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Data Assimilation Strategy and Development Plan for NCEP's Environmental Modeling Center

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Executive Summary

The 2021 Priorities for Weather Research (PWR) report by NOAA's Science Advisory Board identifies three pillars to enable a weather-ready nation: (1) Observations and Data Assimilation (DA), (2) Forecasting, and (3) Information Delivery. These pillars are interconnected. For example, improved DA leads to better forecasts which requires the forecast information to be delivered in a timely and reliable manner. In this document, we focus specifically on the first pillar, observations and DA. This document outlines a development strategy and philosophical shift for the NWS to advance the state of infrastructure and science for operational DA to realize improved operational predictions and better meet the agency mission. Several grand challenges and overarching priorities have been identified and will need to be addressed in the coming decade, including:

- Multiscale DA;
- Improved assimilation of remotely sensed observations;
- Enhanced use of the established suite of in-situ observations;
- More agility toward the use of emerging data sets;
- Better representation and estimation of system uncertainties and systematic errors;
- Handling nonlinearity and non-Gaussianity;
- Coupled Earth system DA;
- Processing and assimilating growing volumes of observational data;
- Integration and hybridization of artificial intelligence/machine learning.

As NOAA has embraced the concept of the Unified Forecast System (UFS), the need for a unified DA infrastructure across applications and to enable community development has grown. The Joint Effort for Data assimilation Integration (JEDI) will be this infrastructure, and the need to advance the capabilities and work toward operational transition is critical to the near-term strategy. Work is already underway, and a high-level introduction to JEDI transition activities is discussed. However, the full transition to JEDI for all operational applications is going to take significant resources and several years to complete. In parallel, several research and development priorities will continue to be pursued. This includes the continued optimization of current assets and integration of new components of the global observing system. Decisions will need to be made on an ongoing basis as to which things should be developed with current and legacy infrastructure versus deferment to JEDI and future applications. This document discusses several aspects of the development priorities and future operational readiness across the spectrum of DA activities. While JEDI infrastructure is critical, many aspects of the strategy touch on institutional and cultural challenges. If these are not also addressed, the maturity, functionality, and impact of JEDI for operational utilization will not be fully realized or consequential.

Finally, this strategic document outlines some of the potential risks that will need to be addressed in the coming decade, particularly those related to resources, observational data, management, dependencies, and high-performance computing.

Vision for Success

1. **JEDI as the foundation for data assimilation** – *infrastructure designed to realize innovation*;
2. **Engagement in research and development across the spectrum of readiness levels** – *new funding and joint collaboration with external partners*;
3. **Embracing change** – *reimagination of how we do data assimilation*;
4. **New technology and best practices** – *exploitation and integration of AI/ML;*
5. **Cultivating and sustaining a vibrant workforce** – *people are the key to our future success.*

1. Introduction

The steady increase in the skill of numerical weather prediction (NWP) and Earth system model forecasts has been described as representing a quiet revolution (Bauer et al. 2015). In particular, deterministic global NWP skill continues to improve by about one day of forecast lead time per decade of development. The gains in skill can be attributed to many factors, including increased computing power to facilitate more complexity and higher spatial resolution, improvements in the data assimilation (DA) systems, as well as quality and number of observations being assimilated (Simmons and Hollingsworth 2002). The importance of DA in improving predictive skill is nicely demonstrated by evaluating forecast skill obtained from various reanalysis products. Dee et al. (2011), for example, show the skill of forecasts for a period in 1989 from three different systems, including the ECMWF system at the time, and reforecasts initialized from reanalysis states that had utilized more advanced modeling and assimilation systems in retrospective mode through the same period. The skill is demonstrably improved through each subsequent reforecast dataset (Fig. 2; Dee et al. (2011)).

The National Weather Service, and NOAA more broadly, has initiated a new effort to engage in a community-based, coupled, comprehensive Earth modeling system, the Unified Forecast System (UFS). The UFS is designed to be the source system for NOAA's operational NWP application as documented in the UFS Strategic Plan: 2021-2025 (UFS Steering Committee & Writing Team, 2021). Part of this strategy involves an evolution toward a unified DA system through new infrastructure. The new DA infrastructure will have to meet the needs of the UFS coupled applications, along with addressing several challenges throughout the coming decade. The NWS DA grand challenges and priorities are consistent with those that have been identified and discussed at several meetings, including the NCAR/JCSDA DA Blueprints Workshop in Boulder, CO (March 2016), the Unified DA Planning Meeting in College Park, MD (April 2017), and WWRP-WCRP Joint Symposium on DA and Reanalysis (Valmassoi et al. 2023). These priority areas include:

- Multiscale DA (spatial and temporal): from global to convective scales; assimilation across scales;
- Improved assimilation of remotely sensed observations, such as all-sky/all-surface data and Doppler radar;
- Enhanced use of the established suite of in-situ observations;
- More agility toward the use of emerging data sets, both traditional (e.g., satellite) and novel (e.g., smartphone pressures);
- Better representation and estimation of system uncertainties and systematic errors;
- Handling nonlinearity and non-Gaussianity;
- Coupled Earth system DA; and
- Processing and assimilating growing volumes of observational data.

In the time since those workshops, additional challenges and drivers have revealed themselves including:

- Need for reengineering of observation processing;
- Computational efficiency with a path forward to exascale and cloud HPC;
- Integration with other elements of cross-cutting infrastructure;
- Requirements for reanalysis; and
- Leveraging of new technologies such as artificial intelligence (AI) and machine learning (ML).

More recently, NOAA and NWS have identified a series of priorities and vision areas through multiple documents, including the NWS 2019-2022 Strategic Plan (NWSSP), NOAA's 2020-2026 Research and Development Vision Areas (R&DVA, NOAA Research Council 2020), and the NOAA Science Advisory Board's Report (2021) on Priorities for Weather Research (PWR). One common theme that applies to a majority of NOAA's mission areas is the emphasis on collaboration and engagement both within different line offices across NOAA, but also with the broader U.S. weather enterprise, including the research community and private sector (NWSSP Items 1.9, 2.1, 2.10, 2.11, 3.9; R&DVA Key Question 3.1; PWR Priority Areas FE-4, FE-10). Additionally, observations and DA together have been defined as the first of the "three interconnected pillars" to support a Weather-Ready Nation in the PWR. The other two pillars are Forecasting and Information Delivery, which include areas like model development and reliable data dissemination. This document focuses primarily on the first pillar, Observations and DA, which further features three priority areas: the improved use of existing observations (see also NWSSP Item 2.5); advanced DA methods, capabilities and workforce (NWSSP Items 2.1, 2.5, 2.11, 3.2, 3.3; R&DVA Key Questions 1.1, 3.1); and identifying gaps in the observing system and then the use and assimilation of new observations (NWSSP Items 2.4, 2.5, 3.8; R&DVA Key Question 3.2).

In this document, we outline a vision and present a strategy for DA development for the next decade to meet the needs of operational NWP for the NWS. The critical element for the first phase of the next decade will be the replacement of much of the current DA infrastructure with software from the Joint Effort for Data assimilation Integration (JEDI). JEDI is the next-generation DA infrastructure that is being led by the Joint Center for Satellite Data

Assimilation (JCSDA), and will provide a basis about which the NWS will be able to achieve the goals of a unified DA infrastructure along with addressing the scientific grand challenges to incorporate innovations into operational systems. In addition to the new JEDI infrastructure, the evolution toward coupled DA across the spectrum of UFS applications will be central to the strategy.

Operational NWP systems are complex and contain many interdependent pieces. In addition to DA and observation processing, they include the forecast model, verification utilities, and workflow superstructure. In order to advance the performance and predictive skill from UFS-based applications, these pieces need to come together with sufficient HPC resources and support, as well as the availability of scientific and computational diagnostic tools. We note that while the success of DA innovation is dependent on these aforementioned pieces, this document will solely pertain to the DA and observational components of the UFS.

2. Advanced Infrastructure for Data Assimilation

The transition of assimilation infrastructure for the complex, critical components of the production suite, such as for the Global Forecast System (GFS) and its associated Global Data Assimilation System (GDAS), takes meticulous planning and execution. Since May 2007, the GDAS has used the Gridpoint Statistical Interpolation (GSI) software to produce global operational analyses (Kleist et al. 2009b). Before that, the Spectral Statistical Interpolation (SSI) software, upon which the GSI was built, was the bedrock of global DA at NCEP, with a combined history of over 30 years of operational activity. The transition from the SSI to GSI for the GFS/GDAS took several years and considerable resources to complete. Because of the long history of the codebase, the GSI system is very mature, and is the basis by which most NWP systems at NCEP are initialized. While the GSI has served the operational Earth system prediction enterprise well for the past decade and a half, we have begun to encounter the upper limits on the GSI's capabilities as the size, scope, and complexity of the Earth system prediction continues to grow. A review of the history of DA development activities and a summary of the current state of the operational systems can be found in Kleist et al. (2023).

The advent of JEDI presents a community-driven approach to comprehensive Earth system DA, underpinned by modern software development standards that accommodate the inclusion of advanced scientific developments in a sustainable manner. The JEDI infrastructure is being developed with several specific principles that make it attractive for pursuit as the next-generation Earth system DA framework for use by the NWS: separation of concerns; flexible, modular, mutualized solutions; and an agile framework to enable direct development and collaboration across line offices, agencies, and partners. Through the lens of JCSDA and its partners, the decision was made to adopt the JEDI infrastructure as the solution for unified DA for the UFS. For more information on JEDI, its design, and major components, see Appendix B, or the JCSDA online JEDI documentation for comprehensive details. ***The evolution to JEDI-based DA is the critical element of the strategy to realize future scientific innovation to advance the state of the science utilized for operational DA systems at NWS.***

While formal JEDI transition plans will be drafted and published for specific operational DA systems, in this section, we provide an overview of the three primary areas of focus: 1. validating components, 2. optimization and robustness, and 3. balancing progress in transition and science.

2.1 JEDI Validation

JEDI will ultimately provide a promising foundation for operational DA, but the transition itself is a resource-intensive process. In particular, we must ensure the new JEDI-based framework performs within the rigors of operational Earth system prediction and meets current requirements. This includes careful validation of all components, operators, and algorithms to ensure that new software performs precisely as designed relative to present-era systems (e.g., the GSI). This baseline ensures that initial performance will be maintained at a minimum, eliminating substantial risk in this complex transition process.

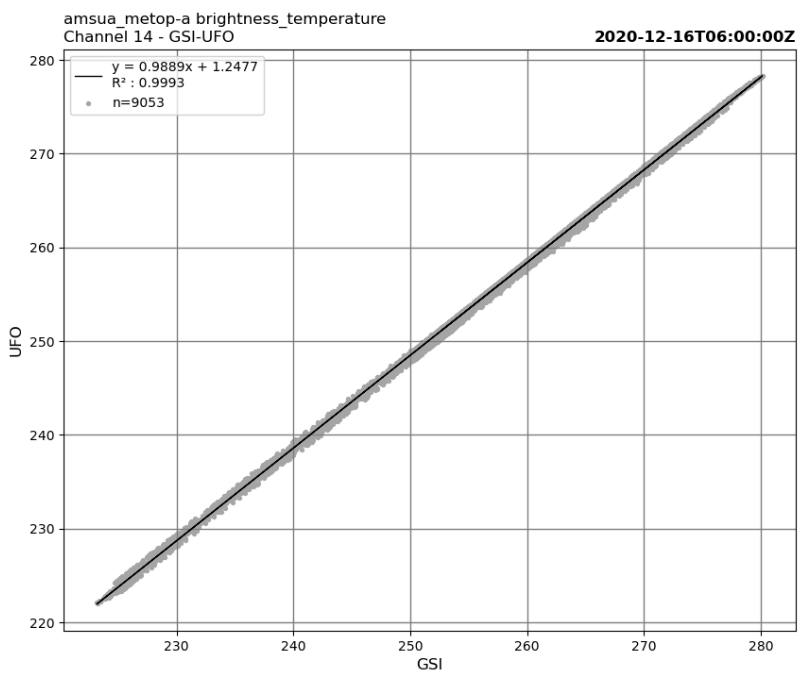

Figure 1. Scatter plot comparing simulated brightness temperatures from AMSU-A MetOp-A Channel 14 between GSI and JEDI UFO valid 06 UTC December 16, 2020.

Validation efforts are presently underway for the suite of observation operators (the Unified Forward Operator, or UFO). In Fig. 1, we see one such example of the validation step associated with the transition effort. Here we compare GSI and JEDI simulated brightness temperatures for AMSU-A MetOp-A Channel 14 for one analysis cycle. In this example, we see that both systems produce similar results, with a correlation nearly equal to unity.

Comprehensive validation requires the proper suite of tools, including those that are currently available for operational monitoring (Kleist et al. 2023). The transition to JEDI presents an opportunity to re-engineer NCEP's assimilation monitoring system as we adopt new standards for observation-space and minimization diagnostics. This effort involves the development of a generic suite of tools that supports operational assimilation monitoring across all UFS applications, facilitates automated generation of diagnostic figures and statistics, and can be leveraged in the validation process. The unified DA monitoring and validation system will be developed using modern software and programming practices and leveraging open-source libraries and those developed by our partners. These tools will be developed in conjunction with web infrastructure so that developers and customers can freely view the performance of UFS DA applications with minimal effort. Information such as whether or not an observation was operationally assimilated into the NCEP systems is regularly requested. Work is already underway to build such a set of tools that can meet internal needs as well as fulfill obligations to things like the expanding World Meteorological Organization Integrated Global Observing System (WIGOS) Data Quality Monitoring System (WDQMS).

In addition to real-time assimilation monitoring, the web infrastructure shall include pages for DA and observation configuration information. We may also include tools provided by community verification systems such as the Model Evaluation Tools package, the established community software for verification and validation of UFS-based applications.

Finally, validation will be carried out for all components and systems for which there exists a pre-existing operational baseline (Fig. 2). While resource intensive, such an approach minimizes risk in the transition process.

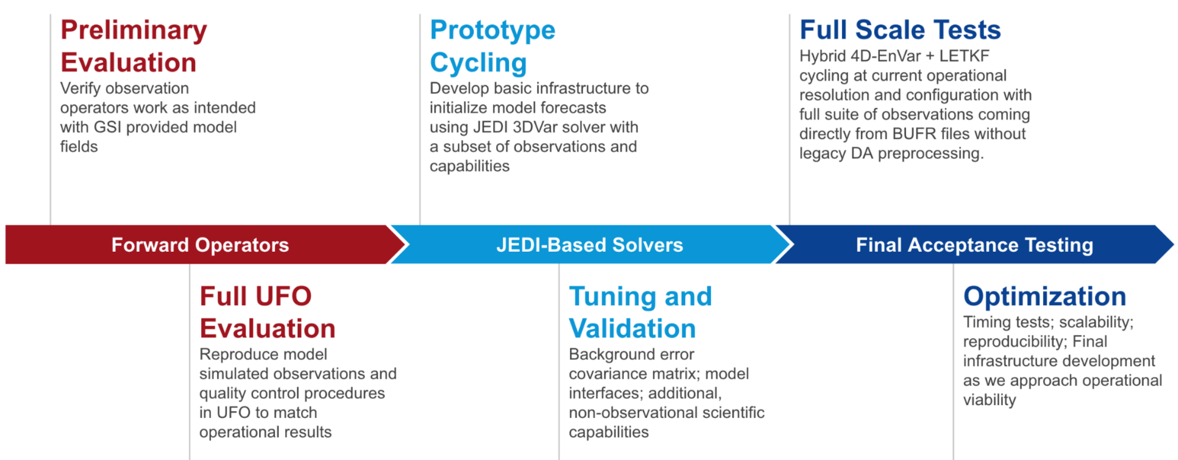

Figure 2. Simplified timeline of the evaluation process for full JEDI acceptance testing and transition to operations for GDAS.

2.2 Optimization and Robustness

Applications intended for operations must be fast and efficient. As a part of the transition process, JEDI will undergo optimization procedures such that its performance meets or exceeds the operational baseline for a given configuration. Here, performance considers computation and memory used along with the time required for execution. This shall also be extended to measures of I/O bandwidth, owing to the high I/O demands associated with DA. With the transition to exascale and cloud computing, JEDI applications should be highly scalable and able to efficiently run in a variety of computing environments. These considerations will be examined as part of the optimization procedure with an emphasis on operational requirements. Bottlenecks shall be identified and addressed in this procedure in order to meet future operational constraints. Time and resources conserved create space for more advanced algorithms and better utilization of observations while maintaining timely delivery of skillful forecast products.

Application performance also includes reproducibility. Given the same inputs to JEDI, applications should generate identical results across repeated executions of the code on the same computing architecture. Reproducibility is important for scientific and technical integrity. It also enhances the effectiveness of collaboration since all partners can have confidence in independently generated results. For some applications, reproducibility may only be obtained when using the same job configuration. More desirable is reproducibility independent of the job configuration, e.g., across varying task counts or threads. Finally, reproducible codes are a requirement for operational systems at NCEP. Therefore, this operational requirement also applies to JEDI.

Operational applications must be robust and able to properly respond to unexpected real-time situations (missing or corrupted input data, unphysical computational results, etc.). JEDI applications for operations will be stress-tested for a wide variety of operational failure scenarios. A hierarchy of error messages shall be standardized across JEDI applications to provide actionable information for a timely response by NCO staff and EMC developers. Checkpointing, if possible, shall be built into applications to allow quicker recovery in the event of system or application failures. Many of these requirements are outlined in existing operational implementation standards documents (e.g., WCOSS Implementation Standards). JEDI applications will conform to these and future updates or replacement documents.

2.3 Balancing Progress in Transition and Science

Transitioning the entire operational DA enterprise requires a substantial investment of time and resources. This substantial investment will create opportunities for scientific progress in the future, but it comes at the cost of making scientific advances in our operational DA systems today. While the challenge is presented in a binary manner, a balance between transition and scientific progress can be achieved with careful planning through an intermediate, stepwise transition. Such a process would involve transitioning components of the JEDI framework as they reach operational readiness. For example, one could begin by replacing the observation operators in one upgrade that would then be followed by a replacement of the solver(s) in the next. Given the unified nature of JEDI within the larger UFS framework, lessons learned from the JEDI transition of one DA system (e.g., global) offer the potential for accelerated JEDI transition of subsequent DA systems (e.g., RRFS, HAFS, etc.). This method lowers the stakes by removing pressure from an "all or nothing" forklift upgrade, thus raising the likelihood of success. Additionally, there is room for integration of innovation as part of the JEDI transition process itself. The goal is not to implement JEDI solely for the purposes of reproducing what is already operationally utilized.

Formal transition project plans are being developed for all relevant future UFS-based applications and will be made available. These will be coordinated with the various project plans for individual applications that are part of the 5 year EMC Implementation Plan.

Transition to JEDI Infrastructure

1. **Separation of concerns** – *generic, modular code that can be applied to numerous modeling applications*;
2. **Joint effort** – *development shared between multiple agencies, can more rapidly introduce new observations or techniques;*
3. **Scientific validation** – *all JEDI components need to meet or exceed current operational systems' scientific capabilities;*
4. **Operational hardening** – *essential to ensure that JEDI applications are robust enough for NWS operations, including running in a timely manner;*
5. **Delicate balance of resources** – *make progress in transition efforts without stifling innovation, else the cost associated with transition will delay any advancements in the science.*

3. Research and Development

3.1 Improved Use of Observations

While our current DA systems assimilate a variety of observations from a diverse range of instruments (Kleist et al. 2023), a subset of observations are presently assimilated but remain underutilized. There is also an exciting array of emerging datasets that have the potential to improve the current observing network. Such examples include Uncrewed Aircraft System (UAS) technology, web cameras (Carley et al. 2021), new satellite constellations in geosynchronous and polar orbit, as well as a growing industry toward providing small, (relatively) inexpensive satellites. Over the next decade, development will include efforts to improve the use of today's observing system while also focusing on emerging observation technologies.

In modern-day NWP systems, some of the largest impacts on reducing forecast errors generally come from the infrared and microwave-sounding instruments on polar-orbiting satellites as supported by evidence from Observing System Experiments (OSE) and Forecast Sensitivity to Observations Impact (FSOI), e.g., such as Bormann et al. 2019; Boukabara et al. 2020. Until recently, however, observations from infrared sensors were assimilated solely in clear sky conditions, significantly limiting the number of observations that can be used. Microwave DA (AMSU-A/ATMS) in non-precipitating, non-convective, cloudy conditions was implemented in 2016 for the operational GFS/GDAS. Since then, work has extended this capability to more microwave instruments and to include precipitation hydrometeors (see GFSv16.3) and convective clouds. Greater use of these observations in cloudy conditions and the extension of this capability to the infrared (where 90% of available fields-of-view are cloud-affected) are major priorities for the next decade (Geer et al. 2019). This effort will require further advances in radiative transfer and a thorough re-evaluation of quality control and observation error modeling capabilities.

A common criticism of using observations in NWP systems, particularly radiance observations, is the underutilization of many observing systems. The reasons for this are multifaceted:

1. Redundant information in the observations. The most notable example of this is the hyperspectral sounders, where channel selection has been employed so that NWP systems assimilate less than 10% of the available channels. However, the information content of those channels represents the bulk of the available information as many channels have similar sensitivities (Collard 2007).
2. The forward model is not sufficient to accurately simulate a given observation. The uncertainties in the forward model have been the situation with cloudy radiances until recent years and continue to be an issue for certain surface types.
3. Observations in the presence of significant model biases may need to be excluded from assimilation. Observations in the areas where the forecast model has significant bias may result in first-guess departures with unphysical signals, thus preventing the data from being assimilated correctly. Areas associated with significant cold air outbreaks is one such example. These occur in the winter at high latitudes where cold and dry air with low temperatures below the freezing point is advected over the relatively warm ocean, forming low-level shallow convective clouds. As a result, supercooled water clouds form at low temperatures far below the freezing point. The microwave observations detect supercooled liquid water in the cold air outbreak area, while the forecast model predicts otherwise. The discrepancy between the observation and forecast creates unphysical first-guess departures and leads to biased analysis. Therefore, excluding observations in cold air outbreak regions may be necessary.
4. Complex error characteristics. The existence of spatially and spectrally correlated observation errors has resulted in the need to downweight observations and/or spatially thin the data. Currently, the thinning distance in the GDAS is 145 km and needs to be revisited, including a strategy to employ more adaptive data selection strategies. While advancements have been made in the application of inter-channel correlated

observation errors, particularly for hyperspectral infrared satellite observations, much work remains to expand this capability to a more general application of correlated errors.

