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SHORT ABSTRACT FOR DISSEMINATION PURPOSES

Abstract

This document presents an overview of the potential of the Artificial Intelligence to Monitor our Seas (AIMS) project, which aims to improve satellite data quality and address spatial and temporal resolution gaps in climate monitoring. By analysing key variables such as sea surface temperature and ocean salinity, the report identifies main data demands and deficiencies. AIMS, through artificial intelligence, can enhance data density, supporting sectors like renewable energy, agriculture, and public health, thereby providing valuable tools for environmental monitoring and strategic decision-making.





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ABBREVIATIONS

Acronym	Description
AI	Artificial Intelligence
AIMS	Artificial Intelligence to Monitor our Seas
CEOS	Committee on Earth Observation Satellites
CIMR	Copernicus Imaging Microwave Radiometer
CNSA	China National Space Agency
EO	Earth Observation
ESA	European Space Agency
EUMETSAT	European Organisation for the Exploitation of Meteorological Satellites
GEDI	Global Ecosystem Dynamics Investigation
GEO	Group on Earth Observations
JAXA	Japanese Aerospace Exploration Agency
ML	Machine Learning
MODIS	Moderate Radiation Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NOAA	National Oceanic and Atmospheric Administration
OLR	Outgoing Longwave Radiation
OSCAR	Observing Systems Capability Analysis and Review Tool
PMW	Passive Microwave
SMAP	Soil Moisture Active Passive
SMOS	Soil Moisture and Ocean Salinity
SST	Sea Surface Temperature
TROPOMI	Tropospheric Measuring Instrument
WMO	World Meteorological Organization





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EXECUTIVE SUMMARY

This report seeks to explore the potential of the Artificial Intelligence to Monitor our Seas (AIMS) algorithm, designed for ocean winds and waves, through new variables and applications.

The study reviews the potential benefits and applications of comprehensive data records of key variables and identifies the minimum requirements to achieve these goals. This analysis is performed by reviewing the literature and online databases provided by the World Meteorological Organisation (WMO) and the European Space Agency (ESA). Furthermore, instrument specifications are taken into account to assess specific capabilities.

The study shows that an improved data set with higher spatial and temporal resolution could directly benefit different applications and positively influence our understanding of climate processes as well as improve critical decision making.





1. Overview

1.1 Introduction

The "Artificial Intelligence to Monitor our Seas" (AIMS) developed throughout this research project provides a new and powerful tool for extrapolating climate data, enabling the achievement of higher spatial and temporal resolutions with a high degree of fidelity. The initial focus of this project is on the maritime environment, more specifically the offshore renewable energy sector; therefore, the main emphasis is placed on winds and waves. However, it is beneficial to explore the full potential of this new methodology for the mapping of further applications.

Satellites represent one of the most significant sources of climatic data for a vast array of applications, with their utilisation being widely embraced across the globe. Both official authorities and a diverse range of scientific disciplines rely on the data delivered from space to draw accurate conclusions and make crucial decisions. While Earth observation (EO) space programmes are being expanded at an impressive pace worldwide, which will have significant impacts on the available data resources, the demand for accurate data with very high spatial and temporal resolutions is increasing at a similarly fast rate to levels that are not attainable with the current resources. Additionally, new satellite applications are being explored that can provide valuable conclusions, but the spatial and temporal resolution of satellite programmes is not dense enough to satisfy this demand.

These challenges are being addressed with the development of modern machine learning algorithms, such as AIMS, which are designed to substantially improve the available data density with a high degree of fidelity.

The relationship between demand and supply of data differs significantly between application areas. This is due to the fact that the nature of some parameters can be very different in terms of spatial and temporal variability. Furthermore, future trends within study fields are uncertain and can develop rapidly.

Determining the gaps and anticipating possible future demands is challenging due to the dispersed nature of both the data and the demand. This report reviews the expected demand within academia, industry, and the





data supply of several satellite data providers, in order to determine the gaps in which machine learning algorithms have the greatest potential for a positive and noticeable impact.

