Especially when accounting for the need for reliability in weather data.

From an engineering perspective, degradation modeling is predictive. Engineers can forecast performance decline and incorporate safety margins into power budgets. This approach transforms degradation from a risk into a quantifiable design parameter.

For weather satellites, continuous power availability is mission-critical. The engineering solution must therefore balance efficiency and durability. Oversized arrays, radiation-resistant coatings, and thermal-control systems collectively ensure that the satellite remains functional across thousands of orbital cycles.

In conclusion, this research reinforces that spacecraft power systems are designed not for ideal conditions, but for endurance under extreme ones. Engineering judgment lies in anticipating degradation, validating models against empirical data, and designing systems that maintain functionality long after theoretical efficiency has faded.

Signed:

Alexia Savage

08/15/2026

Appendix C: Figures

A)

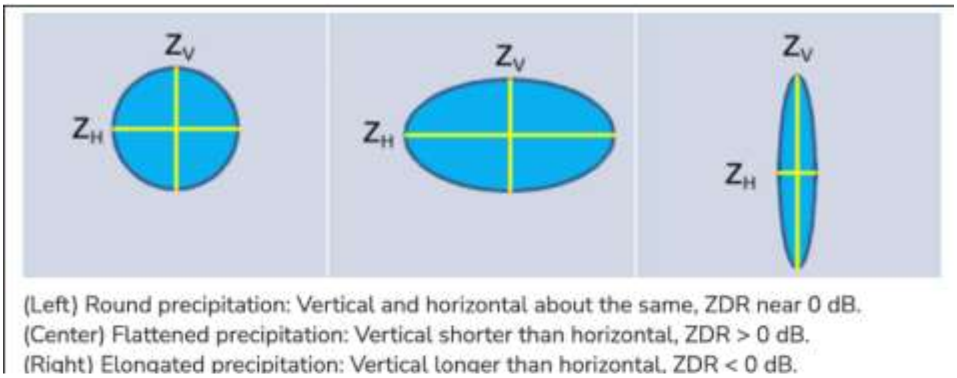

Figure 1: Different shapes of precipitation particles indicate different ZDR values. [2]

B)

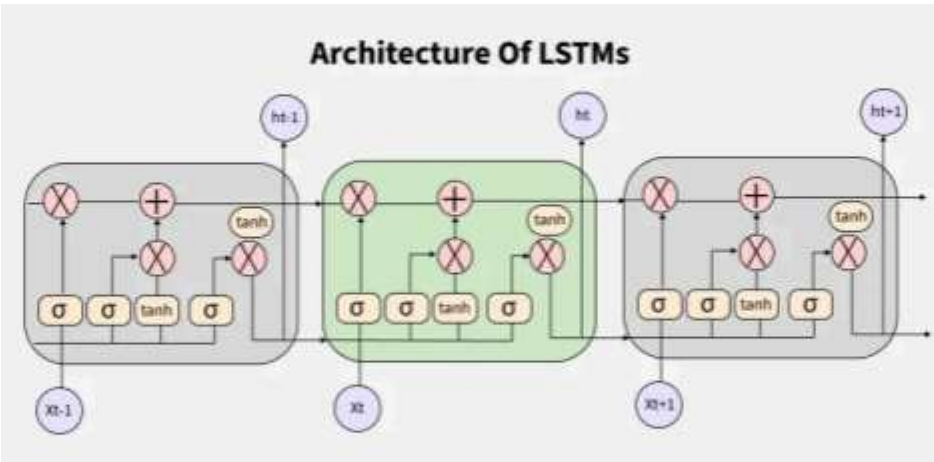

Figure 1. Architecture of an LSTM showing how information is processed across sequential time steps. Source: GeeksforGeeks [2].

C)

Category	Reversibility	Timescale	Representative phenomena	Main consequence	Modeling approach
Performance variation	Partially or fully recoverable	Instantaneous to short-term	Attitude deviation Orbital maneuver Temporary shadow	Output fluctuation	Attitude analysis and power simulation [5]
		Long-term	Temperature excursions Orbital seasonal effects Annealing effects	Periodic performance changing	Power-balance simulation [6]
Degradation	Irreversible	Instantaneous	Micrometeoroid impact Debris impact electrostatic discharge	Structural damage and power loss	Risk assessment and fault analysis [7]
		Long-term	Optical darkening Thermo-optical evolution Maximum power decrease Minority-carrier lifetime reduction Reduction of electrolumi-nescence (EL) intensity	Cumulative DDD/TID effects; Progressive loss in power generation and lifetime	1 [8]. 2 [9,10]. 3 [11,12]. 4 [[13], [14], [15], [16], [17]]. 5 [18,19]. 6 [[20], [21], [22]].
			Interfacial fatigue Crack propagation Delamination	Structural damage and power loss	7 [[23], [24], [25]].

From reference [4], describing the various kinds of degradation affecting satellites and the results of the particular degradation.

D)

Table 2. Power loss comparison (%).

Altitude of An Orbit (km)	Si Coated	GaAs	TJ	CIGS
300	12.5	7.0	3.0	9.0
400	10.7	6.0	2.3	7.7
500	9.0	5.0	1.8	6.5
600	8.2	4.7	1.6	6.0
700	7.8	4.5	1.5	5.5

From reference [5], depicting the relation between material and altitude as they impact power loss in orbit. This is further detailed and explained above in the findings section 2.2.