5. Dataset volumes are too large to process. Reduction of data volumes is necessary to ingest a number of datasets, most notably Doppler radial wind and geostationary imager radiances. Strategies such as super-obbing can reduce the need for data thinning, while multi-channel observations may be represented through principal components.

The implementation of the direct use of satellite radiances and inline variational bias correction instead of relying on retrievals was a significant leap in operational DA for numerical weather prediction (Derber and Wu 1998; Zhu et al. 2015; Zhu et al. 2016). However, for various reasons, several derived products remain critical for use within DA systems for the Earth system. In particular, this includes retrievals of ozone, atmospheric motion vectors, sea ice, and soil moisture. The further utilization of all-sky/all-surface satellite radiances and further algorithmic advances may allow for the more direct use of data from satellites and allow for continued evolution away from retrieved products and issues inherited therein, such as the specification of error characteristics, additional processing and dependencies.

3.1.1 Toward Improved Use of "Conventional" Observations

The WMO began a push for a transition from Traditional Alphanumeric Codes (TAC) to Table Driven Code Forms (TDCF), such as BUFR, in the early to mid-2000s with a goal of full transition to be completed by the end of 2014. However, this full transition to dissemination of the relevant observation types to TDCF has not yet been completed and lingering issues remain. NCEP has already successfully completed reengineering projects to enable utilization of data from both TAC and BUFR disseminated formats for many data types; a few data types such as radiosondes and dropsondes are still in the final stages of development. There are advantages to the TDCF/BUFR disseminated data such as additional information content, like GNSS-based position, an improvement over current methods to derive and estimate drift information.

High-resolution radiosondes are now becoming available through the BUFR dissemination process. The capability of using high-resolution radiosonde data has been developed in GSI. Compared to the current radiosonde data, the new radiosonde measurement reports more frequently in the vertical (see Fig. 3). Observation values, time, and location are recorded automatically and accurately. The descent data (after balloon burst) may also be included. The observation errors may need updating and tuning before turning on in operations. Work is underway to encode the BUFR transmitted data into the legacy PrepBUFR format, while efforts are pivoting toward making more optimal use of the additional information content in the future. For example, the inclusion of the data into PrepBUFR requires a subsetting of individual profiles to no more than 255 elements, which is suboptimal as good data may be thrown away. The initial effort will allow for continuity of operations, particularly as countries are slowly turning off transmission of their parallel TAC feeds. Future efforts within JEDI will focus on more optimal use of the higher resolution data and additional content therein.

Observations from surface platforms such as ships, buoys, and land metar/synoptic stations provide a tremendous amount of near-surface meteorological information with high temporal

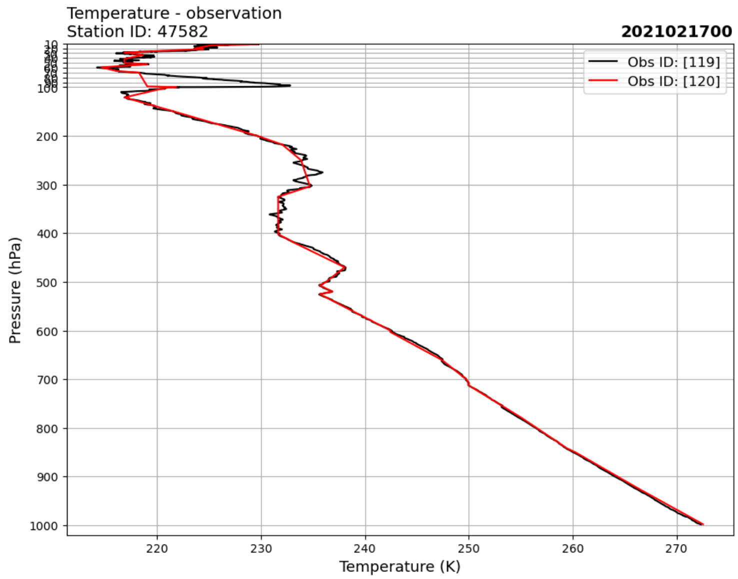

Figure 3. Radiosonde temperature reports: regular (red) and high-resolution radiosonde (black) from station identifier 47582 (Akita, Japan).

frequency. This is further complemented by regional mesonet networks in places such as the United States. Such data has been regularly assimilated into regional systems such as the RAP/HRRR and is an important dataset (James and Benjamin 2017).

However, for global NWP systems, the application of surface data is a bit more complex. While it is standard practice to assimilate surface pressure observations from the entirety of the platforms across applications, the assimilation of wind, temperature, and humidity data from land surface stations is treated differently owing to issues related to representativeness. In the GDAS, temperature, humidity, and wind information is assimilated from marine surface data and only monitored for land surface stations. Some operational centers utilize the two-meter temperature and dew point observations to drive a "screen-level analysis" that is separate from the atmospheric assimilation system. This screen-level/surface analysis is then leveraged to drive updates to soil moisture (Mahfouf 1991). This two-step approach is still the practice at places such as ECMWF (Seuffert et al. 2003). Some initial work has been done to explore options in the GFS/GDAS, including 1) direct assimilation of 2-meter temperature and humidity data into the atmospheric assimilation system, and 2) leveraging EnKF-based strongly coupled assimilation to simultaneously update soil and near-surface atmospheric states. The latter option will continue to be developed for eventual implementation.

3.1.2 Improved Use of Satellite Radiances

The use of radiance observations in NWP may be advanced in a number of ways:

1. Improved and increased use of observations over differing surface types. While surface-sensitive radiance observations are presently used over most surface types,

much of the impact from these measurements is over the ocean. This is because uncertainties in emissivity and first-guess temperatures are lower for oceanic surfaces and issues with inhomogeneity within the instruments' field of view for non-ocean surfaces.

The uncertainties in emissivity can be demonstrated through a systematic bias identified in the emissivity estimation from the operational CRTM for ocean-surface emissivity at the infrared range. The comparison of first-guess departures under clear-sky conditions calculated from CRTM and RTTOV using the same set of model background fields revealed that the ocean emissivity estimation from CRTM is consistently higher when compared to that from RTTOV (Fig. 4). The systematic biases can also be observed through the first-guess departures, especially for higher latitudes (Fig. 5). The root cause is that the current CRTM ocean emissivity does not take into account the sensitivity of sea surface temperature to emissivity. This improvement to the emissivity calculation has been included in CRTM v3.0 (Liu et al. 2019).

Moving towards greater impact for all surface types will require improved surface characterization, through a combination of improved background information and use of the observations themselves, and improved radiative transfer. Improved land surface radiative transfer will be provided via the Community Surface Emissivity Models module to be released with CRTM v3.0. At the same time, the move towards coupled modeling and DA will improve the background estimates of the land surface emissivity and temperature as well as allow for a consistent solution between atmospheric and surface states. In particular, land-surface emissivity at microwave frequencies is strongly dependent on the soil moisture content. Separately, the use of emissivity as a control variable within the assimilation problem may continue to be pursued as early demonstrations have shown some promise and this methodology has already been demonstrated (as a preprocessor) at other NWP centers (Pavelin and Candy 2013) .

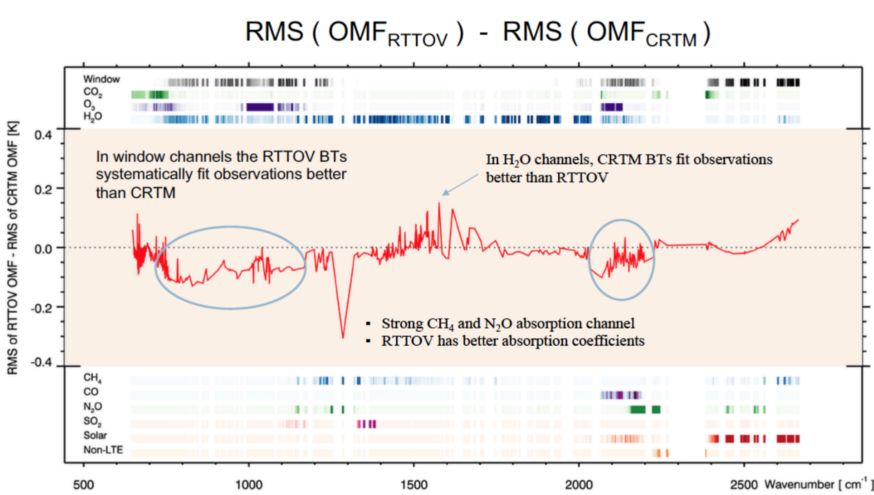

Figure 4. Root-mean-square difference of first-guess departures from RTTOV and CRTM for IASI.

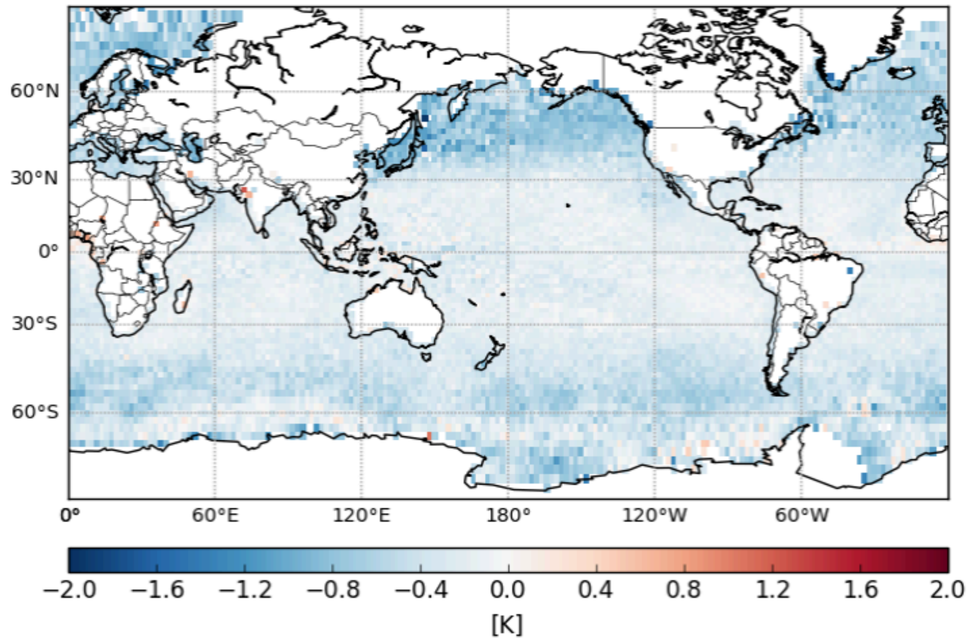

Figure 5. First-guess departure of IASI at 801 cm^{-1}.

2. Increased use of observations in cloudy and precipitating conditions. The move towards cloudy radiance assimilation has been a major theme of the last decade. We currently assimilate all-sky microwave observations, including in the presence of precipitating clouds in the operational GDAS. The move towards true all-sky assimilation for both microwave and infrared measurements will continue over the next ten years. The main challenges concern the more complex radiative transfer for scattering scenarios (which requires more detailed knowledge of hydrometeor size and shape distributions), how to accurately account for cloud fraction (which necessarily requires the use of multiple independent column radiative transfer), and the correct characterization of precipitation and convective clouds in the radiative transfer models.

   The most computationally cost-effective approach to calculate hydrometeor-affected radiance is using the two-column method, as introduced by Geer et al. in 2009. This approach simplifies the satellite field of view representation into two distinct columns—one for the clear portion and the other for the cloudy one. Effective cloud coverage is determined by assuming a specific cloud overlap scheme for each field of view. The radiance from the hydrometeor-affected field of view is then computed as a linear combination of the radiance from the cloudy and clear columns, with weights assigned based on the effective cloud coverage and cloud-free coverage, respectively. While the two-column approach is practical for simulating cloudy microwave scenarios, it is less suitable for handling infrared observations, which demand a more nuanced consideration of cloud characteristics such as amount, height, and coverage. For precise simulation of cloudy radiance, the multiple independent column radiative transfer method, as outlined by Geer et al. in 2019, becomes imperative. This method utilizes the number of columns necessary to represent all conceivable permutations of cloud layers, with each column accurately representing the fraction of the grid box. By treating the atmosphere as a collection of independent columns, this approach acknowledges the spatial variability of atmospheric conditions, thereby significantly enhancing the accuracy of radiative transfer simulations within a sensor's field of view.

3. Consistent use of assumptions between the observation operator and the forecast model. In the assimilation of radiance with cloud and precipitation, many assumptions need to be made about the microphysics (including particle size distributions) and subgrid variability, such as cloud and precipitation overlap in both model and observation operators. These assumptions are often inconsistent, even within different parts of the forecast model. For the next development phase, it makes sense to think about the observation operator and forecast model as part of a unified system, possibly sharing components such as sub-grid cloud-generators and particle habit models.

4. Improved modeling of cloud and precipitation in the forecast model. The forecast model, used as the background state for the assimilation, often has large biases in regions with clouds and precipitation. The biases can be observed in the first-guess departures. For example, all-sky MW departures reveal biases in the modeled clouds in maritime stratocumulus regions and cold air outbreaks due to less than optimal moisture physics representation (Forbes et al. 2016; Kazumori et al. 2016). Biased first-guess fields from the model result in less optimal analysis, with the impact further complicated by interaction with the bias correction scheme. Improving the modeling of moist physics can greatly increase the number of observations assimilated under all-sky conditions and prevent the model bias aliasing into the analysis.

5. Improved modeling and development of observation operators. The ability to assimilate observations in a DA system relies on the quality and robustness of the observation operator to simulate the observed from the model background. For example, the quality of the simulated observation from CRTM for the GMI sensor can be improved greatly by including a surface reflectance correction model (Deblonde and English 2000) for better simulation of radiance reflected by surface (Fig. 6). To support all-sky and all-surface radiance assimilation, the radiative transfer model must include a more robust representation of surface emissivity/reflectance properties, polarization, particle shape, and distribution. As the forecast model becomes more sophisticated in modeling subgrid clouds and moisture processes, it is necessary to account for the subgrid variability of cloud fraction (such as the cloud overlap) and precipitation in the forward calculation. CRTM version 3 has extended its capabilities to support ultraviolet sensors and full Stokes polarization simulation across all wavelengths. It also includes multi-threaded parallelization using OpenMP directives, vastly improving wall-clock performance. In the future release, CRTM will implement a physically-based surface reflectance model based on the bidirectional reflectance distribution function (BRDF). The combination of full polarization and BRDF is expected to improve the accuracy of the simulated radiances under scattering conditions.

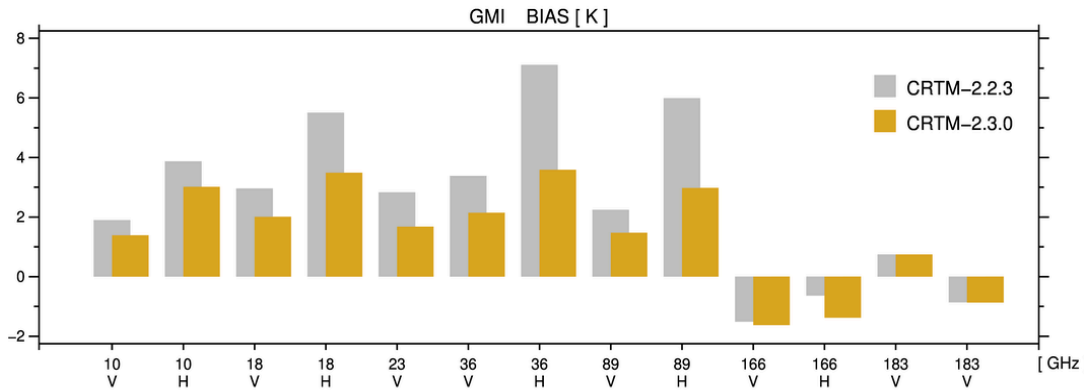

Figure 6. First guess departures from GMI with (orange: CRTM-2.3.0) and without (gray: CRTM-2.2.3) the proper surface reflectance model implemented in CRTM.

6. Better characterization of observation errors and improved QC. Most observation errors in the current DA system are uncorrelated and derived in often *ad hoc* ways (usually based on first-guess departures). Spectrally correlated observation errors have been introduced to the GSI (Bathmann and Collard 2021), using error estimation procedures introduced by Desroziers et al. (2005). The extension of correlated observation errors to other observation types will continue, with particular attention paid to all-sky conditions, as the forward model and representativeness errors are expected to be highly correlated and situation-dependent. The issue of spatially correlated observation errors remains a significant challenge and longer-term goal.

7. Apply variational quality control (VarQC). While the VarQC with a Huber norm distribution (Tavolato and Isaksen 2014) has been implemented for in situ data (Purser 2018), it has not yet been applied to satellite radiance data. In the assimilation of cloud and precipitation-affected radiances, the uncertainties in the observation operator and the forecast model result in a large range of first-guess departures with more outliers in the distribution. VarQC is not a criterion for rejection; rather, it is a re-weighting of observations. VarQC makes it possible to significantly loosen or do away with the gross check and accept outliers into the assimilation. Consequently, more observations can contribute to the analysis, and those with large first-guess departures will be strongly down-weighted.

8. More efficient use of data. In addition to increasing the impact of data through extension to more surface types and hydrometeor scenarios, as described above, there is also potential to make more use of data that is currently available but not assimilated as it is computationally too expensive. The hyperspectral sounders are the best example of this, where only 1-2% of channels are actually used. These channels are chosen as they contain the majority of the information contained in the spectrum. However, the full spectrum may be represented through principal component analysis in a more compressed form. Data from the EUMETSAT MTG-IRS instrument will be distributed in

principal component form, and the assimilation of these data will be the first step towards more efficient assimilation of hyperspectral radiances.

9. Use more satellite radiance data. ECMWF conducted a series of observing system experiments (OSEs) examining the addition of temperature and humidity sounders from a baseline that includes no MW sounders, aiming to evaluate the incremental benefit of adding sounders to the assimilation system (Duncan et al. 2021). The study found that while significant improvements in forecast skill and background fit to independent observations are gained from the first sounder added, beneficial impact from the subsequent sounders added to the system is also evident, showing no apparent saturation in skill improvement with the increasing number of sounders assimilated. A separate study by Geer et al. (2017) reviewed the forecast sensitivity to satellite radiance observations in the ECMWF operational system based on the FSOI technique. The study showed that while the beneficial impact from MW temperature-sounding observations (e.g., AMSU-A and ATMS) is significant, the beneficial impact from MW humidity-sounding (e.g., MHS and ATMS) and imager observations (e.g., GMI and AMSR-2) is increasing rapidly as the more humidity-sensitive observations are assimilated. Their overall performance slightly outperformed the temperature observations in recent periods. For IR sensors, temperature information still dominates the impact compared to humidity. However, a more beneficial impact from Himawari-8, which is assimilated hourly and has more water-vapor channels than other similar sensors on geostationary satellites, is observed, indicating that potentially more data impact can be extracted from IR humidity channels.

   In the operational GDAS, MW radiances from AMSU-A and ATMS are assimilated under all-sky conditions; those from SSMIS sounding channels and MHS are assimilated in clear-sky conditions. No data from MW imagers are included. Radiances from IR sensors, including IASI, CrIS, ABI, AHI, and SEVIRI, are assimilated under clear-sky conditions. The number of humidity channels assimilated from hyperspectral sensors is limited due to non-linearity. The path forward for radiance assimilation is clear. We must extend the use of MW radiance to include humidity information from imagers such as GMI, AMSR-2, and SSMIS and assimilate all MW sensors under all-sky conditions. Increasing the use of IR humidity channels should be explored, eventually moving the IR humidity-sounding channels to all-sky assimilation.

3.1.3 Improved Use of GNSS Radio Occultation

As described in Kleist et al. (2023), GNSS-RO data has become a critical component of the global observing system for NWP, providing critical information on temperature and humidity, with small biases, and serves as anchoring observations for bias correction. NCEP has been utilizing and improving on the NCEP Bending Angle Model (NBAM, Cucurull et al. 2013) for many years. Recent efforts have focused on optimizing the assimilation of new suites of available data, including those now being purchased from commercial vendors. This includes optimization of the forward operator, modernizing and updating quality control procedures, and optimizing assigned observation errors.

In addition to the integration of new satellites and sensors as they come online, there are still some limitations that need to be addressed to further utilize the observations at both high and low altitudes. Within and near the planetary boundary layer, large gradients of atmospheric refractivity render the assimilation of bending angles from GNSS-RO an ill-posed problem. New methodologies and improvements to the current one-dimensional forward operator are under development (Cucurull and Purser, 2023). Beyond improvements to the current operator that is utilized in GSI, there are already several observation operators being developed within the JEDI UFO framework, including two-dimensional operators such as the Radio Occultation Processing Package. Such capabilities through the JEDI/UFO infrastructure will allow for the exploration into advanced techniques and further open avenues for broad, international collaboration and coordination. This could potentially include expanding to more complete ray-tracing techniques and accounting for ionospheric effects as well as space-weather, coupled ionospheric assimilation.

There has been an expansion in the use of GNSS radio occultation to be deployed from aircraft to supplement targeted observing, particularly for high-impact events such as tropical cyclones and atmospheric rivers. Significant progress has been made in the assimilation of such airborne GNSS observations from research missions in previous years as part of several atmospheric river reconnaissance programs (Haase et al. 2021). Such observations are likely to continue to be deployed and will provide a potentially valuable data source for operational utilization.

The NCEP prediction systems have also been underutilizing ground-based GNSS data as a source of precipitable water information for NWP. The assimilation of ground-based GNSS Zenith Total Delay (ZTD) has proven successful in many NWP systems, and there is a growing international network of such observations (e.g., Yang et al. 2020). Forward operators for ZTD assimilation already exist in both GSI and JEDI/UFO. The development of capabilities to leverage the growing number of ZTD observations from ground-based GNSS networks will be a high priority in the coming years.