1.2 Literature Review

Climate data delivered from earth observation satellites is crucial for understanding and addressing climate events, with recent trends highlighting its increasing importance. The advent of big data and technological advancements has significantly enhanced the field of climate change studies (Hassani et al., 2019). However, the aggregation and digitization of historical climatological measurements remain a challenge, underscoring the need for open-access comprehensive digital data (Mateus et al., 2020).

The demand for climate data is growing in both industry and academia, with a focus on past and short-term data for practical applications (Tart et al., 2020). This demand is particularly high in sectors such as agriculture, energy, and climate research (Larsen et al., 2021). However, there are challenges in aligning supply and demand, and in ensuring the reliability of data and climate services (Halsnæs et al., 2020). The use of climate risk analytics is also on the rise, with a focus on actionable assessments for business, industry, and governments (Sain, 2023). These trends suggest a continued need for reliable, practical, and actionable climate data in the future.

Integrating in-situ data with satellite information is important for earth observation, as it allows for the collection of multilevel data from different sources and disciplines (Rustamov & Hasanova, 2014). This combination of data is particularly important for advancing global Earth surface modelling, as it can handle both random and systematic errors, leading to effective model improvement (Balsamo et al., 2018).

The shift towards user-oriented approaches in data acquisition and analysis, as well as the use of high-resolution modelling and remote sensing, is necessary to improve our understanding of the Earth system (Balsamo et al., 2018). The migration of space-based systems and data into Earth observation architectures that support interoperable models is crucial for decision support (McCuistion & Birk, 2005).

Giuliani et al. (2017) emphasizes the importance of geospatial technologies in efficiently sharing and integrating climate data. Huebener et al. (2022)





highlights the need for improved satellite spatial and temporal resolution, to better meet the needs of climate impact researchers and decision makers.

Recent research has highlighted the potential of machine learning (ML) and artificial intelligence (AI) in climate science. Kolevatova et al. (2021) demonstrating the effectiveness of ML, in analysing the impact of land cover changes on local climate. Huntingford et al. (2019) further emphasized the role of ML and AI in understanding the full climate system and enhancing weather warnings. Sleeman et al. (2023) proposed a hybrid AI climate modelling approach for discovering climate tipping points, with promising results in predicting the collapse of the Atlantic Meridional Overturning Circulation. These studies collectively underscore the significant potential of ML and AI in advancing climate research and preparedness.

2. Methodology

The identification of data gaps that can be filled with AIMS is a multifaceted process that involves an analysis of several parameters. These include an assessment of the demand for environmental datasets by academic fields and industry stakeholders. The current availability of datasets must be considered in terms of past, present and future missions, as well as data quality, spatial and temporal resolution. This information is necessary to ascertain the feasibility of AIMS in producing reliable datasets.

Given the complexity of this process, tools such as OSCAR (Observing Systems Capability Analysis and Review Tool) (OSCAR, 2024), play a crucial role. Developed by the World Meteorological Organisation (WMO) (WMO, 2024), OSCAR serves as a centralised platform containing comprehensive information on the minimum recommended requirements for each variable and its application. It collates data on measurement instruments, their utilisation in different missions, as well as the quality, resolution, and demand for the data they provide.

Similarly, the Committee on Earth Observation Satellites (CEOS) (CEOS, 2024) provides another valuable resource through its database. The CEOS, particularly through its European Space Agency (ESA) web portal (ESA, 2024a) provides comprehensive information on Earth observation missions, including satellite-based observations relevant to meteorology, climatology, and hydrology. By accessing both the OSCAR database and the CEOS database, researchers can streamline the analysis of data gaps,





thereby facilitating informed decision-making for both scientific research and industrial applications, that rely on accurate meteorological and hydrological data.

Ultimately, the objective is to align the information specific to each variable in a concise and summarised manner that facilitates decision-making and leads to recommendations regarding the optimal applications for AIMS.