3.1.4 Improved Use of Ozone and Atmospheric Motion Vector Retrievals

In general, it is considered desirable to assimilate observations in a form as close to the instrument level as possible. The reasons for this are a) the characterization of the measurement errors is normally less complex at this level and b) derived products usually include some *a priori* assumptions that can dilute the information content of the observations if not handled correctly. The most often cited example is the background error covariance that is used to constrain 1DVar retrievals from radiance measurements, but more subtle constraints also exist. These considerations drove the move from assimilating retrievals to radiances in the 1990s, aided by the development of fast radiative transfer models (and their adjoints) such as CRTM. Ozone and AMVs (atmospheric motion vectors) are two examples of derived products that are assimilated in most major NWP models. There is scope to make progress on these and other remaining derived products outlined below in the next ten years.

Ozone

For ozone assimilation, the main reason we are currently unable to use more measurements is that the retrievals from various sources as presently implemented, are inconsistent with each other. It was found that the retrieved total ozone from OMPS nadir mapper onboard NOAA-20 was not consistent with those retrieved from OMI onboard the Aura satellite. The inconsistency could lead to a suboptimal ozone analysis.

Direct assimilation of the ultraviolet measurements that are used in ozone retrievals is already being explored. The key to this is the development of a fast ultraviolet forward model as part of the CRTM (Liu et al. 2021). In the context of coupled systems, particularly for the regional application which will feature reactive tropospheric chemistry, future assimilation capabilities to better constrain lower-tropospheric ozone for air quality products should be developed.

Scatterometers

Scatterometers measure the back-scattered signal from a radar measurement of the ocean at three different view angles from which the sea state and then the wind speed and direction can be inferred. Usually, multiple solutions for the wind field are possible, and *a priori* information is required to choose between them. The contemporary approach in DA is to assimilate level-1 measurements where possible. However, this requires a fast and accurate observation operator to produce simulated observations using the model background as input. Simulating backscatter measurement is still challenging; therefore, in GDAS, we currently assimilate level-2 scatterometer-derived wind direction and speed. Very early work is being done at ECMWF, funded by EUMETSAT, to develop a forward operator and its adjoint to directly model the backscatter (S. Healy, ECMWF, 2024, personal communication). Work is also underway to make better use of higher-resolution scatterometer data, and efforts should be pursued to utilize data that is impacted by precipitation.

Atmospheric Motion Vectors

It is well established that the assimilation of tracer species such as ozone or water vapor in a four-dimensional DA system can cause increments in the wind fields through the so-called "tracer effect" (Peubey and McNally 2009). It seems to be a natural progression, therefore, to replace AMV-derived products (which are ultimately derived by tracking the radiance signals from clouds and water vapor) with the direct assimilation of the radiances themselves. This would have the advantage of circumventing the most challenging aspect of AMV characterization, namely the height assignment of the winds. An obvious first step would be to use the many water vapor channels of the MTG-IRS to infer time-resolved and vertically-resolved water vapor information. The use of the information in the cloudy radiances is more challenging and would first require an infrared cloudy radiance assimilation strategy to be implemented. It is probably fair to say that the replacement of AMV products with a direct radiance assimilation strategy in the next ten years is, at best, aspirational. In the meantime, incremental efforts toward optimizing the use of AMV products will be pursued, such as advanced techniques to thin or create super-observations and better account for uncertainties in height assignment. Additional developments such as the proposed variational Feature Track Correction (Hoffman et al. 2021) should be pursued.

3.1.5 Improved Use of Radar Observations

3.1.5.1 Radar Observations and Quality Control

NCEP has had real-time access to level-II radar data from the network of Weather Surveillance Radar-1988 (WSR-88D) Next-Generation Weather Radars (NEXRAD), which deploy 158 Doppler radars and cover the United States. NCEP also receives Tail Doppler Radar (TDR) observations from NOAA aircraft in operations. Radar radial winds, reflectivity and Velocity Azimuth Display (VAD) winds are used to improve forecast skill in global, regional and hurricane DA systems.

While the NEXRAD network provides reasonable coverage over the United States it still suffers from gaps in coverage. Such gaps can be ameliorated to a degree by expanding to include other networks. Such networks include (1) the Terminal Doppler Weather Radar (TDWR) network operated by the Federal Aviation Administration (FAA); (2) the Canadian weather radar network and (3) the Caribbean radar network.

Using these real-time data in operational DA requires the data to be processed reliably and efficiently through rigorous data quality controls. Advanced radar data quality control (QC) techniques are developed and used in radar data processing systems at NCEP (Liu et al. 2016). However, with the implementation of the new radar scan strategies the QC algorithms should be adjusted and improved to resolve the data quality problem encountered in new volume scan modes. The current QC algorithm was developed for the WSR-88D S-band radar. Dealing with the QC problems in radar observations by C-band TDWR radars is a significant challenge. To properly handle the QC problems from the TDWR network, new QC algorithms should be developed. Furthermore, efforts are required to either develop a new QC algorithm or improve an existing QC algorithm to process Canadian or Caribbean radar data before assimilating it in NCEP's various DA systems. Assimilation of radial wind observations beyond the NEXRAD network has shown potential to include short-term forecasts in a recent global observing system experiment (Lippi et al. 2023) and should be explored.

3.1.5.2 Radar Reflectivity Assimilation

In regional NWP systems, 3D reflectivity is currently assimilated through a latent-heating method (Benjamin et al. 2016). During model integration, the latent-heat specification can be combined with a digital filter initialization (DFI), which reduces noise in the subsequent forecast. The latent-heat specification can also be used to initialize the NWP model without DFI with a full hour of latent heating and a time-varying temperature tendency based on sub-hourly radar data. This computationally-inexpensive approach promotes mesoscale circulations and/or convective-scale structures in regions of ongoing observed precipitation while suppressing development of these features in regions of radar coverage. The method can be implemented to global, regional and hurricane forecast systems to improve convective-scale feature initialization.

Direct assimilation of radar reflectivity is challenging in a variational framework, because of the high nonlinearity of its observation operator and its close involvement with the complex microphysics. A direct reflectivity assimilation method was recently developed within a GSI-based EnKF and EnVar framework. Reflectivity, rather than hydrometeor mixing ratios, is used as a state variable in an EnVar framework. This approach has the advantage of avoiding the need for the linear tangent or adjoint of the reflectivity operator (Wang and Wang 2017). The method relies on ensemble-based background error covariance to spread the impact of radar reflectivity to other variables. The direct reflectivity assimilation method may potentially improve storm scale assimilation as model resolution and ensemble member size increase. Future work into methods which relax parametric (i.e. Gaussianity) assumptions should be explored in order to continue to realize the benefits of reflectivity assimilation (e.g. McCurry et al. 2023).

3.1.5.3 Radar Radial Wind Assimilation

The QCed radial winds at elevation angles lower than 5º are currently super-obbed to 5º x 5 km resolution to reduce overall data volume, decorrelate observation errors, and reduce representativeness error. These super-obbed radial winds are then assimilated directly in the current regional DA systems. As resolution and model physics continue to improve, they may be assimilated with less super-obbing, though the impacts of correlated observation errors should be considered (e.g., Simonin et al. 2019). Fine-scale radial wind assimilation may potentially improve convective-scale forecasts. A demonstration of improved use of radial wind observations is documented in Lippi et al. (2019).

In the absence of level-II radial winds, Velocity-Azimuth Display (VAD) winds will be assimilated as a supplement to provide high resolution wind vertical structure. The high temporal and vertical resolution VAD wind profiles have been derived from Level-II radar wind observations at NCEP. The temporal resolution is equal to the period of the radar volume scan, which is less than 10 minutes for WSR-88D radar. The vertical resolution is 50 meters. The international radar network can also provide VAD wind profiles to NCEP. However, instead of employing VAD winds, more radar radial wind will be included into the DA system as level-II radar data transmission capability grows (e.g. Lippi et al. 2023).

3.1.5.4 Dual-Polarization Variable Assimilation

The enhanced, dual-polarization capable WSR-88D radars offer greater details about the size, shape and type of hydrometeors. With this advantage, assimilation of dual-polarimetric radar data is expected to improve precipitation system initialization even further (e.g., Putnam et al. 2021). The dual-polarimetric variables typically considered for assimilation include differential reflectivity Z_{DR}, reflectivity difference Z_{dp}, and specific differential phase K_{DP}. To properly realize the advantages of assimilating dual-polarimetric observations, forward operators should be constructed in such a way that they are fully consistent with the model microphysics scheme. Further, it is likely that at least a double-moment microphysics scheme will be required to realize the full potential of these data (e.g. Jung et al. 2012).

3.1.5.5 Tail Doppler Radar Data Assimilation

Tail-Doppler Radar (TDR), also known as airborne doppler radar, observes the 3D hurricane structure with radial wind and reflectivity. After automatic quality control is conducted on the aircraft, the TDR radial winds are transferred to NCEP. The radial winds are then thinned and assimilated in HAFS. Similar efforts to improve the assimilation of land-based Doppler radar data are also applicable to reconnaissance observations: reduced thinning/super-obbing as the forecast model improves, consideration of correlated errors, improved quality control, and expansion toward the assimilation of dual-polarimetric variables as airborne radar technology advances.

3.1.6 Continuous Optimization

The global observing system continues to change rapidly, meaning new processes and procedures need to be developed to more rapidly integrate new observations. Once things are integrated into operations, the work to make best use of the observations is never completed. There is no such thing as the "last mile" and "maintenance mode" in this context. The optimal use of observations is a function of all aspects of the system, which is ever evolving. For example, the introduction of a new observing system may render the utilization of other types of observations sub-optimal without additional, significant changes. Aspects of the assimilation of observations in an operational system requires a sustained effort to be resourced and maintained to continually optimize the system, including but not limited to observation error calibration, quality control decisions, and improved operator development. There is hope that aspects of this could potentially be automated through the integration of AI/ML-based technologies.

Enhancement of Existing Observations

1. **Improved use of conventional observations** – *such as the use of screen-level observations in the global system or utilizing high-resolution radiosonde data*;
2. **All-sky and all-surface radiance assimilation** – *use of satellite radiances in a variety of cloudy and precipitating conditions across the entire planet;*
3. **Quality control and error assignment** – *ensure observation errors and quality control filtering procedures are optimized and evaluated continuously;*
4. **Reduce use of retrievals** – *move from retrieved products to direct assimilation of observations including for ozone and derived motion vectors;*
5. **Improved use of radar data** – *reflectivity, radial wind, and dual-polarization observations from both ground-based and airborne radars present unique challenges for their proper use.*

3.1.7 Improved Use of Observations with JEDI

The coming decade will see the transition of operational DA from GSI to the JEDI framework. This will potentially give a number of advantages when assimilating new observations and improving the use of existing systems. Together with the other JCSDA partners (NOAA-NESDIS, NOAA-OAR, NASA, US Navy, US Air Force) plus the Met Office, the JEDI is a joint project using the same core system but configurable and expandable according to individual centers' needs. An obvious advantage of this is the ability to share configurations and code innovations and potentially speed up the implementation of new systems.

The JEDI framework is built around two key ideas: separation of concerns (which, among other advantages, has the potential to simplify the implementation of coupled modeling and DA) and generic algorithms that may be configured for multiple uses and instruments without duplicate code. The separation of concerns concept is intended to allow different components, e.g., forward operators and minimization algorithms, to be interchanged and compared within the same framework. Some early work on the intercomparison of radio-occultation operators has benefitted from this concept. The standardization of data storage (both input and output) through the IODA framework has also allowed the development of common tools for pre- and post- processing as well as making interrogation of these data easier.

These advantages do not negate what is often the most crucial element in testing and implementing changes in the DA system, which is the need for multi-month testing of the full system to demonstrate statistically significant forecast impact.

The ability of JEDI to have a positive impact on implementation ease, speed, and effectiveness will crucially depend on how these new systems interact with the operational side of the NWS forecasting endeavor. At the current time, it is much more straightforward to get a change in scripting or configuration files approved for operational implementation than a change to the (mostly Fortran) code. When new instruments become available, the GSI code needs to be modified in various places to read, process, and quality control the data. With JEDI (in theory), the existing high-level applications within the code need only be called with new configuration files to achieve the same effect. But we should also acknowledge that this transition will require the acquisition of new skills and knowledge from both the development and operational sides, including the adoption of the Agile change management processes that are the cornerstone of the JEDI project.

3.2 New and Upcoming Observations

3.2.1 In Situ and Non-Satellite Platforms

In situ observations, such as from surface stations and radiosonde balloons, have been a key component of operational DA at NCEP/EMC for decades. In addition to the enhanced use of existing observations described above, there are a number of new and upcoming in situ and non-satellite remotely-sensed observations that have potential for use in operational NWP. These include but are not limited to:

- Super-pressure balloons (SPBs; Loon balloons, e.g. Lukens et al. 2023) that could be used for both assimilation and validation of winds in the stratosphere;
- Long-duration, controllable balloons for multiple profiling during a single mission, targeting regions void of radiosondes (e.g. such as those from WindBorne);
- Uncrewed drone systems (Saildrones; uncrewed aircraft vehicles; etc) that contain observation payloads;
- Observations derived from the renewable energy sector, such as wind turbine power, tall tower, and turbine nacelle;
- Crowdsourced observations, such as smartphone pressure observations, and low-cost, Internet of Things (IoT) networks are an emerging source of environmental data;
- Additional surface observations from professional-grade personal weather stations, government/academic mesonets, and private sector networks; and
- Web cameras (Carley et al. 2021).

Some of the above have already reached high readiness levels and even operational utilization. For example, SST observations from marine autonomous vehicles (Saildrones) are already operational in the NCEP GDAS to help constrain near-sea surface temperature (NSST). The atmospheric observations from the same platform are undergoing development and will be included in operational applications in the coming years. This is an area of development that is rapidly growing that will come with significant challenges such as quality assurance/quality control, privacy (for things like smartphone data, observations from vehicles), and potentially complicated forward operators for assimilation.

3.2.2 Satellite Radiances

There will be abundant meteorological satellites with legacy and innovative instruments available to the NWP community in the next few decades. The JPSS and GOES programs from NOAA will continue their next series with the same set of instruments and provide measurements for the next two decades. The future low-Earth orbit environmental satellites from NOAA's Near Earth Orbit Network (NEON) program, a collaborative mission with NASA, will supplement and eventually replace JPSS in the 2030s. The first stage of the NEON mission will launch QuickSounder, a small satellite with an ATMS sensor, the same as those flown on the JPSS series, and a new Sounder for Microwave-Based Applications (SMBA) instrument. The innovative GeoXo satellite system with hyperspectral sounding capability will expand observations of the GOES-R series from geostationary orbit and become operational in mid-2030. The continuation of the MetOp and Meteosat satellite series from EUMETSAT will carry the traditional sensors from their predecessors and new sensors such as Ice Cloud Imager (ICI) and Infra-Red Sounder (IRS). A detailed timeline of various satellite programs for NWP applications is illustrated in Figures A1-A3, and instruments onboard and their potential usage in the NWP systems are listed in Tables A1-A4.

We categorize these observations in terms of their implementation priority for operational NWP systems, except for data not allowed to be used due to security concerns. The highest priority will be the observations from the instruments on board the extended satellite programs, such as the US JPSS and GOES series and the European MetOp and Meteosat Series that are already assimilated in the current NWP systems (legacy sensors). The second priority will be given to new sensors that provide additional information to the observing system and require minimum developments. New sensors that require significant scientific development will be ranked third. The lowest priority will be given to sensors with unknown or questionable quality or with potential scientific issues complicating their usability for NWP.

3.2.2.1 Microwave Radiances

Satellite MW radiances were initially assimilated only under clear-sky conditions in the NCEP operational system from 1995. They have been assimilated in cloudy regions over the ocean since 2016 and extended to precipitation conditions in 2022. All-sky assimilation builds on many developments at NCEP over the last 20 years. Much of the breakthrough in using MW radiances under all-sky conditions comes from improvements in multiple DA components, including the radiative transfer modeling, representation of moist physical processes in the forecast model, situational-dependent observation and background error covariance estimation, and assimilation algorithm.

So far, the GDAS all-sky framework includes MW radiances sensitive to temperature, moisture, and hydrometeors from AMSU-A and ATMS. All AMSU-A channels (23, 31, 50-57, and 89 GHz) and ATMS, with the additional high-frequencies 165 GHz and 183 GHz sounding channels, are assimilated over the ocean in the all-sky framework and under clear-sky conditions over non-ocean surfaces. The current framework gives us a good foundation to prepare for assimilating radiances from the continuing legacy ATMS and a more advanced Microwave Sounder (MWS) on board the next generation of satellites. In the meantime, we are extending the use of data over non-ocean surface types. The 183 GHz humidity-sounding channels are not particularly sensitive to the surface. Potentially, they can be assimilated over various surface data types. The MW 183 GHz channels are good candidates for extending the all-sky framework to an all-sky and all-surface framework.

We have not used radiance data from MW images such as GMI and AMSR-2 in the operational GDAS. The data from imagers are sensitive to the surface and total column water vapor across all sensor frequencies. Sensitivity to hydrometeors varies enormously with frequency. The low-window frequencies (5-20 GHz) give information on the column-integrated rainwater. The mid-window frequencies (30-90 GHz) are more sensitive to cloud liquid water. There is also sensitivity to scattering from large frozen particles (snow and graupel) around 90 GHz. The humidity-sounding capability is found at higher frequencies, around 183 GHz, with stronger sensitivity to large frozen particles. Efforts to use MW image radiances from GMI and AMSR-2 in GDAS are underway. The experiences will better prepare us for future sensors such as AMSR-3 and MWI, which are scheduled to be launched in 2024 and 2025, respectively.

EUMETSAT will include an Ice Cloud Imager (ICI) on its next generation polar satellites, which will observe selected frequencies in a sub-millimeter range between 183 GHz and 644 GHz. This part of the MW spectrum is underutilized in NWP applications. It contains water vapor and oxygen absorption lines that provide sounding capability and window channels offering additional information on clouds and precipitation. Uniquely, the sub-millimeter frequencies provide information about cloud ice particles and are strongly sensitive to ice water content and particle size distribution.

Table A1 summarizes instrument data selected for enhancing the operational DA systems for the coming decades. MW instruments available for NWP, which cover the spectra from microwave, millimeter-wave, and submillimeter-wave, will provide extensive information regarding surface and atmospheric temperature, moisture, winds, as well as clouds and precipitation. The expanded channels in higher frequencies (Fig. A4) also enables ice cloud profiling. The main features of sensors with new frequencies from the next-generation satellites, which have higher priority for assimilation, are as follows:

> Microwave Sounder (MWS) will replace AMSU-A and MHS on the current MetOp satellites. The spectral characteristics of MWS are enhanced, compared to AMSU-A and MHS, by adding two temperature and three humidity-sounding channels. The new MWS channel at 229GHz (Table A5) will provide information on cirrus clouds, which improves humidity-sounding information.
>
> Microwave Imager (MWI) is a conically scanning radiometer with spectral coverage from 18 GHz up to 183 GHz. It has heritage from MW imaging missions such as SSMIS, GMI, and AMSR-E. The innovative channels in the oxygen band near 50-60 GHz and 118 Hz provide information on weak precipitation and snowfall. MWI Channels at 165 and 183 GHz are less sensitive to the surface and provide information on water vapor profiles and snowfall information, enabling cloud slicing.
>
> Advanced Microwave Scanning Radiometer 3 (AMSR-3) is a successor to the conically scanning AMSR-2. There are three new high-frequency channels for moisture and snowfall. Additional channels at 10 GHz with reduced noise levels will provide better sea surface temperature information.
>
> Ice Cloud Imager (ICI), also a conically scanning passive imager, is the first MW radiometer designed for remote sensing of ice clouds, providing cloud penetration capability and sensitivity to a significant portion of particle size range not covered in the millimeter-wave or the IR range. Channels near the weak absorption lines around 325.15 GHz and 448 GHz provide information on cloud height.

3.2.2.2 Infrared Radiances

The current constellation of infrared instruments is currently divided into four main categories. In polar (low-Earth) orbit, there are the hyperspectral sounding instruments (IASI, CrIS, AIRS) as well as imaging filter spectrometers (AVHRR, VIIRS) whose primary role in DA is cloud and surface characterization. The imaging filter spectrometers have their analogues in geostationary orbit (SEVIRI, ABI, AHI) which allow for time-resolved observations of the planet including the derivation of wind products. The fourth group of hyperspectral geostationary sounders, combining high spectral resolution of the polar sounders with the temporal information of the geostationary imagers, is currently represented by the Chinese Geostationary Interferometric Infrared Sounder (GIIRS).

The launch of EUMETSAT's MetOp Second Generation, currently scheduled for 2025 will carry the next generation IASI, IASI-NG. IASI-NG will have similar spatial resolution to IASI, but will have improved noise characteristics as well as twice the spectral resolution (and hence twice the number of channels - 16921). Also on MetOp Second Generation, the AVHRR will be replaced with METimage. This will have 20 channels spanning from the visible to the thermal infrared frequencies of the spectrum, as opposed to the 4 channels on AVHRR, with a spatial resolution improved from 1.1km to 0.5km. As with MetOp, the METimage on Metop-NG will provide sub-field of view context for IASI-NG observations as well as providing important information on ocean temperature, ocean color, land and ice properties and atmospheric motion vectors at the poles.

EUMETSAT's Meteosat Third Generation (MTG) series started with the launch of MTG-I1 on December 13 2022, initiating its 12-month commissioning period. The -I (imager) series of satellites will carry the Flexible Combined Imager (FCI), the successor to SEVIRI. The FCI will have 16 channels from the visible to the thermal infrared with a channel-dependent spatial resolution of 0.5 - 2.0km (SEVIRI has 12 channels with 1.0 - 4.8km resolution).

MTG will also comprise the -S (sounder series of satellites), with the first expected to be launched in late 2024. The MTG-S series will carry the MTG-IRS (infrared sounder). This will be a hyperspectral sounder with 1720 channels at spectral resolution of 0.625cm^{-1} and a spatial resolution of 4km at the sub-satellite point. The volume of data expected from MTG-IRS has resulted in the decision to distribute a spectrally-compressed dataset to NWP centers through principal components.

A similar concept is under development at NOAA in the form of the Geostationary Extended Observations) GeoXO mission, with a currently scheduled first launch in 2032. The GeoXO sounder, GXS, will have a similar design to MTG-IRS with 1550 channels and a 0.625cm^{-1} spectral resolution. There will also be an enhanced imager, GXI, with 18 channels - two more than the current ABI - and enhanced spectral resolution.

3.2.3 Small Satellites and CubeSats

CubeSat and SmallSat MW sounder missions (Fig. A5) offer the possibility to provide a higher temporal sampling. These MW sounders with fewer frequencies (see Table A8) than the 3-orbit backbone developed and flown on SmallSats and CubeSats hold promise. They could potentially complement the backbone MW sensor configuration. Several missions such as TEMPEST-D and TROPICS have been launched or planned. From the NWP perspective, efforts are required to ensure the NWP can benefit from these novel observations:

- Further studies are needed to define an ideal MW sounder constellation that includes the backbone and supplemental missions. These studies should have the selection of frequencies for augmentation and different orbits.
- Need to demonstrate effective calibration and validation capability for quality assurance
- Demonstrate ability to handle the challenge of shorter mission lifetimes. It generally takes at least six months to two years to use data from a new satellite operationally after launch. With the shorter lifetime of SmallSats and Cubesats, the NWP centers need to be engaged in the characterization and quality assessments for these missions to ensure data will be assimilated in a timely manner.
- As with all observations, NWP centers require data received with minimal latency (less than 10 minutes for some nowcasting and short-range weather forecasts).

The use of smallsat data in operational NWP will require additional attention to the implementation procedure outlined in Kleist et al. (2023). This will involve additional responsibilities on the data providers, the radiative transfer model team, the development team at EMC and NCO.

Data provider responsibilities:

1) Demonstrate value for NWP.
2) Provision of the instrument and launch.
3) Detailed characterization of the instrument well in advance of launch (six months or more). In particular, instrument spectral response functions need to be characterized and communicated for inclusion in the fast radiative transfer models (currently CRTM and RTTOV). Bespoke radiative transfer models are not acceptable.
4) Precise requirements for instrument noise and stability will be channel dependent, may vary with time and may depend on other factors (trade-offs with field of view size, for example), but for each individual instrument these requirements need to be agreed in advance.
5) Timely delivery of data to NCEP. Data needs to arrive within defined thresholds for the operational application. The data should be provided through an established data exchange mechanism e.g., GTS, NOAA PDA (or replacement such as established cloud delivery mechanism), EUMETCast or equivalent. Data should be provided in BUFR format as that remains the WMO standard for observational data exchange.
6) Data should be made available to the wider community. The success of the international NWP modeling efforts rely on the free exchange of observations between countries. As the NWP forecasts from our international partners are used by NOAA forecast offices, it would be counterproductive to pursue exclusive use policies.

Radiative transfer model team responsibilities:

1) The updating of radiative transfer model (CRTM in our case, but RTTOV should also be included) coefficients is currently performed by the JCSDA CRTM team and is therefore external to EMC. It is a requirement that the RT team coordinate with the data providers to obtain the instrument spectral response function; to produce the fast model coefficients and to deliver to EMC.

EMC team responsibilities:
1) Ingest data provided and made available for DA testing.
2) Evaluate the data by running in the DA system in passive mode. Ensure the data quality is as expected and modify observation errors as appropriate. Ideally this should be done in the operational system if changes can be provided in advance (see NCO responsibilities below).
3) Run a data impact study to ensure non-negative impact from the data. Current policy is to perform this for a minimum of two months. Sufficient resources (workforce and computation) need to be made available for this. If resources are not available, this requirement may be relaxed by senior management decision (this may be appropriate if multiple identical instruments are launched over time). Alternative mechanisms to assess value/impact may also be pursued (FSOI, ensemble spread reduction, etc.).
4) Provide code and configuration changes to NCO to implement through a git tag.

NCO responsibilities:
1) As we move to more frequent updates to the observing system, new mechanisms and policies to allow more frequent updates to the assimilation system need to be developed.

3.2.4 Atmospheric Composition

While there are not currently any observations of aerosols or atmospheric composition assimilated in the NCEP production suite besides ozone retrievals, there are a variety of observations available now and in the near future from both LEO and GEO platforms. With the exception of AOD (from GOES ABI), all other observations relevant to atmospheric composition are currently only on LEO platforms. Existing LEO platforms such as VIIRS, TROPOMI, and OMPS provide retrievals of AOD and various trace gases such as nitrogen dioxide (NO_2). Given the nature of the instruments, most composition-related observations are only available during the daytime due to the need for passive shortwave from the sun. One main limitation of regional air quality DA currently is the lack of observation coverage, as most of these LEO platforms can only provide observations over CONUS once per day. The Tropospheric Emissions: Monitoring Pollution (TEMPO) instrument, launched in 2023, will provide hourly observations of AOD and multiple trace gases over the United States. TEMPO, combined with Sentinel-4 (Europe) and GEMS (E. Asia), will form a constellation of geostationary air quality relevant observations across the globe. For more information on current and future satellite-based atmospheric composition observations, please refer to Frost et al. (2020).

3.2.5 Ocean, Land, Ice, and Waves

The follow-up missions to nadir-looking altimeters consist of Sentinel-3C, Sentinel-6B, CRISTAL A/B and Sentinel-6 NG, ensuring a minimum of 3 operational nadir looking altimeters at all time throughout the next decade. In addition to the above, the Surface Water and Ocean Topography (SWOT) mission was launched in December 2022. Unlike previous ocean topography missions, SWOT will observe the ocean circulation at an order of magnitude finer resolution than the current missions. The altimeter instruments onboard these missions will provide observations of significant wave height, absolute dynamic topography and sea-ice freeboard.

The maturation of the use of the Visible Infrared Imager Radiometer Suite (VIIRS) has opened up new opportunities for the study of the cryosphere. This technology will enable the DA process to better constrain the surface sea ice temperature and its interior thermodynamics by assimilating the retrieved sea ice surface temperature or brightness temperature observations. This will lead to a more accurate representation of the ice-air interface.
At the time of writing, the Gravity Recovery and Climate Experiment Follow-On (GRACE-FO) mission, initially set to conclude in mid-2023, is still ongoing. The European Space Agency (ESA) Next Generation Gravity Mission (NGGM) is a continuation of GRACE-FO's low-orbit satellite train. While gravity missions have been underused in the past, the advent of a mature coupled modeling and coupled assimilation infrastructure will facilitate the development of the multi-domain (ocean, land, land-ice, atmosphere, etc.) forward operator for the simulation of low orbit trajectory of satellites such as NGGM. The information content of gravity missions will allow better constraint of coupled model's mass balance.

The Plankton, Aerosol, Cloud, ocean Ecosystem (PACE) mission is set to launch in February 2024 with the goal of observing and studying the ocean and atmosphere. It will gather information on biogeochemical water constituents and atmospheric parameters such as aerosols and clouds. This information will provide added insight into the upper ocean biogeochemistry that affects the light penetration depth and upper ocean heat content as well as supplement VIIRS aerosol optical depth observations for use in atmospheric constituent DA, and even provide information on surface albedo and normalized difference vegetation index (NDVI) for land surface applications.

Global Navigation Satellite Systems Reflectometry (GNSS-R) is an emerging area for various components of the Earth system including ocean altimetry, ocean-surface wind speeds, soil moisture, and surface vegetation. In addition to recent missions such as CYGNSS, there are some private sector vendors (including those from which government agencies are purchasing data for operations) that are already producing products from GNSS-R that may be of relevance for DA in some of the aforementioned areas. While initial efforts could focus on the integration of such L2 products (e.g. ocean surface wind speeds, soil moisture), forward-looking developments focused on advanced forward operators for use within coupled systems should be explored and exploited.

3.2.6 Space-based Lidars and Radars

Observations providing 3D information of clouds and precipitation from the space-borne active instruments on board CloudSat and CALIPSO have been available since 2006 but are now rapidly approaching end-of-life. New efforts, such as EarthCARE, will be launched in 2024 and beyond. Even though radar and lidar combined provide detailed clouds and precipitation, there are still many challenges to using this information effectively in the DA system. Some encouraging studies have been performed using these data at ECMWF (Janisková 2015; Fielding and Janisková 2020). Most crucial to the development of assimilation systems for these measurements is the availability of accurate radiative transfer models of these active measurement systems. The forecast model also needs a reasonable representation of the physical processes related to the observations (e.g., moist processes related to large-scale and convective cloud formation). Finally, the development of appropriate QC, error models, and bias correction schemes is required. The development of forward models in the Community Active Sensor Module (CASM) within the CRTM framework is a crucial first step in developing active sensor assimilation at EMC. Evaluation of these forward models within the EMC DA system will lead to developing an appropriate error model, quality control, and bias correction procedures and providing crucial information to feedback to both the radiative transfer model and forecast model developers.

The ESA launched the Aeolus mission on 23 August 2018, an initial foray into operational production of space-based Dopper wind lidar. One of the goals of the mission was to provide 3D wind data from the Mie and Rayleigh channels of the Atmospheric LAser Doppler INstrument (ALADIN). 3D wind observations from space, particularly in the tropics, has long been identified as having potential for improving operational NWP forecasts. Several NWP centers are operationally assimilating the data with varying degrees of documented improved forecast skill (see Rennie et al. 2021 as one example). Initial development activities were carried out for NCEP systems to demonstrate the potential benefit (Garrett et al. 2022; Marinescu et al. 2022). However, the assimilation of the observations was never implemented into operations owing to the short mission life that was expected and other external factors. This is a good example of a need for more rapid development and deployment of such capabilities. It is very likely that there will be similar, follow-on missions for space-based lidar winds given the current and ongoing success of Aeolus.

3.2.7 WindBorne Balloons and Uncrewed Aircraft System (UAS)

WindBorne balloons provide a low-cost platform for collecting surface-to-stratosphere meteorological data in underserved areas.It offers long-duration observations, high-altitude data collecting, global coverage, and fine-scale resolution. These observations could be employed in DA to improve more accurate and timely weather forecasts. Early trials have already been completed with promising results for predictions of tropical cyclones and atmospheric rivers. NOAA/NWS is nearing completion of a plan to begin procuring such data for operational utilization.

UASs are increasingly being used to collect data at NOAA. These platforms can capture important, high-accuracy, time-sensitive data in regions and scenarios that may otherwise be hard to reach. UAS can give high-resolution observations in pre-event zones as well as at sea. Such activities have ramped up significantly in recent years. There is now a UxS Research Transition Office within NOAA as well as significant efforts within the NOAA Office of Marine and Aviation Operations (OMAO). As an example, the FY21 Use Report for NOAA UAS documents the support across NOAA and highlights several significant programmatic developments. Observations from such platforms are going to continue to expand in availability for use in operational DA systems.

Incorporating Emerging Observing Systems

1. **Embracing remote controlled in situ observing platforms** – *balloons, drones, and other platforms to provide complementary information;*
2. **Crowdsourcing observations** – *internet of things, personal weather stations/mesonets, and renewable energy derived observations;*
3. **New Products** – *leveraging AI processing to derive novel products from visible imagery or other data sources;*
4. **Next-generation satellite instruments** – *new microwave and infrared sensors aboard future polar-orbiting and geostationary missions to replace legacy platforms;*
5. **Small satellites and CubeSats** – *can provide additional information but present unique challenges due to their relatively short useful lifetimes*;
6. **Earth system DA observations** – *extending DA capabilities to the ocean, land, atmospheric composition, etc. requires the use of observations of all aspects of the Earth system, not just the atmosphere.*

3.3 Algorithms and Enhancements

3.3.1 Algorithms

The mathematical framework by which the analysis is derived, whether through cost function minimization or more direct computation, plays a primary role in the character of the analysis. Many of NCEP's applications currently use the GSI framework containing a variational solver (see Kleist et al. 2023 for details about the current algorithm usage at NCEP). The construction of the variational cost function has the advantage of allowing additional terms, such as constraints and online bias correction. This was part of the appeal of the extended control variable form of the hybrid DA system. It allowed the continued use of the 3DVar system already in place while incorporating the advantages of flow dependence and multivariate correlations that ensembles provide. It was easily extended again to include 4D information with the 4DEnVar. See Bonavita et al. (2017) for details concerning many of the DA algorithms discussed in this section.

Another 4D algorithm, 4DVar, is favored by some other operational centers and has been in use for decades. While 4DEnVar constructs its time dependence by sampling the ensemble throughout the assimilation window, 4DVar relies on tangent linear (TL) and adjoint (AD) models to represent the time evolution in the assimilation window. This results in additional maintenance; whenever the nonlinear model is updated, the TL and AD models may need updating for consistency. There are additional complications regarding the linearization of physical parameterizations, particularly in handling triggers and on-off switches. Some centers have adopted strategies of either utilizing simplified physics in the TL and AD integrations as well as using perturbations models in place of full TL models for the dynamics. Looking to the future with coupled Earth system modeling and assimilation, creating fully coupled TL and AD models to enable more strongly coupled 4DVar assimilation is a difficult task. Within this context, some viable alternatives to the full TL have been proposed and are being pursued such as the Local Ensemble Tangent Linear Model (Frolov and Bishop 2016; Frolov et al. 2018), hybrid TLM (Payne 2020), as well as leveraging of emulation through machine learning. This is ripe for exploration, particularly within the context of coupled assimilation (discussed later).

The incorporation of ensembles into the global and regional atmospheric solvers has been invaluable and will continue to be utilized for the foreseeable future. Ensembles add a great deal of skill due to the characterization of flow dependence and multivariate information in the background error, however this comes at the computational cost of running many additional forecasts. There is typically also a maintenance cost as many ensemble-based algorithms require a separate ensemble perturbation generating system apart from the deterministic solver. One alternative to using EnKF variants to update the ensembles that is not yet utilized by NCEP is the concept of ensemble of data assimilations (EDA). Similar to having a deterministic system, a suite of (possibly) lower-resolution perturbed versions of the parent system are run. Since each member of the EDA system can be run independently, this type of system is highly scalable. Having both the lower resolution and higher resolution DA using the same system can also increase maintainability since upgrades can be more easily included in both the deterministic system as well as the EDA. There are many additional alternatives to variational-based hybrid assimilation schemes, including the mean-pert method, Ensemble-Variational Integrated Lanczos, and block-Lanczos EDA. A thorough review of hybrid variational and ensemble-variational schemes can be found in Bannister (2017).

The discussion thus far has been focused on algorithms that generally assume Gaussian distributions. As models continue to increase in resolution and complexities, nonlinearities and non-Gaussianities will become increasingly important to represent, both in the model states as well as the observation operators. Though there have been attempts to represent different types of distributions in existing algorithms (Dee and da Silva 2003; Fletcher and Jones 2014, Yang et al. 2020), increasing focus has been given to particle filters, which are able to capture nonlinearities that other variational and EnKFs typically cannot. It has been difficult, however, to apply pure particle filters in geophysical applications (Snyder et al. 2008), especially with the number of particles needed to represent the nonlinearities accurately. With typically a much larger number of observations than particles, the weights of the particles tend to collapse around one solution and resampling is required. Other techniques borrowed from existing DA algorithms, such as localization (Poterjoy 2016), have been applied in particle filters to aid against collapse, but this is an ongoing challenge in applications such as NCEP's. Initial tests are already underway with a GSI-based localized particle filter application for use with a prototype version of the HAFS. Demonstrations within operational-like systems have been pursued for global NWP with some success (Potthast et al. 2019). A review of particle filters for high-dimensional problems including extensions to EnKF and variational hybrid variants can be found in van Leeuwen et al. (2019).

The atmospheric applications have traditionally been at the forefront of DA algorithm innovation. However, more traditional algorithms, such as 3DVar, still have a role to play in many systems. Several applications within the NCEP production suite are evidence of this, such as 3DVar-based ocean DA (GODAS and RTOFS-DA), initial aerosol optical depth and constituent DA, and initial OI-based snow assimilation to initialize land states. However, in the case of each of the aforementioned applications, work is already underway to develop hybrid-EnVar and/or EnKF-based assimilation components to best leverage ensemble-based information for prescribing background errors. As will be described elsewhere, there is also a push toward coupled Earth system assimilation, driving a need for better coordination and consolidation. The leveraging of an ensemble generated from a coupled model integration (e.g. truly coupled perturbations) opens many avenues for exploitation across media within a coupled assimilation system.

The JEDI framework will provide access to a variety of algorithms and general flexibility (for both variational and ensemble-based approaches) in terms of configuration for application-driven needs. The framework already allows for multiple configurations of variational and hybrid ensemble-variational solvers, multiple minimization options for variational solvers, Ensemble Transform Kalman Filter updates, and preliminary work to allow for EDA. However, as is already being demonstrated, it is possible to use the same underlying infrastructure to perform flexible configuration of assimilation schemes for very different applications.

3.3.2 Background Errors and Algorithm Enhancements

The choice of algorithm in a DA system is crucial to its performance, but within the same algorithm, there are many means by which to improve skill. For example, the analysis is sensitive to the specification of errors for the background, observations, and prediction model. The background error covariance matrix provides spatial and intervariable correlations, determining the structure and magnitude of the observation impact. However, we are often forced to make assumptions about these statistics because of the overwhelming size of the covariance matrix and the fundamental limitation on knowing the true state of the Earth system. See Bannister (2008a,b) for an overview of previous background error constructions at many operational centers.

NCEP has traditionally used the NMC method (Parrish and Derber 1992) to estimate background error statistics. This method of lagged pair forecasts has been a mainstay in NWP across the globe in the decades since its first usage, though recently estimation through ensemble perturbations has become increasingly prevalent. The implementation of GFSv16 used ensemble perturbations rather than lagged forecast pairs for its background error generation, but the method of background error application remained the same. Improvements to the estimation of the background error statistics can continue to be pursued, for example by adding a seasonal dependency. However, as applications increasingly rely on dynamic ensembles and hybrid methods, improved representation in the static covariances will have reduced benefit and lower return on development investment.

Spatial correlations in many of NCEP's applications are defined by recursive filters (Purser et al. 2003a,b). These filters provide a good approximation to a Gaussian distribution and have the ability to include anisotropy as well, however they are hard to parallelize due to their sequential application. With increasing analysis resolution, the lack of scalability of the recursive filter quickly becomes a bottleneck. Spectral-based and wavelet correlations are additional approaches that also have the advantage of being easily incorporated into a multiscale assimilation approach. While the aforementioned methods for spatial correlations rely on structured, orthogonal grids, the B matrix on an Unstructured Mesh Package (BUMP[1]) is defined in such a way that it can be used on both structured and unstructured grids. Already incorporated into the JEDI framework, BUMP performs its most costly computations on a sampled subgrid and then interpolates back to the chosen grid. BUMP's grid-agnostic approach is convenient, the extra interpolation step may introduce a nontrivial computational cost. On the other hand, the recursive filter has served operational DA admirably well for nearly two decades, but as our computational grids continue to increase in size we are encountering limits of scalability.

A new approach, known as the multigrid beta filter (Purser et al. 2022), has emerged as an area of focus owing to its attractive combination of computational efficiency and fidelity with covariance modeling. The multigrid beta filter algorithm leverages the compact support from the use of a beta function and constructs the quasi-Gaussian response through the application of successive generations of filter grids, from fine to coarse scales. Together, the beta filter with compact support and the multigrid algorithm yield a highly scalable and efficient approach to background error covariance modeling, especially relative to the recursive filters, which have effectively infinite support and are applied sequentially. The multigrid beta filter is applied across successive grid generations (Fig. 7), during the minimization of the cost function. Simple single observation tests that exercise all aspects of the variational minimization have been done to compare scalability between the recursive filter and multigrid approach. As expected, the multigrid beta filter depicts much improved scaling as processor count increases relative to the recursive filter (Fig. 8).

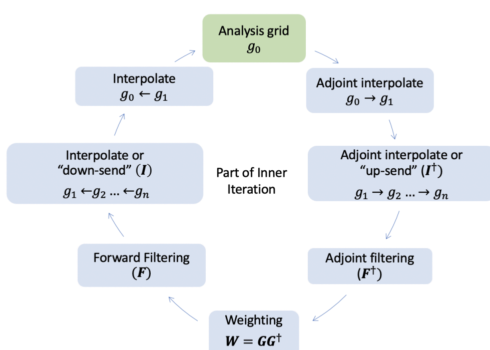

Figure 7: The steps in the application of the multigrid beta filter algorithm. From Fig. 3 of Purser et al. (2022).

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1 https://jointcenterforsatellitedataassimilation-jedi-docs.readthedocs-hosted.com/en/latest/inside/jedi-components/saber/theoretical_documentation.html

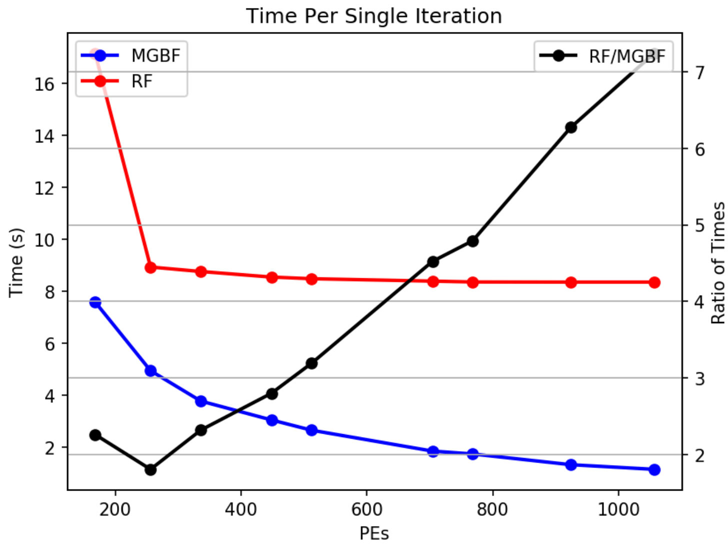

Figure 8: Time, in seconds, taken for a single iteration with the multigrid beta filter (MGBF; blue) and recursive filter (RF; red) as a function of the number of processor elements (PEs). Also shown is the ratio of recursive filter and multigrid beta filter times (RF/MGBF; black). Adapted from Table 2 in Purser et al. (2022).