3. Optimal Data Types for AIMS Approach

The AIMS system has been designed with the objective of producing consistent and dense data records from a multitude of scattered spatial and temporal satellite and in-situ measurements. This objective can only be met with data that exhibits spatial and temporal correlation. The AIMS algorithm exploits the intrinsic interconnections between climate variables over time and space, rendering it particularly efficacious for specific types of data while less suitable for others. While variables such as wind, waves, temperature and salinity are well-suited to AIMS, very local phenomena and occurrences such as lake levels or forest fires cannot be easily extrapolated through time and space, rendering this methodology ill-suited and unreliable.

AIMS will have the most notable impact on areas and variables where in-situ measurements are either too complex or expensive, especially in remote but sensible areas such as remote ocean regions, large deserts, and deep forests.

The most significant potential for AIMS lies in applications where there is a substantial gap between the resolution provided by current satellite measurements and the resolution required for specific applications. In such instances, AIMS can serve to bridge the aforementioned gap by providing data of a higher resolution that meets the needs of various fields. In light of these framework conditions, the potential applications of AIMS are extensive, with the capacity to make a meaningful impact on climate modelling and environmental monitoring.





4. Available Satellite Data

4.1 Missions and Agencies

The inaugural Earth Observation missions were established in 1959 through the Vanguard 2 satellites, which were capable of monitoring cloud dispersion on the Earth's surface. Since that time, the number of missions has increased exponentially, accompanied by a corresponding expansion in the range of applications.

Nowadays, there are more than 300 registered EO satellite missions, coordinated by several national and international agencies, with highly diverse capabilities and philosophies regarding the free access and usage of data. Furthermore, some private institutions such as Planet Labs (Planet Labs, 2024) and Digital Globe (Maxar Technologies, 2024) operate specialized missions to market and sell data to various stakeholders.

Nevertheless, the most significant developers and providers of open access space data are the National Aeronautics and Space Administration (NASA) (NASA, 2024e), the ESA (ESA, 2024a) and the National Oceanic and Atmospheric Administration (NOAA) (NOAA, 2024).

The most enduring and successful earth observation missions have been the Landsat and Earth Observation System (EOS) by NASA. Their long time and continuous data records have supported a wide range of studies within climate research and other relevant fields. Although new missions, particularly Sentinel developed by ESA, are expanding the capabilities and aiming to ensure continuity in the data collection. In addition to a high spatial and temporal resolution, it is of the utmost importance to ensure the continuous provision of data without any gaps.

While there are other significant missions that collect valuable climate data, such as the Gaofen satellites deployed by the China National Space Agency (CNSA), their data records are not freely available. Organisations such as the Group on Earth Observations (GEO) and the Committee on Earth Observation Satellites (CEOS) advocate for open access to EO data, thereby facilitating international cooperation and innovation.

4.2 Instruments





Modern satellites are equipped with a wide range of sensors that operate throughout different regions of the electromagnetic spectrum. As a result of technological advances, more than 400 sensors have been developed, each of which is capable of determining one or more variables with a relatively high degree of certainty. Certain key instruments have been employed by a significant number of missions, resulting in the generation of a comprehensive dataset for the respective variables.

4.2.1 *Optical Imaging Instruments*

Optical imaging sensors are capable of capturing data within the visible and near-infrared regions of the electromagnetic spectrum, thereby providing high-resolution imagery of the Earth's surface. These sensors are of great value in the analysis of land cover, vegetation health, urban development, and natural phenomena such as wildfires. The typical spatial resolutions for optical imaging instruments range from sub-meters to tens of meters, depending on the specifications and operational parameters of the sensor in question. An illustrative example is the Multispectral Instrument, which is employed on the Sentinel-2A and 2B missions (ESA, 2024).