As spatial resolution increases, we need to reevaluate portions of the algorithms that are no longer appropriate for finer scales. Representations of balance in the background error have traditionally focused on large-scale geostrophic or hydrostatic balances, considering mainly the wind and mass components. Even with atmospheric models incorporating non-hydrostatic prediction, the DA components have remained largely hydrostatically defined. Caron and Fillion (2010) found that the prescription of linear geostrophic balance assumptions in the background error are less representative as the intensity of precipitation increases. There has been some exploration in defining different balance and variance statistics for precipitating and non-precipitating areas (Montmerle and Berre 2010) as well as incorporating additional control variables to represent non-hydrostatic processes (Wang and Wang 2021). Further, with the advent of hybrid ensemble methods and their application at the convective-scale (Gustafsson et al. 2018), it is conceivable that comparatively complex representations of balance in the background error may be superseded by the inclusion of ensemble covariance. More research is needed on this topic.

3.3.3 Multiscale Assimilation

Multiscale analysis capabilities have been highlighted as a priority research topic across operational centers (Gustafsson et al. 2018), especially as our Earth system prediction systems continue to increase in spatiotemporal resolution. With these systems, it is critical that our DA algorithms also contain the ability to simultaneously analyze all scales of motion present in our observation network that are also resolvable by our models. Historically this has been challenging, especially at the convective-scale (≤ 3 km) when trying to assimilate observations that are often considered to be high resolution owing to their spatiotemporal density, such as

Doppler radar radial winds, alongside those that are assumed to be rather coarse, like rawinsondes. In the context of traditional variational assimilation methods, typically formulated in model space, the correlations in the background error are typically associated with synoptic scales, thus making the information content in dense observation networks difficult to extract and often ignored. Past research has attempted to address this by running multiple passes with a variational solver, with each successive pass having shorter decorrelation lengths that are often decided a priori (Xie et al. 2011; Gao et al. 2013; Xu et al. 2016).

With the present era of hybrid ensemble-variational techniques, the inclusion of ensemble information improves the resolution of the background error covariance, assuming the ensemble covariance is of the same resolution as the high-resolution analysis. However, with increasing resolution comes additional degrees of freedom as we expand the spectrum of resolvable atmospheric phenomena. In order to accommodate the additional degrees of freedom, research suggests that we may need a minimum of 200 members at the convective-scale (Necker et al. 2020). At present, our high resolution prediction systems only have enough computational resources to allow for a fairly limited set of ensemble members, on the order of 30-40 members. To address the issue of rank deficiency, localization is employed, typically a Gaussian-shaped function that truncates long-distance correlations to zero to minimize spurious analysis increments. While localization helps with issues related to rank deficiency, it inherently places a strict limit on the ability to extract the most effective information content from any given observation. To obviate this issue, past studies have prescribed specific localization radii for observations that are considered to be coarse (e.g., rawinsonde) or high resolution (e.g., Doppler radar) to some degree of success (e.g., Zhang et al. 2009). However, the characterization of individual observations as having a particular resolution is ad hoc and inevitably results in the loss of potentially valuable information.

Emerging methods address the multiscale DA challenge in a way that is more seamlessly integrated into analysis algorithms, and helps ameliorate the need for ad hoc procedures (e.g., multipass variational methods) and a priori scale-based characterization of observations. Two such methods are: scale-dependent localization (SDL) which has been tested for global applications directly in the ensemble-variational framework with promising results (Huang et al. 2021) and the second is in the dual localization method integrated within the ensemble Kalman filter framework (Yang et al. 2017). Exploration of multiscale, multi-resolution applications will be a common theme over the next decade for many applications.

3.3.4 Balance and Initialization

While not necessarily incorporated into the algorithms themselves, initialization plays an important part in the maintenance of balance within the system. Full-field digital filters have historically had a place at NCEP, but this method has drawbacks, particularly where hydrometeors are concerned. Digital filters smooth fields over time, which is detrimental for features with sharp gradients or where nonlinear processes dominate, increasingly common with increasing spatiotemporal resolutions. In the global system, NCEP has recently incorporated a 4D incremental analysis update (4DIAU, Lei and Whitaker 2016) for initialization as a replacement for the full field digital filter. The GSI also contains a normal mode initialization scheme incorporated into the minimization, the tangent linear normal mode constraint (TLNMC, Kleist et al. 2009). Despite the considerable computational expense, the TLNMC provides enough benefit to warrant its inclusion into the GDAS. Ensuring initial conditions are balanced at the appropriate spatiotemporal scales is important for a good forecast and shall be an important component of future DA algorithms. Such future endeavors may include introducing a machine learning-based emulator to replace the time tendency model in the TLNMC to improve computational efficiency or leveraging the model interface directly within JEDI to compute tendencies consistent with the application (e.g. calling the model directly).

Another method known to improve overall balance and the effectiveness of a DA algorithm, as well as the prediction model, is via the systematic investigation of physics tendencies and analysis increments between DA cycles (e.g., Wong et al. 2020). A model with a bias will be susceptible to imbalance when assimilating observations, particularly those observations which correspond to fields that are biased. Further, a biased model violates core assumptions in the underlying DA equations typically employed. However, it is rare that our models are without bias. A coordinated effort between DA and model (physics) developers to remove the bias through routine investigation of these tendencies and analysis increments will offer fundamental improvements to the prediction system as a whole. This approach to systematic model and DA improvement shall be a priority.

3.3.5 Summary

We envision the prioritization of improving our algorithms such that they capture the full range of spatiotemporal scales inherent in our Earth system, measured by our evolving observing network, and also resolvable by our models. Rather than committing to particular solvers for specific applications, ***JEDI infrastructure will be leveraged to explore various solvers and generate evidence to inform decisions as to how to proceed.*** For example, studies to do direct comparisons between Hybrid 4DEnVar and 4DVar for the GFS will be possible in the near future. Similar studies have been performed at places like the UK Met Office (Lorenc et al. 2015; Lorenc and Jardak 2018) and have been extremely valuable in informing a path forward, considering all aspects of the system including impact on skill, maintenance, computational cost, etc. This will be especially critical for exploring paths forward for radically different applications such as those designed for S2S versus warn-on-forecast, as an example. We will also prioritize further investments into JEDI infrastructure to enable forward-looking algorithms such as localized particle filters.

3.4 Alternate Cadence Strategies and Continuous DA

Today's operational production suite features intermittent DA systems with a variety of cadence frequencies. The GDAS, for example, features a six-hourly cadence with analyses valid at so-called synoptic times (0000, 0600, 1200, and 1800 UTC). This supplements the GFS initialization that is similarly run with a six-hourly cadence but with earlier data cutoff times. Other systems, typically those running at finer spatial resolution, perform analyses more frequently, such as hourly or every 15 minutes. These cadences are loosely tied to the spatiotemporal scales of motion for which the respective Earth system prediction models are intended to resolve and predict. As spatial resolution improves, phenomena that exist on shorter timescales are resolved as well - e.g. boundary layer circulations, convective-scale motions, and so on. Error growth at these scales is typically much more rapid than at comparatively coarse resolutions (e.g., Lorenz 1969), which often leads to the choice of a more rapidly updated cadence with high-resolution systems to mitigate errors associated with non-Gaussianity and nonlinearity. Such choices are self-evident in the inherent designs featured in present-day convective-scale DA systems, especially when radar observations are introduced (Johnson et al. 2015; Wheatley et al. 2015; Jones et al. 2016).

In addition to the typical, high-frequency cadences often employed at the convective-scale, there also are numerous benefits to having global analyses at a shorter cadence. This includes providing more recent lateral boundary conditions to regional models and having a frequently updated analysis available for forecast verification, calibration, as well as situational awareness. There may also be a benefit to having global forecasts updated more frequently and available to the meteorological community for high-impact weather events such as land-falling tropical cyclones and for the aviation industry. However, we must be cautious as higher frequencies in both regional and global systems is often accompanied by the introduction of model imbalance, which should be assessed and may need to be ameliorated through the use of a variety of initialization procedures, such as with a digital filter (Peckham et al. 2016) or the incremental analysis update (Lei and Whitaker 2016) that were previously discussed.

We note that the intended effect offered by a more frequent cadence need not only be addressed by running an intermittent DA cycle at a higher frequency. Algorithmic advances may also prove effective, such as extensions to 4D, which in some cases even allow for longer assimilation windows rather than shorter ones. ECMWF extended its global assimilation window from 6 to 12 hours in 2000 (Bouttier 2001) and later explored extending it further to 24 hours (Fisher et al. 2011). Using 4D algorithms, longer windows combined with sufficient observations to constrain the trajectory can lead to smaller error growth within the window and increase consistency between cycles. Increased window length in a 4D system can also be combined with a strategy of overlapping windows so as to not sacrifice a regularly produced analysis while accounting for late-arriving observations. Additionally, as we move towards increased coupling in our systems, we also need to consider the timescales represented by each component, some of which may require longer windows for both representation of their inherent scales of motion as well as differing data latency.

While the question of cadence is important, we foresee an emerging need and opportunity to extend beyond intermittent methods to a more continuous assimilation approach. The traditional 6 or 12-hour NWP cycle was originally tied to the observations being clustered around synoptic times, but the landscape of the observing system has changed dramatically with observations now being largely evenly distributed across the assimilation window. Initial efforts at ECMWF have already demonstrated a quasi-continuous assimilation application within their 4DVar by incorporating newly arrived observations during the outer loop iteration (Lean et al. 2020). Continuous assimilation is particularly advantageous for those systems which have update cadences on the order of one hour to minutes. Intermittent methods are cumbersome and add computational overhead. For example, each assimilation involves regular stops/starts of the forecast model with each cycle, substantial I/O, and necessitates the enforcement of somewhat arbitrary data-cutoff times. In a continuous framework, the model and DA system are combined into a single application that runs continuously, all data motion is handled in-memory and the only I/O necessary is to ingest observations as they arrive and output files for diagnostic and post-processing needs. While our current suite of high-performance computing platforms are not designed to accommodate such an approach, novel cloud-based high-performance computing platforms can accommodate such applications.

The cadence for our current and emerging suite of operational DA systems will be examined and considered alongside opportunities for developing a continuous assimilation capability as the body of scientific knowledge and supporting technology grows. Initial attempts at pursuing hourly updating strategies with overlapping windows have proven to be successful for prototype versions of the GDAS (Slivinski et al. 2022). Such efforts should continue to be pursued and expanded as a pathway toward more continuous DA.

Improvements in DA Solvers

1. **Ensembles** – *provide invaluable information and will continue to be an area of exploration and expansion*;
2. **Background error covariance** – *modeling methods are crucial for both scientific and computational performance and new methodologies such as the multigrid beta filter are being explored;*
3. **Multiscale assimilation** – *helps more realistically resolve features in the analysis at all spatial scales and removes the requirement for ad hoc procedures to maximize performance;*
4. **Balance and initialization** – *analysis needs to be physically realistic but also consistent with the model equilibrium to not cause imbalance in the subsequent forecast;*
5. **Continuous DA and overlapping windows** – *allow for a shift from existing DA systems' cadence paradigms built on legacy needs;*
6. **Nonlinear and non-Gaussian applications** – *toward relaxation and removal of suboptimal assumptions.*

3.5 Coupled DA

The need for coupled Earth system modeling has long been embraced for extended range prediction as a result of sources of predictability stemming from non-atmospheric components, particularly for subseasonal-to-seasonal time scales (National Academies of Sciences, Engineering, and Medicine 2016). For example, NWS/NCEP has been running coupled models for extended range prediction for nearly two decades, with the original implementation of the

Climate Forecast System version 1 implemented in August 2004. The HWRF and HAFS systems are another example of a coupled atmosphere-ocean modeling application that were operationalized. Coupled models bring the need to initialize multiple components, some of which may have different maturities with respect to assimilation capabilities, unique observing systems, and incompatible temporal and spatial scales for a single assimilation system. The Earth system components in this context may include the atmosphere, ocean, waves, sea ice, ocean biogeochemistry, land/hydrology, and atmospheric composition/aerosols, or combinations thereof.

The push toward the adoption of "seamless prediction" will require the utilization of Earth system coupled models across the spectrum of applications and temporal scales. This introduces unique challenges for DA, even for NWP models. Historically, the assimilation systems for the various Earth system components have been developed independently, focusing on the aspects that are unique to each component. However, there is now a need for effective and consistent assimilation methods across components and advancement of coupled assimilation. This is important in order to extract maximal information content to constrain the coupled state, minimize initialization shocks, and ensure consistent initialization information across the interfaces. Initial forays into coupled DA were pursued within the context of version 2 of the Climate Forecast System (CFSv2). The Climate Forecast System Reanalysis (CFSR) and its real-time extension were pioneering in the implementation of a weakly coupled assimilation system (Saha et al. 2010).

Before considering specific aspects, it is important to note that coupled DA covers a broad spectrum of possibilities, even if sometimes subclassified into "weakly" or "strongly" coupled DA (Penny et al. 2017). Weakly coupled assimilation generally implies the use of a coupled model for advancing the model state, but the assimilation for each component is done independently. Using an atmospheric-oceanic coupled system as an example, this would mean that there are separate assimilation systems for the ocean and atmosphere, respectively, while the background for each component's update would be generated by advancing the state through the use of the coupled ocean-atmospheric model. The aforementioned CFSR and CFSv2 utilize such a paradigm. Weakly coupled assimilation is a natural progression and allows for the development of appropriate assimilation capabilities for each component. However, such schemes are limited in that observation utilization is limited to the component for which those observations reside and impacts to other components are only carried through the system by forward integration of the coupled model itself. Further, there are potential issues at the interfaces if there are inconsistencies in the initialized states.

On the other end of the spectrum, "fully" or "strongly" coupled assimilation generally treats the entire coupled state together, allowing for all observations to have instantaneous impacts on all components of the Earth system for which there is meaningful information. In the simplified atmospheric-oceanic example, this could mean that there are observations that would directly impact the updates to both the atmospheric and oceanic states, e.g. observations directly at or near the ocean surface. The treatment of the entire coupled state in a consistent way has two potential direct benefits: 1) more extraction of useful information from observations across components, and 2) reduced or minimized shocks as the information is used to propagate forward in time with the coupled model. However, there are many potential difficulties to overcome in such a paradigm such as the treatment of coupled error covariances, differing spatial and temporal scales of phenomena across the component, and radically different observing systems to constraint aspects of the coupled state.

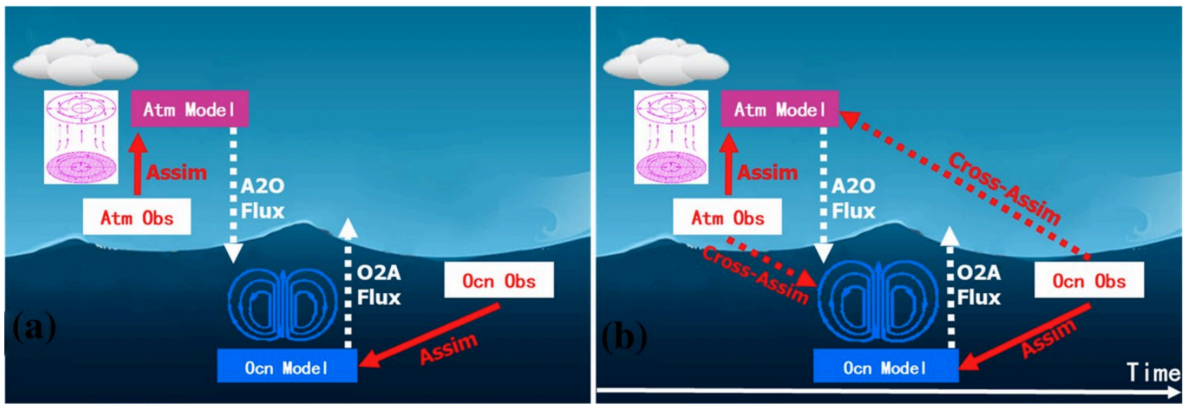

Figure 9. Schematic of the implementation of a Weakly Coupled Data Assimilation system (left) versus a Strongly Coupled Data Assimilation system (right). Figure from Zhang et al. 2020.

There are additional options that reside between what some generally think of as either "weakly" or "strongly" coupled assimilation. One such example has been demonstrated at ECMWF whereby the coupling occurs through the utilization of the coupled model as part of the outer loop configuration of the variational solver (Lalayoux et al. 2016). This option has occasionally been referred to as quasi-strongly coupled assimilation. While the minimization is handled separately between the oceanic and atmospheric solvers, information is passed across the components as part of the outer loop update and re-linearization. This is a step beyond the weakly coupled assimilation as was done in CFSv2. Other options, such as the utilization of coupled observation operators for observations that have information relevant to multiple components, are also an option. This is a particularly attractive option for things such as satellite radiances that are sensitive to surface temperature, and provides a natural extension to the idea beyond the already operational near-sea surface temperature (NSST) scheme that is used as part of the GDAS.

The plan for implementation of the UFS to simplify the NCEP production suite explicitly maps out applications that will require some form of coupled DA for initialization, including MRW/S2S, SFS, HAFS, and RRFS. Within this context, coupled assimilation is going to be a central strategic element moving forward. While there is a natural starting point to utilize weakly coupled assimilation for components as ready and available, prioritization of coupled assimilation research and development will be critical for future successes within the context of the aforementioned applications. The decision to move to JEDI as the central, unifying infrastructure for assimilation should enable better synergy and allow for the exploration of substantive advances in coupled assimilation for UFS applications.

One example of the potential for significantly accelerated innovation is within the context of land and coupled land-atmospheric assimilation. For the operational global NWP system run at NCEP, soil moisture and temperature are not directly constrained by observations[2] and the snow analysis that is utilized is offline and outdated. Initial work is already progressing to build DA capabilities for soil (moisture and temperature) and snow within JEDI for future use by UFS applications. Further, initial attempts of doing more strongly coupled land-atmosphere assimilation to constrain soil moisture with observations of two meter temperature and humidity have shown some promising results. These developments have set the stage for a significant leap in capabilities for initializing some land variables within the context of MRW/S2S and SFS. In addition to the direct effect of better constraining the land states, such capabilities, through unified infrastructure, have the potential to be exploited to enable better utilization of observations sensitive to those components, e.g. all-sky/all-surface satellite radiances.

Initial attempts at wave assimilation highlight the need for coupled considerations for some specific applications. While it was relatively straightforward to perform the state estimation for the significant wave height, early efforts demonstrated difficulty in the retention of the analysis information in the forward model integration. Within the context of the forced wind-wave problem, this makes sense in the absence of also correcting the forcing information. Coupled assimilation should be designed to extract information from wave observations to then constrain the forcing (in addition to the initial wave state itself).

A similar problem to wave assimilation exists for reactive trace gasses for air quality applications. Near-surface ozone (O_3), a hazard to human health, is generally a product of photochemical reactions controlled by emissions of volatile organic compounds (VOCs) and nitrogen oxides (NO_x). Thus, while one can update the initial 3D state of the O_3 model field, the analysis information will not be retained without simultaneous adjustment of the precursor emissions. Improved estimation of emissions is also key for aerosols and greenhouse gasses (GHGs), but because the atmospheric lifetimes of aerosols (days) and GHGs (years) are much longer than the strong diurnal variability caused by photochemical reactions, state estimation impacts last much longer in the free forecast. Accurate state estimation of aerosols in coupled models leads to improved radiative forcing from both the direct and indirect effects of aerosols, and can be used to also improve the assimilation of other observations (i.e. aerosol impacted radiances).

Within the context of space weather applications, the coupled Whole Atmosphere Model-Ionosphere Plasmasphere Electrodynamics (WAM-IPE) Forecast System was implemented into NCEP operations in 2021. The WAM is an extension of the GFS model up to 400-600 km, with its own DA system (Whole Atmosphere Data Assimilation System, WDAS) that mimics the GSI-based GDAS (Wang et al. 2011, 2012). Recent research has been expanding to improve the representation of variability and initialization of variables in the

[2] Soil moisture is nudged by the GLDAS as forced by an observed precipitation product.

mesosphere, and ionosphere. In particular, recent progress has been made in the assimilation of total electron content (TEC) observations within the context of whole atmosphere models (Pedatella et al. 2020). Initial results show promise for this challenging coupled assimilation problem. Such applications are poised to take advantage of underutilized data from GNSS measurements, such as those from the Constellation Observing System for Meteorology, Ionosphere, and Climate (COSMIC-2) mission. Space weather has important implications for communications, electric power transmission, GPS accuracy, and satellite drag. Applications of modeling and DA in this arena are expected to grow as an emerging area in the next decade, bringing with it unique challenges for coupled DA for whole atmosphere modeling and assimilation.

A more comprehensive survey and summary of coupled assimilation success in applications are summarized nicely in Penny et al. (2017). Similarly, the NWS strategy for coupled DA is well aligned with many of the recommendations outlined therein following the workshop in 2016. Progress is underway to build JEDI-based capabilities for most components that will be considered for future UFS-based coupled applications. Weakly coupled assimilation will be the assumed starting point, with advancements on "more strongly" coupled sub-components as they become available and demonstrate maturity. The plans for GFS version 17 are consistent with this philosophy. Specific priorities over the next decade will include, but not be limited to:

- Engagement in research and development on coupled assimilation activities that cover the entire spectrum of strength of coupling and readiness level.
- Explore and exploit multiscale capabilities for coupled assimilation to assist in handling the differing temporal and spatial scales across media.
- Leverage coupled ensemble perturbations to explore coupled error covariances and exploit hybrid EnVar and/or EnKF methodologies.
- Evolve toward new innovations to handle nonlinearity and non-Gaussian components from which linear and Gaussian assumptions do not apply.
- Specific emphasis on innovations with respect to assimilation at the coupled interfaces, e.g. handling SST within coupled ocean/atmosphere applications.
- Explore the viability of alternate algorithmic choices. For example, in addition to the general issue of coupled error covariances, (fully) strongly coupled DA may be difficult to execute within the context of 4DVar given the need for full tangent-linear and adjoint models of the coupled system. However, the exploitation of AI/ML (see next section) for model components may open new avenues for coupled assimilation applications.

While some aspects of things like weakly coupled assimilation are fairly mature and have yielded significant advancements in skill, coupled assimilation, more broadly, is still a relatively new area of research and development. This is particularly true for strongly coupled assimilation, which while showing promise in some simplified and idealized settings, still has a long way to go until it is realized for something like NWS operational applications.

Coupled DA Highlights

1. **Seamless prediction** – *Earth system coupled models across the spectrum of applications and temporal scales requires coupled DA;*
2. **Work towards strongly coupled** – *allowing for observations to have instantaneous impacts on all relevant components of the Earth system;*
3. **Improvements in use of observations** – *better constraint of some formerly parametrized states allow for better use of observations (e.g. all-sky/all-surface radiances);*
4. **State and parameter estimation** – *some applications (e.g. waves, land, and air quality) are more sensitive to forcing than initial conditions, but these forcings can be improved by DA.*

3.6 Incorporation of AI/ML

DA and NWP continue to grow more resource intensive with increased spatial and temporal resolution, larger ensemble sizes, and solver complexities. The inclusion of coupling also drastically increases the size of the system as well as the number of observations used. Observation platforms themselves are also being constructed with higher spatial, temporal, and spectral density. With computing capacity not increasing as rapidly as other innovations, we need to find ways to not only reduce computational costs of our existing systems, but also reduce the increase in cost for future systems.

Machine learning (ML) is a form of artificial intelligence (AI) that "learns" from a set of inputs to produce an output. Once the ML models are trained, they can identify patterns, make decisions and typically run much faster than the process they were trained to replicate. Forms of ML have been used in NWP for many years, i.e. linear regression (Malone 1955), but with increased computing power and the accessibility of open-source tools (e.g. Pedregosa et al. 2011, Abadi et al. 2015, Chollet 2015), artificial neural networks with increasing complexity, also known as deep learning, are becoming prevalent in many far-reaching fields such as stock market predictions (Chong et al. 2017), galaxy classification (Dieleman et al. 2015), and cancer diagnoses (Manogaran et al. 2018). These methods are becoming increasingly used within NWP sectors as well, including severe weather prediction (Gagne et al. 2019; McGovern et al. 2019), physics parameterizations (Gentine et al. 2018; Price et al. 2018), and post-forecast correction (van Straaten et al. 2018).

Recent advances in NWP emulators from PanguWeather (Bi et al. 2022), ForecastNet (Pathak et al. 2022), and GraphCast (Lam et al. 2022) demonstrate impressive performance with respect to the ECMWF IFS (Bouallegue et al. 2023). These models, trained with ERA5 reanalysis, run at a fraction of the computational cost of the full IFS and, yet, generate medium-range forecast skill comparable to the IFS. Given this success, ECMWF recently launched the alpha version of its Artificial Intelligence/Integrated Forecasting System (AIFS).

Within EMC, ML techniques have been applied in various parts of the NCEP model suite, including the operational retrievals of SSMI (Krasnopolsky et al. 1999), the wave-wave interaction parameterizations of WAVEWATCH (Tolman et al. 2005), and long- and short-wave radiation parameterizations in climate modeling (Krasnopolsky et al. 2008). Means calculated through neural networks have been explored as an alternative to ensemble means for both precipitation (Krasnopolsky and Lin 2012) and waves (Campos et al. 2019). From the EMC DA perspective, early exploration has been conducted on the intelligent thinning of AOD observations (Boire et al. 2020). EMC has recently begun exploring the use of the GraphCast NWP emulator trained with GDAS data.

There is an equivalence between the theory of DA and ML techniques (Hsieh and Tang 1998; Abarbanel et al. 2018; Geer 2020). They are both inverse problems that can be defined in a Bayesian framework. While the terminology is different, the concepts are the same: neural networks construct a loss function, which is equivalent to a variational cost function, and minimize that function iteratively. ML takes input “features” to train against output “labels” and solve for the “parameters” that minimize the loss. DA uses those labels and parameters to instead solve for the input or state. Neural networks also iterate using back-propagation, which is equivalent to an adjoint. This equivalence motivates the exploration of crossover techniques between DA and ML. In fact, the idea of combining DA and ML has been formally proposed as Data Learning, see for example Buizza et al. (2022).

ML can be potentially applied to many parts of the DA process, particularly in the treatment of observations. Observation platforms are increasing in resolution with only a small portion of the observations currently used. Traditional thinning algorithms used to reduce data volume can be reexamined in light of ML development. The ML technique of autoencoders could quickly reduce the dimensionality of a dataset while retaining the important features, making better use of observations that are already available. ML can also provide automated data monitoring by identifying periods of anomalous data quality or anomalous sources. There are several possibilities concerning the treatment of clouds in satellite data from cloud detection and classification (Jeppesen et al. 2019) to cloud clearing (Chang et al. 2015).

Forward models could potentially largely benefit from ML. Radiative transfer models used operationally already include assumptions to speed up calculations, so an ML emulation of a full physical model could be comparable to the fast versions already in use. Look-up tables could be replaced with neural networks (Scheck et al. 2021) or more extremely the full radiative transfer model could be replaced (Liang et al. 2022). Retrieval algorithms could also find some benefit. More efficient feature tracking methods could enhance AMV observations, producing observations with much fuller coverage (He et al. 2019) or producing better uncertainty estimates (Teixeira et al. 2021). Land DA could improve as well with ML-generated soil moisture retrievals, like those recently operational at ECMWF (Rodriguez-Fernandez et al. 2019).

ML techniques have been shown to generate efficient and accurate emulators of tangent linear and adjoint codes (Hatfield et al. 2021). This has direct application to 4DVar. ML emulators could be explored for application to even more complex DA algorithms such as hybrid 4DVar and weak-constraint 4DVar (Bonavita and Laloyaux 2020). Other components of the DA system could also benefit from application of ML techniques. Deep learning could be applied to large databases of model error to develop highly efficient background error models. Analysis increments could be examined to develop ML-based bias correction schemes as demonstrated for a prototype version of the GFS (Chen et al. 2022). Furthermore, ML could potentially provide an automated mechanism to learn a representation of the model error (Bonavita and Laloyaux 2020).

In addition to the applications mentioned above, ML has potential application to the post processing of DA system output. Neural networks have shown promise in the area of statistical downscaling (Baño-Medina et al. 2020). The use of neural networks is being actively explored for dynamic downscaling of near-surface real-time mesoscale analysis grids to high-resolution grids. Research has shown improved utility of ensemble precipitation forecasts through the application of ML-developed decision trees (Hewson and Pillosu 2020). Similar approaches could be applied to enhance the usefulness of ensemble analyses.

Given the rapid advances in ML and demonstrated benefits from preliminary studies, EMC needs to develop more internal expertise with the toolbox of ML techniques. As an initial step, the DA group has established an AI/ML study group to foster training, planning, and initialization of projects to explore within this context. The AI/ML study group completed the ECMWF Machine Learning in Weather and Climate MOOC during the spring of 2023. Upon completion of the course group members developed and submitted AI/ML projects ideas in the areas of observation processing, emulation, and post-processing.

Work has begun in EMC on developing ML-based techniques to improve the quality of and error estimates for atmospheric motion vector super-observations. Another observation-related project is applying unsupervised and supervised ML methods for the classification and detection of observation anomalies in the upper air data. ECMWF is also pursuing ML-based observation anomaly detection methods. ML techniques can also be applied to observation quality control. Proposed projects include the application of ML to develop automated QC procedures for high-resolution observation sets assimilated by the RTMA and URMA. Another study will explore the replication of existing aircraft quality control procedures with an ML approach.

ML techniques are being used to explore accurate and efficient methods to emulate complex and computationally expensive land surface emissivity models. Longer term ML emulation projects include (1) using ML-based models to significantly increase ensemble size for use in hybrid ensemble-variational assimilation, (2) efficient calibration of the multigrid beta filter, and (3) the use of ML-based short-range, and high-resolution forecasts as the background in the 3D-RTMA.

Investigation of ML techniques for post processing are not limited to bias correction of model output. ML techniques are being explored to bias correct radiances in regional DA systems. Success in this project could help address a long standing challenge of limited sample when bias correcting radiances in regional DA systems. Another application of ML techniques being explored is to replace the existing dynamic downscaling method applied to RTMA output with a more efficient, flexible, and accurate ML based scheme.

As demonstrated by the planned establishment of a NOAA AI Center and the recent creation of other AI centers across the nation such as the AI2ES center, ML is quickly becoming a major focus of research in the field. Many other operational NWP centers around the world are exploring and employing ML techniques in their DA pipelines. ECMWF recently released a technical memo outlining their 10-year roadmap for machine learning (Dueben et al. 2021) with applications identified across the entire NWP spectrum. NOAA held a workshop in November 2023 focused on prioritization of AI/ML for NWP within the agency. ***The integration and exploitation of AI/ML within the context of DA will be a significant priority for EMC in the coming decade.***

AI/ML for DA priorities

1. **Observations** – *quality control, data selection, bias correction, super-observations, extraction of maximal information content, anomaly detection and operational monitoring*;
2. **Forward operator emulation** – *computational efficiencies, replacement for complex operators*;
3. **Background error** – *computational efficiencies, multivariate aspects and coupled assimilation, parameter estimation for error models*;
4. **Background** – *dynamic downscaling, bias correction*;
5. **Model error** – *estimation and correction;*
6. **Emulator exploitation** – *replacement for TL/AD in 4DVar, efficient creation of huge ensembles to avoid localization;*
7. **Hybridization** – *explicit blending of ML and DA; joint frameworks; pathways to going directly from observations to simulation/emulation.*

3.7 Reanalysis

Reanalysis datasets are key infrastructure to support NOAA's mission, combining historical observations with modern modeling and assimilation capabilities to create spatially and temporally coherent records of the Earth system. NOAA was a pioneer in the science and practice of atmospheric reanalysis. This included the first atmospheric reanalysis (NCEP/NCAR, Kalnay et al. 1996), coupled reanalysis for the climate forecast system (CFSR, Saha et al. 2010), and regional reanalysis (North American Regional Reanalysis, Mesinger et a. 2006). Reanalysis has many purposes and drivers, including the ability to generate hindcasts for historical periods, generation of homogenized datasets for climate monitoring, and as part of the modeling system development process.

It is well documented that reforecasts are essential for realizing skillful operational predictions for a wide variety of applications and products. They are operational requirements for upgrades to medium range and subseasonal-to-seasonal prediction systems (e.g. GEFS and CFS/SFS). The ability to generate hindcasts requires historical initial conditions, making reanalysis development and execution a key priority for DA. The ability to generate reforecast datasets for calibration has been a significant driver for reanalysis efforts within NOAA in the recent past. Recently, NOAA completed an atmospheric reanalysis for a modern period as part of the upgrade to version 12 of the Global Ensemble Forecast System (Hamill et al. 2022).

As with the CFSR and GEFSv12 reanalysis, most efforts utilized state-of-the-science NWP systems as the mechanism for producing a reanalysis dataset. The recent ERA-5 reanalysis (Hersbach et al. 2020) by ECMWF is one such example. However, reanalysis efforts themselves have considerable scientific challenges. This is particularly true if one considers the use of such datasets for things like longer-term monitoring, as is the case of the NCEP Climate Prediction Center. As one example, discontinuities can arise in time series of particular quantities through the introduction of new observing systems. Additional issues can arise when applying present-day systems to historical periods, such as the need for special treatment of background error for particular areas or periods, specific needs for observation quality control and bias correction, or dealing with geographic and temporal voids in particular data sparse areas and periods. Some of the scientific focus areas for future reanalysis are well-articulated in Hersbach et al. (2018).

The EMC effort toward NOAA reanalysis remains a small part of the more holistic solution. Part of the NCEP strategy will be to endorse and support the broader NOAA strategy for sustaining and maintaining a reanalysis development and production program within the agency. To date, reanalysis efforts have been treated as isolated one-off projects. However, it is imperative that reanalysis activities are integrated into regular business, similar to efforts that have been deployed in Europe through the Copernicus project. More specifically, this will include expanding ongoing collaboration with key partners from within NOAA such as OAR/PSL, where the previous efforts for GEFSv12 reanalysis were complete and initial efforts toward coupled reanalysis for a future SFS are now underway. Similarly, EMC should continue to work closely with other governmental partners with reanalysis mandates such as NASA/GMAO. GMAO has continued to invest in reanalysis science, having completed MERRA-2 (Gelaro et al. 2017) and now working toward their next-generation production reanalyses. EMC is currently engaged in a joint project with OAR/PSL and NASA/GMAO in an effort toward building some joint, JEDI-based infrastructure that will be utilized for future generations of coupled reanalysis at both centers. Such efforts need to continue and expand.

Another particularly relevant avenue for additional focus on reanalysis is within the context of the aforementioned AI-based NWP emulators. Most of the NWP emulators that have been deployed in the past few years have been trained upon ERA-5 based reanalysis data. NOAA has already begun experimentation with such emulators, but has yet to build a model based upon training using NOAA data. For example, one could utilize the reanalysis data that was generated for GEFSv12 as an initial starting point to create a NOAA-specific emulator. This also raises interesting questions about requirements for future reanalysis, as drivers for emulators may become more important than drivers for traditional reforecasts. For example, there may be a need for much higher fidelity (in both space and time) to produce emulators for specific phenomena and/or to improve upon some of the current emulators. In this context, ***DA developments for reanalysis, to generate datasets for emulator training, has the potential to become a significant priority in the coming years.***

3.8 Development Practices

3.8.1 Continuous Integration

For large collaborative projects, it is important to have multiple developers working on different components in parallel in separate version control (e.g. git) branches. However, when these parallel branches are merged back to the main branch, code managers face the challenge of ensuring that all of the individual developers' work meets certain requirements. Continuous Integration (CI) is a process in which code is built and tested on one or more platforms automatically as part of the code review process. These automated tests can include:

- unit testing
- code coverage (is the code extensively tested)
- checks that the code follows certain styles/conventions (ex. PEP8 for Python, or the Google C++ style guide)

This can be done on existing HPC platforms, but is more easily facilitated through CI systems such as Circle-CI or GitHub Actions. For the latter two, a suite of checks/tests can run automatically without user intervention for each pull request or commit and be required to pass before code can be merged to the main branch in GitHub whereas the former would likely require cron jobs and supporting infrastructure to be developed to run on NOAA HPC. Automated tools such as these accelerate the development process and allow for faster full-scale scientific evaluation by ensuring that new code adheres to a set of standards and does not break existing capabilities with minimal human effort required.

3.8.2 Continuous Deployment

While CI is an essential modern software development practice, these automated testing tools are limited in scope in that they only work to ensure that each component independently is functioning as expected. However, in a complex application, such as NWP, it is often impossible to see the impacts of code modifications without running full-scale, realistic tests. Currently, EMC developers perform cycled forecast experiments for their individual scientific contributions, generally at a lower horizontal resolution compared to the target operational system. The results from these experiments are then interpreted, and, if favorable results are shown, a full-resolution test incorporating these scientific changes is generally not executed until late in the development process. This full-resolution, pseudo-operational forecast system, due to computational and workforce constraints, often does not start until the scientific choices made for the model upgrade are largely already decided.

Leveraging the concept of Continuous Deployment (CD), in which new software capabilities are deployed in a production environment after testing and delivery, has the potential for EMC developers to more quickly see impacts resulting from scientific code changes in a pseudo-operational model configuration. Not only would this facilitate full-resolution results earlier in the development process, but would also potentially reduce the amount of effort spent by each developer configuring and monitoring their own parallel experiments. However, this approach is not without challenges, most notably the computational expense. Running a full-resolution parallel experiment in real-time alongside the production forecast system will cost at least as much as the production system, and likely more if computationally expensive options/features are incorporated, and this may not be possible using existing on-premises computing resources. The use of high-performance cloud computing resources may alleviate these concerns, but come with others including the variable cost of CPU hours on these cloud platforms as well as the need to arrange agreements with restricted data providers of observations currently assimilated into the operational systems.

3.8.3 Modern Programming

Historically, the Fortran programming language has been the bedrock of NWP and that is still largely true today. Rooted in the era of punch cards and mainframes, Fortran has been modernized through several major revisions with the most recent standard being Fortran 2018. Support for features such as object-oriented programming and derived types have extended Fortran's capabilities far beyond what was envisioned when the language was developed in 1957, but limitations still exist with this legacy language. The Fortran 2003 standard added interoperability with the C programming language, and with that, the ability to include Fortran subroutines into C programs. While Fortran still excels in its computational efficiency and maintains a majority throughout the Earth sciences, it is no longer the sole compiled programming language used in HPC applications.

Components of JEDI such as OOPS and IODA are written almost exclusively in C++, a high-level object-oriented extension of the C programming language. Others, such as the model interfaces and UFO contain significant amounts of modern Fortran at the lower levels, but still include C++ code and utilize the C/Fortran interoperability to move between the two languages. This hybrid approach allows JEDI to use existing scientific code in Fortran where appropriate, but also to take advantage of the more modern features of C++ in the DA software. Because of this, it is essential that the NWS has expertise in multiple languages (C++ and Fortran), and embrace evolving best practices (object-oriented programming as one such example) in order to support not only JEDI development and maintenance but also for any future NWP tools. It is also essential that NWS be adaptable and embrace state-of-science and state-of-practice changes as technology advances.

In addition to compiled code, the use of scripting languages are essential to NWP, as these scripts which stage, set up, archive, and execute the various applications are the glue of any modeling system. Generally, this has been done using shell scripts in the past, and while shell scripting is powerful for filesystem related activities, many pieces of modern workflows require complicated hacks or workarounds (such as using tools including sed, awk, grep) to perform all necessary functions. Python is now the scripting language of choice in the Earth sciences, because of its ease of use and flexibility. Not only can Python replace shell scripting for workflow tasks, but it has also started to replace languages such as NCL (which has been put in maintenance mode in favor of Python) for data analysis and visualization capabilities. Several JEDI utilities/components are developed in Python including R2D2 and EWOK. METPlus, the UFS verification framework, also is written in Python, and it is likely NCEP's unified workflow will also largely be Python-based. Thus, Python will certainly be an essential tool utilized throughout the NWS in the coming decade, and its applications within the DA systems will be numerous.

Language model AI (LMAI) has the potential to significantly impact the entire development (software and scientific) process in ways not entirely clear at present. Raman and Kumar (2022) argue that advances in LMAI require educators to reassess the scope and content of what the next generation of computer scientists learn. Such a change would impact the skillset of future staff and necessitate updating the skills of current staff. Chen et al. (2021) highlight both potential benefits and hazards of the evolving LMAI landscape. Currently, LMAI is routinely used for generating code snippets, answering questions about programming language syntax and improving code readability by adding inline code comments. LMAI may perform tasks of various complexities such as developing a plotting script for a specific application or deriving a tangent linear and adjoint of simple code snippets. These tools have the potential to significantly change the development paradigm and should be embraced.

3.8.4 High Performance Computing

Earth system prediction and high performance computing have been intertwined since their respective inceptions. Advances in computing allow for more sophisticated representations of the Earth, larger ensembles, and ever growing quantities of data. If we look back to the mid 20th Century up to present day we see a clear trend in improving forecast performance alongside technological advances.

As technology advances, so does forecast skill (Figure 10). It is therefore a priority for us to consider the platforms of the future while developing all components of our Earth system prediction systems today. Cloud computing affords one such mechanism to not only meet high performance computing needs of today[3] but is also a highly effective mechanism for managing large, distributed datasets and expanding accessibility. Further, the computing environment undergoes regular and rapid change with the continual introduction of new technology and hardware, and so it is also an attractive environment for developers to test the next CPU, GPU, memory, interconnect, etc. While the community is on the cusp of the exascale era, it is also necessary to look beyond the near horizon to stay abreast of the most active areas of research, such as quantum computing.

[3] Building a Weather-Ready Nation with Intel HPC in the Cloud, 2022. https://www.intel.com/content/www/us/en/customer-spotlight/stories/noaa-customer-story.html

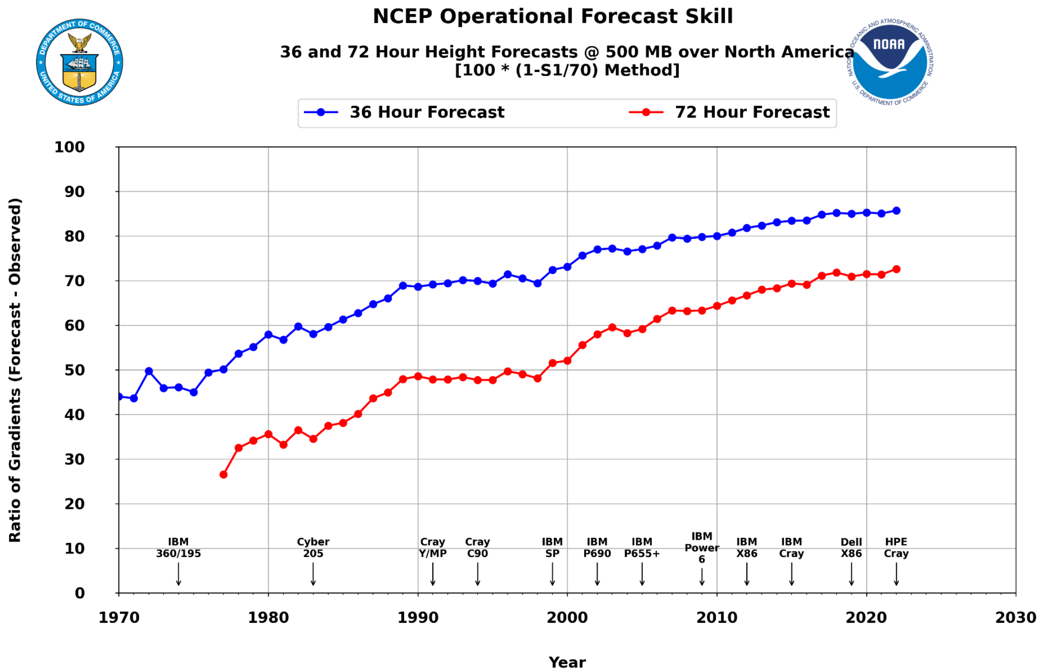

Figure 10: NCEP operational model forecast skill dating back to the 1970. Operational high performance computing systems available at the time are annotated along the x-axis. Image courtesy of Mallory Row (SAIC and EMC/VPPPGB).