4.2.2 *Infrared Sensors*

Infrared Sensors are used to detect thermal radiation emitted by the Earth's surface, providing insights into temperature variations and heat distribution. Such sensors are of great importance for the monitoring of volcanic activity, wildfires, and urban heat islands. The spatial resolution of infrared sensors varies depending on the sensor type and application. Some sensors achieve resolutions in the range of several metres to tens of kilometres. One well-known example of an infrared sensor instrument is the Moderate Resolution Imaging Spectroradiometer (MODIS), which is used extensively due to the data it provides. MODIS is a sensor instrument that is carried on the Terra and Aqua missions (NASA, 2024).

4.2.3 *SAR – Synthetic Aperture Radar*

Synthetic Aperture Radar (SAR) instruments operate in the microwave portion of the electromagnetic spectrum, offering all-weather, day-and-





night imaging capabilities. These sensors are widely used for terrain mapping, land use monitoring, and disaster response. SAR data provide detailed information about surface features and changes, with spatial resolutions typically ranging from several meters to tens of meters, depending on the sensor's configuration and imaging mode. An example of this type of instruments is the C-SAR which is supported by the Sentinel-1 mission (Copernicus, 2024).

4.2.4 Atmospheric Sensors

Atmospheric sensors measure various parameters of Earth's atmosphere, including temperature, humidity, and composition. These sensors are critical for studying atmospheric dynamics, air quality monitoring, and climate change research. Spatial resolutions for atmospheric sensors vary depending on the measurement technique and altitude range, with some sensors achieving resolutions on the order of kilometres to tens of kilometres. Sentinel-5P uses the Tropospheric Measuring Instrument (TROPOMI) sensor that measures atmospheric gases to monitor air quality (TROPOMI, 2024).

4.2.5 Radar Altimeters

Radar altimeters are used for monitoring changes in sea level, ocean currents, and ice sheet dynamics. These sensors provide valuable data for understanding ocean circulation patterns, coastal erosion, and sea level rise. Radar altimeter measurements typically have spatial resolutions ranging from several meters to tens of meters, depending on the altimeter's design and operating mode. One example of these sensors is the Poseidon-3B altimeter which orbits on the Jason-3 mission pursued by NOAA, NASA, and EUMETSAT (NASA, 2024c).

4.2.6 Microwave Radiometers

Microwave radiometers measure microwave radiation emitted or reflected by Earth's surface and atmosphere, offering insights into weather patterns, climate dynamics, and hydrological processes. Spatial resolutions for microwave radiometers vary depending on the sensor's design and application, ranging from several kilometres to tens of meters. An example





of these types of instruments is the Advanced Scanning Microwave Radiometer (AMSR2) developed by NASA and launched onboard of the Japanese Aerospace Exploration Agency (JAXA) Global Change Observation Mission 1st-Water (GCOM-W1) satellite (NASA, 2024a).

4.2.7 Lidar – Light Detection and Ranging

Lidar instruments emit laser pulses towards Earth's surface, enabling precise three-dimensional mapping of terrain features and vegetation structure. Lidar data are used for topographic mapping, urban planning, and disaster assessment. Spatial resolutions for lidar sensors typically range from sub-meter to several meters, depending on the sensor's specifications and operational parameters. The Global Ecosystem Dynamics Investigation (GEDI) is a LIDAR instrument developed by NASA and the University of Maryland. It is equipped with three lasers, enabling it to reconstruct detailed three-dimensional maps of forests and canopies. Currently, it is on board of the International Space Station (ISS) (NASA, 2024d).

4.2.8 Hyperspectral Imaging Sensors

Hyperspectral imaging sensors capture data across hundreds of narrow spectral bands, providing detailed information about Earth's surface composition and properties. These sensors enable the identification of specific surface features, such as vegetation types, mineral compositions, and pollution sources. Spatial resolutions for hyperspectral imaging sensors range from sub-meter to several meters, depending on the sensor's design and operational parameters. The Hyperion sensor on board of the Earth Observing 1 mission and developed by NASA is an illustrative example (NASA, 2024b).

4.2.9 Gravitational and Magnetic Field Sensors

Gravitational and magnetic field sensors onboard satellites measure variations in Earth's gravitational and magnetic fields, offering insights into the planet's geophysical properties and subsurface structures. While spatial resolutions for gravitational and magnetic field measurements are not directly applicable in the same sense as optical or radar sensors, the data obtained provide valuable information about the spatial distribution and





magnitude of gravitational and magnetic anomalies across Earth's surface and subsurface. SWARM, developed by ESA is a constellation of 3 instruments on a polar orbit onboard of 3 different satellites. It is dedicated to monitor the magnetic field of the earth (ESA, 2024b).

5. Demand

The demand for climatic data has been increasing exponentially in recent times. Classic research fields such as climatology and oceanography have ever higher demand for big comprehensive data. In addition, new industries have been exploring the large impact that EO satellite data can have on their operations and returns.

In agriculture, field monitoring using multispectral or hyperspectral observations allows farmers to manage crop vegetation, forecast crop yield and optimise decisions. This allows analysts to make forecasts and investment decisions and evaluate risks for insurance companies (Yang et al., 2016).

With regard to fisheries, remote sensing provides ocean data that can indicate the distribution and abundance of fish populations which can significantly reduce search time for commercial fisheries but also provide valuable data to enforce sustainable fishing practices. Furthermore, in the future this data could provide interesting information on fish migration and dwelling (Yang et al., 2016).

The energy sector is currently undergoing a profound transformation and with the advent of new renewable energy sources rendering them highly susceptible to climatic conditions. Remote sensing data can support a wide range of operations and decisions, such as site selection and safety or reliability assessments.

The health sector has been using satellite data to successfully by associating certain health risks with specific climatic conditions. The distribution of infectious diseases can be associated with the habitat and favourable conditions for mosquitoes. Furthermore, certain gases and aerosols that are known to cause respiratory problems are detectable by remote sensing (Yang et al., 2016).

The monitoring of precipitation, evaporation, snow cover and other variables observable from allow administrations and institutions to determine the water supply within specific regions and developing strategies to establish water security.





The transportation and logistics sector employ data to assess safety hazards, environmental impact, and infrastructure management (Yang et al., 2016).

The advent of new technologies and the expansion of their applications has led to a surge in recent demand for climatic datasets. Furthermore, climate change is causing a dynamic environment which can have significant impacts and should be anticipated.

However, the availability of data is fragmented, and accessibility is therefore a significant challenge for institutions seeking to obtain information in an efficient manner.

6. Gaps and Future Potential

6.1 Relevant Variables

Notwithstanding the extensive coverage of different sensors in Earth observation technology, there remain variables with insufficient temporal and spatial resolution due to the limited availability of sensors. Certain regions and parameters may not be adequately monitored due to the absence of widely deployed sensors. For instance, sensors for monitoring specific atmospheric constituents or sea surface salinity may be less prevalent as optical or SAR instruments. Consequently, there is a deficiency in our comprehension of dynamic environmental processes, such as localised air pollution incidents or fluctuations in sea salinity, which necessitate frequent and high-resolution observations to ensure accurate capture.

6.1.1 Sea Surface Temperature

Sea Surface Temperature (SST) is an essential variable and integral to a vast array of marine sectors with different demands. It is used in climate science applications, particularly for long-term climate records (Kent et al., 2019). The offshore wind energy sector, in particular, can benefit from SST data for various purposes, including the design and operation of wind farms, as well as for environmental impact assessments (O'Carroll et al., 2019). The ideal spatial and temporal resolution for climate monitoring listed by OSCAR is 1 km and 1 hour, while the minimum threshold for usable data is 100 km and 7





days (WMO, 2016). According to CEOS database, there are more than 50 missions currently measuring SST with different capabilities and resolutions. The Copernicus Imaging Microwave Radiometer (CIMR) will enhance spatial resolution, with a real aperture resolution of < 15 km (Pearson et al., 2019). However, with present passive microwave (PMW), the SST parameter is provided with a spatial resolution in excess of 50 km, limiting their ability to capture SST detailed features (Pearson et al., 2019).