Scientific Computing Priorities

1. **Continuous integration** – *automated testing to speed up development process to foster innovative science;*
2. **Continuous deployment** – *rapid prototyping and demonstration of advancements in a production-like environment;*
3. **Modern programming** – *embrace industry-standard practices and newer languages and techniques*;
4. **High performance computing** – *exploitation of exascale computing and cloud resources;*
5. **Leverage artificial intelligence** – *use AI/ML techniques directly in computational science but also as part of the development process (e.g. using language model AI to accelerate writing code).*

4. Data Assimilation Vision: A Holistic Approach

This section will focus on consolidating into a holistic plan for evolving DA innovation and operationalization over the next decade. The realization of some of the articulated vision will require a concerted effort to execute substantial change throughout processes, people, and culture. The plan will also try to identify several specific risks, dependencies, and issues along with potential mitigation strategies.

4.1 Addressing Grand Challenges

To recap, several scientific grand challenges of relevance to the next decade have been identified and documented by the community through a series of workshops, conferences, and similar events. In the time since those workshops, additional challenges and drivers have revealed themselves including a need for holistic reengineering of observation processing; computational efficiency with a path forward to exascale and cloud HPC; integration with other elements of cross-cutting infrastructure; requirements for reanalysis; and leveraging of new technologies such as artificial intelligence (AI) and machine learning (ML).

Addressing these challenges within the context of facilitating changes to operational DA will require several significant steps, some of which are already underway. These include, but are not limited to the following priorities and actions:

1. Full embracement of, and contributions to, the JEDI infrastructure as the DA vehicle for the next decade (and beyond);
2. Engagement by NCEP staff on lower readiness level research and development within the aforementioned challenge areas. This will include growing collaborations and partnerships, co-owning relevant research projects, and taking on higher risk (higher reward) efforts;
3. Willingness to embrace and pursue significant changes in the design of the production suite, including things like moving toward alternate cadence strategies and more continuous DA;
4. Embracement of new technologies and best practices;
5. Investments in workforce sustainment and development.

4.1.1 JEDI as Foundational Infrastructure

As described in previous sections, the JEDI infrastructure is designed such that scientific software development efforts would be distributed and shared between partners in order to reduce redundancy and accelerate the process by which new observations or techniques could be incorporated. In the immediate future, a significant portion of EMC's DA activities will be centered around development, evaluation, and transitioning to operations existing analysis capabilities from GSI-based solutions to those using JEDI. While these activities occur, however, the responsibility to maintain and upgrade existing operational capabilities still remains. This presents a challenging balancing act in which limited resources need to be allocated to both near-term and long-term advancements in parallel. Through these JEDI transition activities, EMC developers must not only learn to be users of the JEDI software, but also contributors. This is necessary from both the perspective of scientific advancement, but also for future operations and maintenance. As the immediate goals are not necessarily for scientific enhancements, but rather (at minimum) replication of current operational capabilities through this wholesale replacement of the DA system, the JEDI transition is equally an engineering problem as it is a scientific one. Thus, while the return on this significant investment may not be immediately realized, once all operational analysis systems are JEDI-based, scientific advancement can then proceed at an accelerated rate. Formal transition plans for integration of JEDI into operational applications are currently under development and outside of the scope of this strategic document.

In addition to the resources being put toward JEDI-based developments to replace current (legacy) operational infrastructure, work is already underway to begin exploring innovations consistent with the previously identified research and development priorities. It is imperative that JEDI-specific expertise and ownership is built within the EMC staff. This will ensure the ability to facilitate operational transition activities, but also ensure research and innovation developments are prioritized and enabled for the future. NCEP staff are more than just JEDI "users" focused on transition to operations of external developments, but rather, core developers and co-owners of the system.

Elements of innovation from within the JEDI infrastructure are already in development and being considered for candidate operational implementations, such as the use of hybrid EnVar assimilation for marine DA, falling under the broader scope of the JEDI-SOCA project. Similar to advancements found in atmospheric assimilation, leaps in skill are expected to be realized for the coupled system with such developments. There are other examples underway through the exploration of novel forward operators within the UFO for atmospheric assimilation. These are only some of the early examples of what will eventually become the use of JEDI for a truly unified DA infrastructure for UFS-based applications.

4.1.2 EMC Engagement Across the "Funnel" and Partnerships

As with other aspects of the operational system, EMC plays a unique role in the facilitation of DA innovations into NWS operations for the purposes of realizing improved predictions and forecast skill. The assimilation team at EMC has been an active, intentional community collaborator on DA for operational NWP for well over a decade. There are many examples of external collaborations through GSI that have resulted in transition-to-operations and improved operational predictions. This has largely happened through two distinct mechanisms which provide a unique perspective and afford opportunities for lessons learned. In one paradigm, collaborators worked on community versions of the GSI, supported by the Developmental Testbed Center (DTC), which then would feed back to the authoritative repository at NWS and potential inclusion for operational utilization. A model such as this minimizes the support role required from scientists within a place like EMC and helps to facilitate broad access to operationally relevant codes. However, the sequential process often makes it difficult to integrate innovations into projects or on schedules that are well aligned with other development activities leading to operational implementations. NWS has had very limited success in integration innovation through this process over the years. The alternate paradigm involved the integration of key partners directly into the repositories and process to facilitate development and testing of specific innovations for eventual inclusion into projects leading to implementations. Many of the hybrid EnVar developments for the GFS/GDAS in the 2010s fall into this latter category, leveraging key contributions from partners in OAR and academia.

The nature of community, collaborative development will continue to evolve through the establishment of the UFS and EPIC and transition to a new unified DA infrastructure through the JCSDA and JEDI. This will necessitate changes in roles and responsibilities for the EMC DA team to best leverage innovations from the community. In addition to community GSI experiences, there are many ongoing efforts from externally funded projects from NWS/STI-Modeling (NGGPS, HFIP, and Weeks 3-4) and OAR/WPO (JTTI, Observations, and Innovations), whereby EMC plays a critical role as the "receiving office" and transition coordinator but often without the required resourcing to handle the transition. These are critically important lessons learned to inform how best to position NWS in the R2O and O2R processes to be able to most effectively realize innovations for improved operational predictions. It is absolutely critical to share responsibilities across the readiness level (RL) spectrum.

Realization of innovation in operations requires active engagement with NWS Central Operations (NCO) and NWS customers. As outlined in Kleist et al. (2023), implementation is a time-consuming process. Much testing and evaluation is required for major upgrades. From the research side, collaborators need to understand and consider these realities as we work together to address grand challenges. For example, changes to the GFS impact not only the GFS but also networks dependent upon GFS output. From the operational side, NCO and customers need to be open to innovations which improve guidance at the cost of restructuring workflows, impacting delivery timelines, or touching on other technical aspects. Careful thought needs to be given to the operational piece of R2O and O2R.

NWS and NCEP/EMC cannot and will not be able to perform scientific development and testing alone. Partnerships with other government agencies, academia, and the private sector will be critical for accelerating the rate at which innovations can find their way into operational realizations. Past experience and lessons learned have shown that this will require EMC engagement throughout the process, including participation and engagement in lower RL activities that may have been deferred to others in the past. Further, NWS will need to bring others up the RL-chain to be aware of, understand, and help facilitate R2O activities. In other words, the lines need to be blurred and responsibilities need to be shared, as much as possible, throughout the entire R2O and O2R process. Absent clearly defined roles and responsibilities, close coordination with accountability, and mutually beneficial outcomes, collaboration becomes unbalanced at best and unfruitful at worst. Some of this is documented in more detail such as in the Organizing Research to Operations Transition plan and UFS Innovations to Operations (2021) series of documents.

In addition to continued engagement with several of the key partners and entities that have already been identified throughout (e.g. JCSDA and associated partner agencies, EPIC, OAR labs, academic collaborators), EMC will focus efforts on several different collaboration and stakeholder pathways. NESDIS is a key partner as one of the main data providers and pathways for observations for the production suite. EMC will continue to engage and expand efforts with various parts of NESDIS (Center for Satellite Applications, Office of Satellite and Product Operations, System Architecture and Engineering) to ensure priorities for NWP are addressed and operational readiness for new observations is emphasized. Similarly, EMC will participate in activities associated with the NOAA Modeling Team working group on Enabling Observations into Models as well as the activities associated with the Interagency Council for Advancing Meteorological Services (such as the DA and Observations working group of the Committee on Research and Innovation). Further, the OAR-led Quantitative Observing System Assessment Program will remain a key component of our efforts moving forward to assess and improve impacts from the assimilation of observations into NWP models.

EMC will also continue to build upon its strong foundation of international collaborations. This includes hosting scientists for 1-2 year visits, attending and hosting joint workshops, exchanging science, and facilitating technology transfer. Such collaborations are an important part of EMC's DA strategy as they are an effective mechanism to bring in fresh ideas, be engaged in lower RL research, and develop longstanding, productive relationships. A recent example is EMC's ongoing relationship with the Japan Meteorological Agency (JMA), which has led to numerous advances in operational DA. Recent examples include advancing the MGBF (Purser et al. 2022) for ensemble covariance localization, the introduction of scale- and variable-dependent localization (SDL/VDL) in the RRFS (Yokota et al. 2023), ongoing development and testing of Ensemble Tangent Linear Model in the RRFS DA system, and testing of convective-scale static background error covariances (Wang and Wang 2021) for RRFS with SDL/VDL.

Examples of EMC International Collaborations	
Japan Meteorological Agency	Visiting scientist program with EMC
Brazil's INPE-CPTEC (Center for Weather Forecast and Climatic Studies)	Visiting scientist program with EMC, science exchange, workshops
Taiwan Central Weather Administration	Transfer of technology, GSI development and implementation, science exchange, workshops
Korea – Korean Meteorological Administration and Korea Institute for Atmospheric Prediction Systems	Transfer of technology, science exchange, workshops.
United Kingdom Meteorological Office	Science exchange, joint development of JEDI, Trans-Atlantic Data Academy (planned)
World Meteorological Organization	Participation in projects and working groups of World Weather Research Programme

This broader engagement also includes closer collaboration and coordination with observational data developers and providers. The DA scientific needs and operational constraints (and viability) need to be weighed when making decisions regarding the maintenance, enhancement, and development of observing networks and systems. This requires end-to-end planning and engagement. When it comes to the use of observations in operational DA systems, there is no such thing as the "last mile", as all observations need continuous monitoring and optimization in order to make best use of the assets available. Investments need to be made to further generate evidence to better understand and define requirements and needs for future observing systems.

4.1.3 Embracing Change and Integration of New Technologies

While decisions have already been made to work toward a significant paradigm shift and fully embrace community modeling through the Unified Forecast System, a similar change in thinking and practice needs to be made when it comes to the actual implementation of operational applications and infusion of innovation. The NWS has long maintained a rather risk-averse posture for a variety of reasons, many justified. However, significant leaps in skill and integration of new science and technology to tackle grand challenges head-on will require disruptive, paradigm-shifting change.

Several examples of areas for fairly radical change relative to current practices have been discussed in previous sections, including the decision to transition to JEDI as the infrastructure for unified DA. The evolution toward UFS-based applications creates a unique opportunity to consider alternate options for assimilation cadence and window strategies, moving toward more continuous (and possibly in-core) DA. This will require significant changes in how observations are ingested, decoded, and made available for the assimilation systems. The UFS-based systems are evolving away from traditional atmospheric-only forecasts, bringing with them new requirements for coupled assimilation. The applications also bring with them new requirements that may need evolution toward new algorithms, such as those that can better handle nonlinearity and non-Gaussianity.

It is also worth remembering that DA does not exist in a vacuum. The algorithms that are used today and in the near future leverage the numerical models themselves as integral components. There is lots of work to be explored to exploit DA tools as part of the model development and optimization process. This includes aspects like quantitative parameter estimation, leveraging analysis increments and short-term model tendencies for reducing, (or correcting for) systematic biases and model errors, and targeting specific model improvements to advance the use of particular observations (e.g. targeting specific issues induced by model physics to make better use of cloud- and precipitation-affected satellite radiances). Closer interactions between DA developers and other aspects of the modeling system should be pursued and embraced.

As technology will continue to rapidly advance and accelerate in the coming decade, it is imperative that the strategy accounts for the embracement and integration of such advances in both technologies and best practices. This includes the incorporation of new philosophies such as CI/CD, utilization of modern programming languages, pursuing advancements to take advantage of next-generation computing architectures (including cloud), as well as exploitation and integration of AI/ML for both development and operational production.

4.1.4 Workforce

NCEP/EMC will only be able to organize around this unified vision effectively through its workforce. In order to execute the vision, it will be imperative to make the investments necessary to develop and grow the workforce in a way that is best aligned with the goals that have been laid out in this plan. ***To solve the challenging problems inherent to operational DA, NCEP/EMC needs an ability to recruit, integrate and retain the world's best scientists in our field.*** Additional challenges will come about through the necessity for more rapid integration of innovations from other fields such as scientific programming, high-performance computing, data science and so on. Further, when considering the fact that EMC helps to bridge the research and operational aspects of the problem, the expertise required for the workforce is quite broad and challenging. The skill sets that are required for effective DA scientists (e.g. strong foundations in mathematics, physical sciences, and computational science) are exacerbated when transition and operational considerations are added on.

Collaboration with key partners and the broader community is an essential component of the DA strategy. In addition to fundamental NWS responsibilities, this will require a dedicated core of world-class scientists to engage, innovate, and interact with partners and collaborators. This will necessitate active engagement in all aspects of the problem, including some elements on the cutting edge of science at significantly lower RLs than may have previously been considered. Partnerships and collaborations need to be established in an intentional way, explicitly leveraging complementary expertise and ensuring that such collaborations are mutually beneficial to those involved. The nature of this type of work will also demand that NCEP/EMC staff have the potential to engage in activities that have not traditionally been a core part of their work plans. This includes, but is not limited to, explicitly pursuing additional funding for lower RL projects, active participation as a member of the international communities through attending meetings, conferences, and workshops, and allocating time and funding for contributing EMC-related developments to the community through publications and other established mechanisms. Collaborations also take time and energy and come with overhead. Opportunities for scientific exchanges, visiting scientist programs or prolonged scientific visits, or possible sabbaticals may be desired to facilitate collaborative projects. These are also examples of activities that will help foster, build, and strengthen intentional partnerships and trust, ensuring longer-term sustained successes.

It is also critical to think about the training and integration of the next generation of scientists, both to contribute to the current 10-year vision, but to ensure sustainability and carry things forward thereafter. This motivates a desire to have EMC staff engaged in activities such as internships, graduate student projects with partner universities, and postdoctoral mentorships. Some staff have already been involved in such activities and they have already paid dividends. For example, the DA group has mentored several students through both the William M. Lapenta NCEP summer internship program and the Ernest F. Hollings NOAA undergraduate scholarship program, and the engagement has resulted in several hires in recent years. EMC staff have also been involved in overseeing graduate research projects and serving on doctoral committees. In addition to being incredibly rewarding for the staff, this has enabled engagement and growth of individuals to train them to be successful in the future on operationally relevant projects. Aspects of this were highlighted in the PWR report recommendations, specifically OD-3.2 to create a university consortium to address critical DA needs. NOAA has begun the process to establish the DA consortium, with a call for proposals released in 2023. NCEP will be an enthusiastic participant in the university consortium.

Consistent with agency goals and principles, it is also critical that NCEP continue to emphasize the importance of diversity, equity, and inclusion amongst its staff. As previously mentioned, DA is inherently interdisciplinary in nature, and thus there is a need for a diverse staff with a wide variety of viewpoints, experiences, and areas of expertise. Outreach, mentorship, and hiring activities must follow practices that lead to a comprehensive workforce spanning from students to senior scientists. In addition to the traditional degrees in Earth/physical sciences and mathematics, computer science, and data science will only increase their roles as we move towards new challenges such as AI/ML or exascale computing. With this diversity in expertise over a variety of subjects and career stages, it is important to pay close attention to equity activities to ensure that each staff member can achieve their full potential, thus enhancing the ability of the group as a whole to meet its mission. In an increasingly interconnected world, where colleagues may live in different cities or even continents, scientific activities must be organized with inclusion in mind. The Covid-19 pandemic has emphasized that there are challenges associated with ensuring that all team members are set up to succeed, and that only one approach or solution may not be best for all involved.

An equally important piece of the workforce puzzle is continued investment in DA staff. Staff must be equipped to rise up and meet the DA grand challenges. This is an ongoing process. Continuous growth, sustainment, and skill development need to become part of the culture and established best practice. This requires continued support from management. It also requires staff to not only understand but also embrace expectations. Growth comes not only from collaboration and mentoring, but also requires study. For example, the EMC DA team recently stood up an AI/ML study group with the goal of kickstarting AI/ML projects to address scientific and technical challenges. Sustainment refers to creating an environment in which staff flourish, not flounder. While supporting the mission is paramount, each staff member brings different passions, talents, and insights to the table. Creating an inclusive environment which stimulates creativity not only improves morale. Productivity increases with a growing commitment to and excitement for striving toward and achieving goals. With the emergence of new ideas and new technologies, there is an ever present need for skill development and enhancement among staff. The status quo is not sufficient to meet the grand challenges. Whether self study, inhouse training or attending off site classes, staff should be encouraged and opportunities provided to keep skill sets fresh.

Addressing Grand Challenges

1. **JEDI as foundational infrastructure** – *short term transition effort to lay the groundwork in order to embrace JEDI as the vehicle by which all DA advancements will be realized in the coming decade;*
2. **Engagement across the funnel** – *EMC DA team will need to continue to be involved in projects of various state of operational readiness through collaboration with key partners and entities;*
3. **Embracing change** – *a team developing and using cutting-edge scientific methods and computational technology will be essential to sustained innovation;*
4. **Workforce development** – *all of this vision is only realized through a dedicated team which requires both efforts to recruit a diverse and capable workforce, but also to ensure continuous investment in the development of existing staff.*

4.2 Risk Management

There is always going to be some risk associated with any endeavor toward integration of scientific innovation. The strategy to address the scientific grand challenges for DA will require a shift relative to current processes. There will need to be a balance toward embracing significant change and/or faster paced, incremental advancements. While a comprehensive strategy defines a path forward, strategy alone does not guarantee success. We outline here anticipated risks and, where possible, identify a risk response strategy that may be suitable. Risk management is a critical component to the successful realization of the priorities identified in this strategy and will be an integral part of the associated projects.

4.2.1 Investment and Resource Risks

The comprehensive vision presented herein requires significant and sustained investment in order to be fully realized. This will require commitment to continually invest in both human and machine resources. Insufficient, or episodic, investment in either will adversely affect the ability to realize this plan.

Risk	Response
Workforce limitations in size and skill.	Invest in continuous learning opportunities to expand the workforce's technical and scientific knowledge. Engage in recruitment efforts, such as NOAA's Office of Education scholarship, fellowship, and internship programs. Create a risk management plan for workforce size changes. Such a plan is likely most well-suited to be a part of the parent organization's risk management profile.

Episodic funds - this category includes funds of limited duration. Such funds accommodate short-term increases in productivity but may not include sustained support for the resulting deliverable at the end of the funding period. This results in an orphaned deliverable.	Robust strategic planning from which to identify priorities (this document) may be leveraged to identify mission-supportive projects. All projects associated with episodic funds should be designed and planned for support after the project concludes, with operations and maintenance resource requirements made clear at the proposal stage and refined through the project's duration. This applies to internal development efforts as well as external efforts from collaborators.
Insufficient high performance computing and fragmented computing. Fragmented computing is a colloquial term that refers to the situation in which high performance computing resources are spread across 3 or more ecosystems. Such situations lead to suboptimal utilization of the aggregate FLOPS and can require considerable staff effort to maintain codes and experiments across multiple platforms.	Invest in the development of software that is portable. Pursue cloud computing options, which give developers more control over the platform(s) on which development is done. Develop a computing strategy with partner organizations to facilitate planning and alignment with resource needs in the next 5-10 years.
Insufficient data storage.	Leverage open and accessible cloud storage options where/when possible, such as through the NOAA Open Data Dissemination Program. Explore and utilize new data compression and big data storage formats. As with high performance computing, develop a data storage strategy with partner organizations to facilitate planning and alignment with resource needs in the next 5-10 years.

4.2.2 Observational Data Risks

Observations are a critical foundation for continuing to advance DA. Technologies for observing the Earth system continue to evolve and expand at a rapid pace. The explosion in observation data volumes, private-public partnerships, and new ways of doing business come with their own risks to our strategy for evolving DA in the next decade. These include but are not limited to some of the following:

Risk	Response
Radio frequency Interference (microwave radiance observations).	Engagement with the wider community (including AMS, WMO) to advocate for retention of protected bands. Develop risk management strategies for any data loss/corruption that may occur.
Increased use of private data sets, reducing free exchange of observations.	Work with WMO and NOAA leadership to ensure that the free exchange of data is a requirement for any commercial purchase.
Inability to use short-lived mission of opportunity measurements due to implementation cadence.	Develop flexible implementation strategies with NCO to ensure that new observations can be assimilated as soon as ready.
Lack of access to observational datasets due to security concerns (currently happening with Chinese satellite data).	Work with NOAA management to define a path for access that will address these concerns.
Kessler Syndrome.	Refocus deployment and development of non-satellite observational systems, although a loss of forecast skill is inevitable.
The effective use of observations in DA is not catching up and matching the amount of available observations and the operational cost of processing, calibrating, and distributing of observations.	We need sufficient development computational resources and staff scientists to allow the timely testing of new and existing observations. New tools will likely also be a requirement. AI/ML may be leveraged.
New observation types are not sufficient for use in operational NWP due to factors such as data availability, latency, or quality.	Work with data providers and NOAA management to ensure that viability of use of observations is determined before significant resources are allotted to implement operational assimilation capabilities.
With the exponential growth rate of satellite data available to NWP, a robust observation monitoring system design and strategy are required to efficiently monitor the status of observations, quickly capture the problematic ones, and respond accordingly.	Transition from GSI to JEDI UFO gives us a chance to reinvent our observation monitoring system. We should learn from our past experience and NWP peers to design a robust observation monitoring system to address the issues (see left).