6.1.2 Atmospheric Temperature

Atmospheric temperature is a crucial parameter in various industries and academic fields. In aeronautics and meteorology, it is used to develop mean seasonal tropospheric temperature profiles (Yee et al., 2012). In remote sensing techniques, such as lidar, it is a key input for determining other atmospheric quantities (Behrendt, 2006). In chemical processes and reactions, temperature is a critical factor, with applications in steam raising, electricity generation, plastics manufacture, and food industry (Hagart-Alexander, 2010). These applications prove the importance of atmospheric temperature in understanding and managing various natural and industrial processes. According to OSCAR the ideal horizontal for climate monitoring is 15 km and the minimum threshold is 500 km. Moreover, the ideal recommended vertical resolution depends on the atmospheric layer and can vary between 0.001 and 1 km. The needed temporal resolution is uniformly listed as 1 hour with the threshold being 24 hours (WMO, 2016). According to CEOS database there are 63 satellite missions that currently monitor the atmospheric temperature. The resolution depends on the specific payload and can vary between 10 and 300 km horizontally.

6.1.3 Sea Surface Salinity

Ocean surface salinity is a crucial variable in various fields, including climatology, oceanography, and marine biology. It is used to study climatological change, trace seawater masses, model ocean dynamics, and determine water mass stratification and mixing rates (Goes et al., 2018; Gu et al., 2022). Furthermore, it is particularly important in coastal waters, where it influences both biological and physical processes (Woody et al., 2000). However, there are challenges in defining and measuring salinity, which need to be addressed (Pawlowicz et al., 2015). Despite these





challenges, satellite-based measurements of sea surface salinity are increasingly being used in ocean and climate studies (Boutin et al., 2021). For oceanic climate monitoring the required spatial and temporal resolution for ocean surface salinity is 10 km and 24 hours respectively, however the minimum threshold indicated to conduct relevant studies is 100 km and 30 days respectively (WMO, 2016). Currently, the Soil Moisture and Ocean Salinity (SMOS) and Soil Moisture Active Passive (SMAP) satellite missions have payloads that allow salinity measurements with a spatial and temporal resolution between 33 and 50 kilometres and with 29 days as revisit time.

6.1.4 Earth Surface Albedo

Surface albedo, the measure of the Earth's reflectivity, is a crucial parameter in energy budget studies and climate change research. It is particularly relevant in the fields of climate science, environmental studies, and meteorology, where it is used to monitor global trends and assess the impact of human activities on the Earth's surface (Chrysoulakis et al., 2019). Marion, (2021) underscores the significance of ground albedo data for estimating the performance of bifacial photovoltaic systems. The availability of high-resolution albedo data is crucial for understanding the Earth's radiation budget and its impact on climate change (Roujean et al., 2019). The ideal spatial resolution of Earth Surface Albedo recommended by the World Meteorological Organization for climate monitoring is 0.05 km and the minimum threshold is 0.5 km, furthermore, the recommended temporal resolution is listed as 24 hours (WMO, 2016). According to CEOS database there are currently around 70 missions primarily monitoring the albedo with future missions being launched in the upcoming years. The current missions list their spatial resolution between 0.5 and 4 km and the temporal resolution is listed between 3 and 29 days.

6.1.5 Specific Humidity

Specific humidity, a measure of the water vapor content in the atmosphere, is crucial for various industries and academic fields. (Tomita et al., 2018) highlights its importance in estimating air-sea latent heat flux and evaporation. (Babaeian et al., 2019) underscores its significance in applications such as drought prediction, water resource management, and





agricultural production. However, (Prytherch et al., 2015) points out the discrepancies in specific humidity data derived from satellite measurements, indicating the need for improved retrieval methods. Therefore, the need for satellite data on specific humidity is evident in these fields to enhance accuracy and reliability. The requirements for the spatial and temporal resolution vary widely according to the specific applications, the ideal resolution varying between 0.5 km and 50 km and between 5 minutes and 12 hours. The high demand and requirements for specific humidity data has prompted a large number of missions that currently measure this variable. The CEOS database lists more than 70 current missions that measure this variable directly with very different resolutions that range from 8 to 300 kilometres.

6.1.6 Surface Soil Moisture

Soil Moisture is the fraction of water in a volume of wet soil. Satellite data on soil moisture is particularly important for applications such as weather and climate forecasting, drought monitoring, water resource management, and agricultural production (Srivastava et al., 2016). However, the effective use of this data in hydrological modelling requires comprehensive evaluations and the development of relevant soil moisture products. The use of satellite-based data mining techniques can improve the accuracy of soil moisture retention predictions (Jeihouni et al., 2020). Furthermore, satellite soil moisture data can help monitor the impacts of climate change, improve early warning systems for extreme weather events, and enhance the accuracy of crop yield forecasting (Forgotson et al., 2020).

The ideal spatial and temporal resolution for climate monitoring is 1 km and 24 hours respectively, the minimum threshold is 25km (WMO, 2016). There are currently 29 satellites with a dedicated payload to surface moisture measurements the instruments have a resolution between 300 meters and 50 kilometres.

6.1.7 Outgoing Long-wave Radiation

The outgoing longwave radiation at the top of the atmosphere (OLR) is a key component of the Earth's radiation budget, influencing weather, climate, and phenology (Qin et al., 2021). Satellite data on OLR is crucial for understanding climate change, as it provides information on the Earth's





energy balance (Dewitte & Clerbaux, 2017). The OLR is affected by various factors, including El Niño and La Niña events, which can lead to significant changes in the Earth's radiation budget (Loeb 2012). However, the accuracy of satellite-derived OLR data can be affected by factors such as cloud cover, which can complicate the retrieval of downward atmospheric longwave radiation (Huang et al., 2007; Schmetz, 1989). Validation studies have shown that radiation models can slightly overestimate OLR and underestimate surface downwelling longwave flux (Zhou & Cess, 2000). Despite these challenges, satellite data on OLR remains a critical tool for understanding and monitoring the Earth's radiation budget.

The ideal horizontal and temporal resolution indicated by the (WMO, 2016) is 10 km and 60 minutes respectively. The minimum threshold is given as 100 km and 30 days. There are currently 55 satellites able to monitor outgoing long-wave radiation in orbit. These satellites have a horizontal resolution within 200 m and 20 km and a temporal between 1 day and 61 days.

6.2 Satellite available variables overview

The implementation of the gap-filling model introduced by AIMS presents numerous possibilities, delivering not only enhanced precision but also significantly improved spatial and temporal resolution across a variety of parameters. This advanced methodology enables the acquisition of detailed and reliable information, facilitating a deeper understanding of the examined processes. Consequently, this approach enhances both the accuracy and practical applicability of the analyses. The table below summarizes some of the satellite data variables identified in Section 3 that could benefit from the AIMS approach.

Table 1 - Overview of variable requirements and instrument capabilities

variables	Requirements		Satellites capabilities		
	Ideal / threshold spatial resolution	Ideal / threshold temporal resolution	Number of current missions	Spatial resolution	Temporal resolution
Sea Surface Temperature	1 km / 100 km	1h / 7 days	53	15 km / 50 km	1 day / 30 days
Atmospheric Temperature	15 km / 500 km	1h / 1 day	63	10 km / 300 km	1 day / 30 days
Sea Surface Salinity	10 km / 100 km	1 day / 30 days	2	33 km / 50 km	29 days
Earth Surface Albedo	0.05 km / 0.5 km	1 day	72	0.5 km / 4 km	3 days / 29 days
Specific Humidity	0.5 km / 50 km	5 min / 12 h	72	8 km / 300 km	1 day / 35 days
Surface Soil Moisture	1 km / 25 km	1 day	29	300 m / 50 km	12 days / 29 days
Outgoing Long-wave Radiation	10 km / 100 km	1h / 30 days	55	200 m / 20 km	1 day / 61 days





The table presented below reviews essential variables, detailing their spatial and temporal resolutions along with the specific requirements that AIMS can potentially meet.

The improvement that AIMS can carry out contribute to obtain more reliable and actionable insights across a range of sectors, including renewable energy, public health, and environmental management.

The AIMS algorithm, by enhancing spatial and temporal resolutions, not only increases the precision of these datasets but also widens their application scope. This approach provides regular, high-resolution data grids that can significantly bolster our understanding of environmental processes, thus supporting informed decision-making across various fields.

This comprehensive evaluation emphasizes the practical utility of AIMS in addressing key data limitations and enhancing the operational effectiveness of satellite-derived datasets across critical environmental parameters.

7. Conclusion

The present work established an analytical approach to evaluating the suitability of key variables for the application of the AIMS algorithm by examining their use cases, specific requirements, and the current status of data records from satellites. This study highlights the demanding requirements needed to perform comprehensive climate and environmental studies, positioning AIMS in a privileged role where it can effectively address critical data gaps.

The satellite data variables identified in Section 6, exhibit substantial potential for improvement through the AIMS approach. Each of these variables presents unique challenges and opportunities that AIMS can address by providing regular, high-resolution spatial and temporal data grids.

For instance, in the case of sea surface temperature (SST), an improvement of the precision and resolution of data records will allow for more accurate monitoring of ocean currents, better understanding of marine ecosystems, and more detailed climate effect analysis. The enhanced SST data can benefit various sectors, including offshore wind energy, which relies on accurate SST data for the design and operation of wind farms.





Similarly, a comprehensive data record of atmospheric temperature is crucial for climate research. AIMS can improve the spatial and temporal resolution of atmospheric temperature measurements, providing valuable insights into seasonal temperature profiles and regional wind phenomena, particularly in coastal areas. This enhanced data can also support meteorology and aeronautics, where precise temperature profiles are essential.

In the field of oceanography, ocean surface salinity is another critical variable that can benefit from the AIMS approach. By improving the resolution of salinity data, AIMS can aid in the study of climatological changes, ocean dynamics, and water mass stratification. This data is particularly important for understanding the physical and biological processes in coastal waters.

The AIMS algorithm also holds promise for improving the accuracy of Earth surface albedo measurements. High-resolution albedo data is essential for understanding the Earth's radiation budget and its impact on climate change. Enhanced albedo data can support climate science, environmental studies, and the assessment of human activities on the Earth's surface.

Specific humidity, a key parameter for estimating air-sea latent heat flux and monitoring droughts, can also benefit from the AIMS approach. Improved resolution and accuracy of humidity data can enhance applications in water resource management, agriculture, and climate forecasting.

Soil moisture data is vital for weather and climate forecasting, drought monitoring, and agricultural production. AIMS can provide more precise soil moisture measurements, improving the accuracy of hydrological models and early warning systems for extreme weather events.

Lastly, the outgoing longwave radiation at the top of the atmosphere (OLR) is essential for understanding the Earth's energy balance and climate change. AIMS can refine OLR data, aiding in the study of weather patterns, phenology, and the effects of phenomena like El Niño and La Niña on the Earth's radiation budget.

Considering the specific gaps between the requirements and the capabilities, as well as the inherent nature of each variable and its use cases, the two variables that present the most imminent potential are the specific humidity and the sea surface temperature, due to their broad range of applications and the current dataset.





In conclusion, the AIMS algorithm offers significant potential to enhance the precision and resolution of various satellite data variables. By addressing the gaps in current measurements, AIMS can provide valuable data that supports a wide range of climate, environmental, and industrial applications. The regular, high-resolution data grids produced by AIMS will play a crucial role in advancing our understanding of complex environmental processes and improving decision-making in various sectors.

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