4.2.3 Management Risks

While the strategy presented in this document is limited to the DA activities at NCEP/EMC, we do not and should not work in a vacuum. Great care must be taken to ensure coordination internally with other parts of EMC, with the rest of NWS and other NOAA line offices more broadly, and also with external collaborators. This would include not only day to day activities but also to ensure synergy through coordinated and streamlined project management.

Risk	Response
With the transition of GSI to the JEDI-based system, there will be a substantial period of time the workforce will be tasked to facilitate the transition as well as to advance the current operational system.	Well defined project plans for JEDI transition as well as aspects of support for current operational continuity with legacy systems. Build appropriate flexibility into schedule to allow for evolving scope.
Growth of administrative task burdens (e.g. overheads from reporting and meetings, transition plans, etc.). These burdens grow in a framework where development is spread across multiple organizations.	Institute formal project reporting guidelines to assemble reporting materials. Manage the frequency of reporting. Assign support staff to handle facilitation of major administrative duties.
Extreme risk aversion that may arise in the enterprise is a risk as it may slow the pace of progress.	Risk should be managed and tolerances adapted to best meet the needs of all stakeholders.

4.2.4 External Dependence Risks

A significant portion of EMC's DA efforts over the next 10 years will be evaluation and transition to operations activities for replacing GSI with JEDI-based solutions throughout the operational production suite. Thus, a significant amount of risk for the success of future operational implementations is associated with the dependence on JEDI and its associated components.

Risk	Response
Reliance on JCSDA core staff/other partners on maintenance/enhancement of key CRTM and JEDI software components.	EMC will need to continue to spin up internal staff to support JEDI transition activities to build in-house expertise. Ensure support for CRTM and coefficient generation is prioritized by JCSDA and other partners to facilitate and ensure operational readiness. Maintain close relationships with JCSDA management and staff to permit and promote synergistic activities.
Requirement of externally developed libraries for JEDI-based applications.	Establish accepted protocols for timely approval, installation, and maintenance of required software infrastructure on operational (WCOSS) and RDHPCS machines.

A rapidly evolving and maturing system leads to a lack of stable software releases for evaluating system scientific and efficiency performance.	Ensure that sufficient EMC resources are allocated towards both freezing stable versions of the software but also continuing to follow enhancements to the system through GitHub and personal communication.

4.2.5 HPC and T2O

The software development philosophy at EMC has undergone a significant change with the recent adoption of Agile practices and the implementation of parallel CI/CD pipelines. This follows the JEDI system development approach. This process ensures faster adoption of new developments in DA, but the EMC software pipeline is not directly integrated into the operational system.

Risk	Response
Lengthy implementations tie up staff and compute resources for an extended duration.	Accelerate implementations by delivering smaller packages. Doing so requires greater confidence in the robustness of the changes. CI/CD can offer robustness and enhance confidence.
Different approaches to software infrastructure enhancement and maintenance.	Streamline acceptance, installation, and support of forward looking software infrastructure. Balance appropriate security concerns with the need to provide cutting edge HPC environments for continued improvement of operational systems.
Different testing and evaluation tools (e.g., different workflow engines) for development and operations.	Adopt unified approaches for development and operations (e.g, use ecflow as workflow engine with developer support on operational and NOAA RDHPCS machines). Add operational metrics to development CI/CD (run time checks, error trapping checks).
Significant HPC resources required to properly implement a CI/CD pipeline	HPC funding and resource allocation (cloud or traditional) needs to take into consideration the cost to implement, maintain, and enhance CI/CD pipelines.
Insufficient CI/CD expertise on both development and operational sides of T2O	Ensure staff receive necessary CI/CD training. Commit to ongoing training to keep abreast of evolving CI/CD capabilities

4.3 Concluding Remarks

As pointed out in the PWR Report (NOAA Science Advisory Board 2021), observations and DA are one of the three foundational pillars to enable a weather-ready nation. Some of the greatest leaps in operational prediction skill can be attributed to advancements in DA and improved initial conditions (Bauer et al. 2015; Benjamin et al. 2018). Operational prediction skill will continue to improve through advancing and improving the operational assimilation components. This document outlines a high-level strategy for advancing the state of infrastructure and science to enable improved operational assimilation capabilities for NOAA/NWS to meet its mission.

The transition from legacy infrastructure to JEDI will be a major theme for the next several years. Significant investments will continue to be required in order for NCEP staff to be able to focus on making contributions to JEDI, building internal expertise and working toward operational hardening. While this is going to incur a significant short-term strain on resources, the implementation of a unified DA infrastructure for use across UFS-based applications and to enable coupled assimilation will set the stage for more rapid infusion of innovation thereafter.

This strategic document outlines some of the specifics to improve the use of observations, begin operational preparedness for future satellite missions, and goals for advancing algorithms to meet some of the grand challenges. More importantly, perhaps, is the stated change in philosophy that will be required to realize the vision. Within the context of community modeling and engagement, NCEP staff will need to expand beyond traditional boundaries and become more involved in activities across the research spectrum rather than staying solely focused on high-readiness-level research and transition activities. Developments and innovation will need to be co-owned in order to be successful. Collaborations and partnerships will need to continue to be fostered and expanded. NWS will need to be willing to invest in, and take on, higher risk activities that have the potential for more significant benefits.

There will also be a need for a philosophical shift away from pursuing incremental change and building on best practices that have been implemented and accumulated over the past. Some things, like moving toward more continuous and possible in-core DA will require a radical departure from how things are done today. Such shifts will also require a pivot to more quickly embrace new technologies and best practices. One example of this is the desire to begin integration of tools like those based on machine learning and the establishment of a study group within the assimilation team. Technology, including computing, will continue to accelerate in their advancements and it is critical to be able to keep pace.

Finally, the workforce is the most important element in order to realize this strategy. Significant investments in workforce training, recruitment, development, and sustainment will be required in order to realize all of the aforementioned goals and priorities. The demands for a skilled DA workforce is high and competition is significant. It will be impossible to execute the vision without putting people first.

4.4 Relevance to NOAA Priorities and Strategic Plans

Summary of relevant key items, priorities, and recommendations being addressed:

- NWSSP Item 1.9. Collaborate across NOAA to increase visibility and access to the full range of integrated environmental information, forecasts, products, and services.
- NWSSP Item 2.1. Build the world's best unified, community-based, numerical Earth system prediction capabilities through collaboration with Enterprise partners.
- NWSSP 2.4. Ensure continuous operations with foundational observing assets, including radar and satellite systems, and adoption of emerging technologies to reduce costs and improve information.
- NWSSP 2.5. Utilize the broad observational capabilities of the Enterprise to establish the best possible analysis of the atmosphere, land surface, oceans, and cryosphere to ensure situational awareness, enable enhanced data assimilation, and meet growing user demands.
- NWSSP 2.10. Partner with the Office of Oceanic and Atmospheric Research (OAR), the U.S. weather research community, and other Enterprise partners to ensure continuous development and transition of the latest scientific and technological advances into operations.
- NWSSP 2.11. Streamline processes for rapid prototyping and adoption of innovative science and technologies into operations to support evolving forecaster roles and improve R2O/O2R efficiency.
- NWSSP 3.2. Implement a comprehensive workforce training and development plan to advance the expanding skill sets required for operational forecasting, including greater emphasis on decision support; ensure expertise in core mission support capabilities including engineering, technology, and administration; and strengthen efficiency and productivity with enhanced capabilities in project management, configuration management, and risk management.
- NWSSP 3.3. Sustain workforce capacity and skills that meet evolving mission needs, with outreach and strategies to improve the recruitment and retention of the best available talent, including those with STEM skill sets; implement hiring efficiencies and align hiring actions with workload needs; expand deployment-ready staff certified to support major events in collaboration with local and regional partners and across NOAA; and formalize knowledge transfer systems to sustain mission operations.
- NWSSP 3.8. Clarify and leverage the unique roles and capabilities of Enterprise partners to respond to the increasing demand for actionable weather, water, and climate information.
- NWSSP 3.9. Expand public-private partnerships that fast-track Enterprise innovations, strengthen relationships, eliminate barriers, and share best practices to focus continuous improvements.
- R&DVA Key Questions 1.1. How can forecasts and warnings for hazardous weather and other environmental phenomena be improved?
- R&DVA 3.1. How can unified modeling be integrated and improved with respect to skill, efficiency, and adaptability for service to stakeholders?

- R&DVA 3.2. How can Earth observations be advanced and their associated platforms be optimized to meet NOAA's needs?
- PWR OD-1. Maximize the use and assimilation of underutilized ground-based, airborne and marine observations - to ensure maximum value is derived from the full suite of observations in the Earth system model.
- PWR OD-2. Maximize the use and assimilation of underutilized satellite observations - to ensure maximum value is derived from the full satellite constellation in support of an Earth system model approach.
- PWR OD-3. Establish new support of novel methodology research and workforce development for data assimilation - to advance weather prediction and develop the future workforce.
- PWR OD-4. Advance coupled Earth system data assimilation for weather, water and sub-seasonal to seasonal forecasting - to enable observations in one Earth system component to influence corrections in multiple components.
- PWR OD-5. Advance the production of regional and global reanalyses - to improve detection of extreme events, forecast performance evaluation, improve use of observations.
- PWR FE-4. Greatly increase university involvement in NOAA research - to gain their assistance in advancing the NOAA mission and in training the next generation of NOAA scientists.

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Appendix A: Figures and Tables for Future Satellites

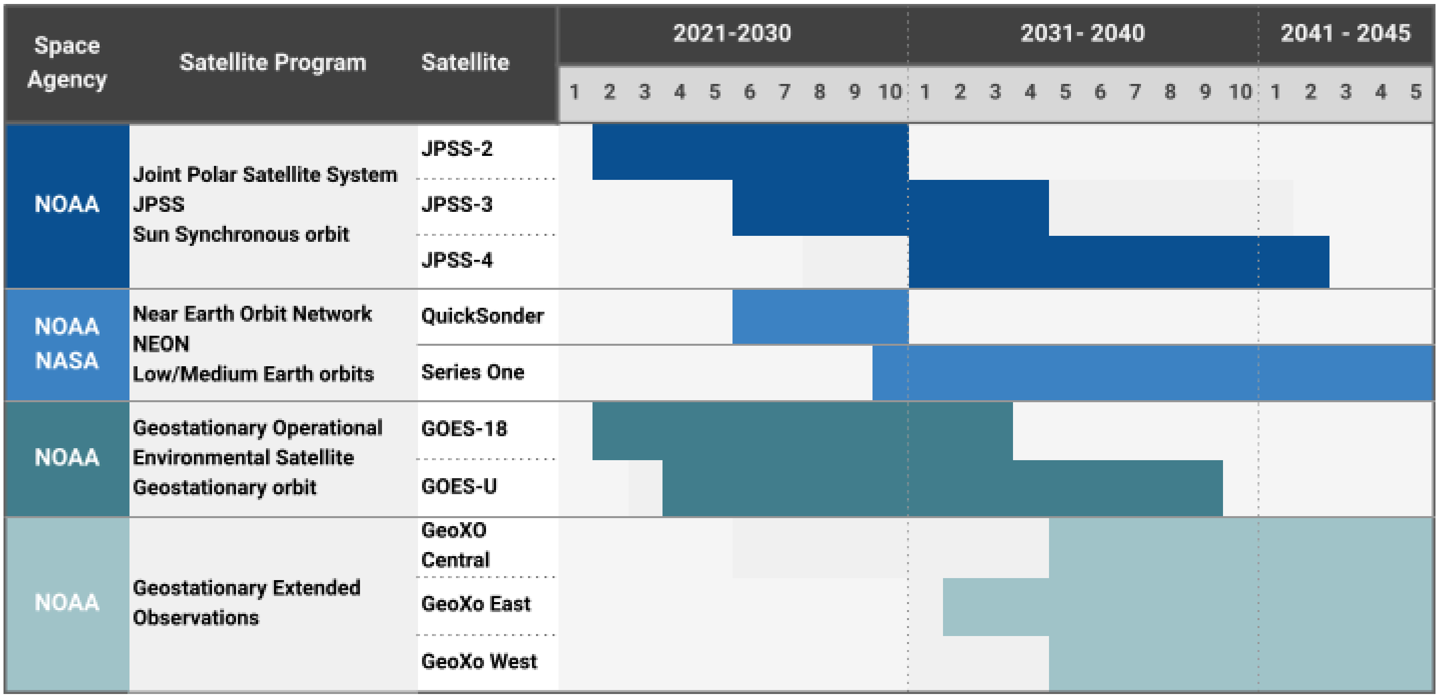

Figure A1. Operational timeline of NOAA satellites in the next few decades. The information was collected from the WMO Observing Systems Capability Analysis and Review (OSCAR) tool.

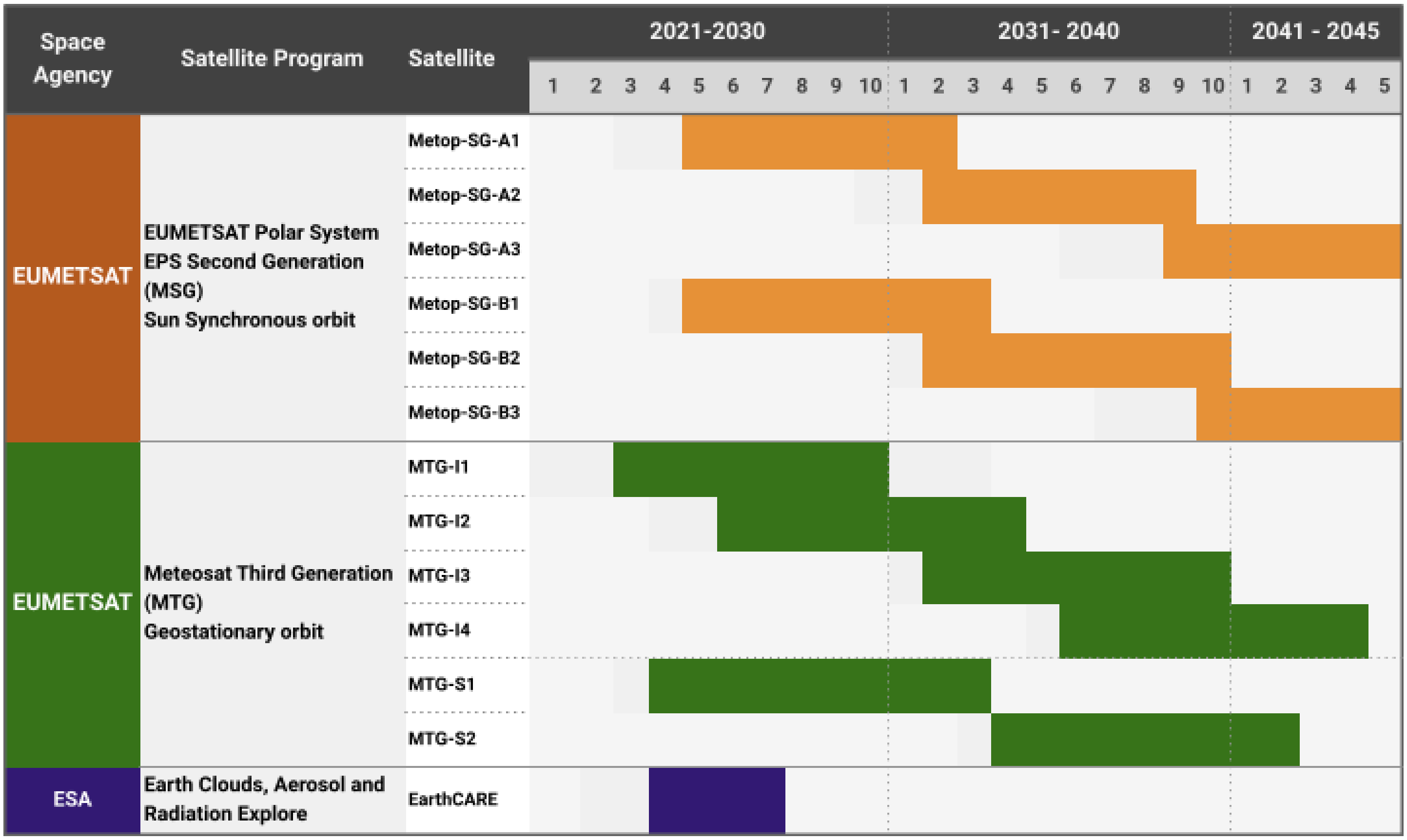

Figure A2. Operational timeline of EUMETSAT and ESA satellites in the next few decades. The information collected from the WMO OSCAR tool as of December, 2023

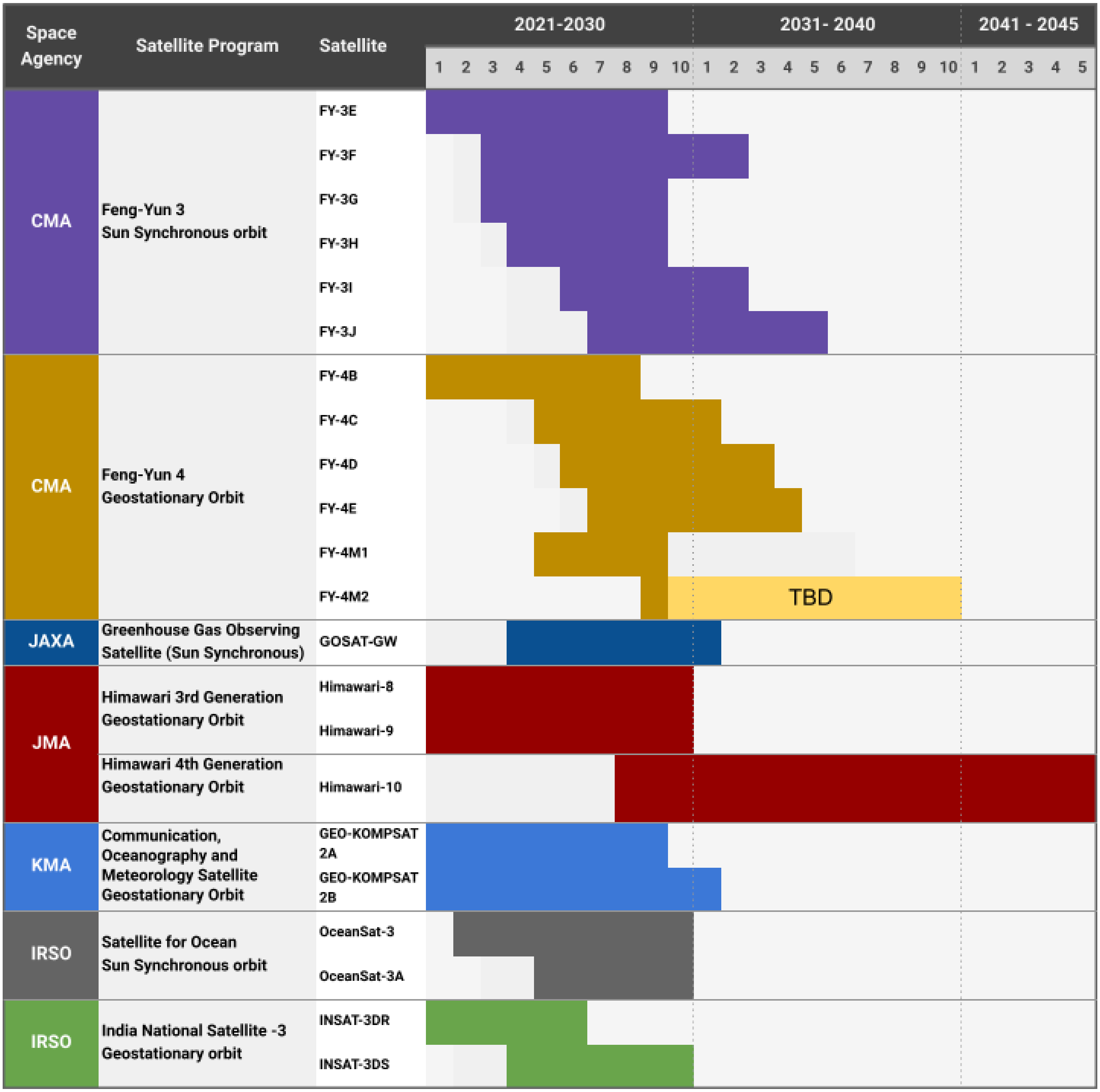

Figure A3. Operational timeline of Asian satellites in the next few decades. The information was collected from the WMO Observing Systems Capability Analysis and Review (OSCAR) tools as of December 2023.

Space Agency	Satellite	Sensor		Usage	Priority
NOAA	JPSS-2 JPSS-3 JPSS-4	ATMS	Advanced Technology Microwave Sounder	MW Radiance (all-sky)	1
		CrIS	Cross-track Infrared Sounder	IR Radiance	1
		OMPS-limb	Ozone Mapping and Profiler Suite	Stratospheric ozone profile	1
		OMPS-nadir	Ozone Mapping and Profiler Suite	Ozone profile Total-column ozone	1
		VIIRS	Visible/Infrared Imager Radiometer suite	IR Radiance Wind derivation by tracking clouds and water vapor features	1
NOAA NASA	QuickSounder	ATMS	Advanced Technology Microwave Sounder	MW Radiance (all-sky)	1
	Series One	SMBA	Sounder for Microwave-Based Applications	MW Radiance (all-sky)	1
NOAA	GOES-T GOES-U	ABI	Advanced Baseline Imager	IR Radiance Wind derivation by tracking clouds and water vapor features	1
	GeoX0	GXS	GeoX0 Hyperspectral Radiometric Sounder	IR Radiance Wind derivation by tracking clouds and water vapor features	2

Table A1. Sensors on board of NOAA satellites listed in Figure A1.
Priorities: 1=Legacy sensor; 2=New sensor requiring minimal additional development (can use existing framework); 3=New sensor that requires significant scientific development; 4=Will explore depending on data quality; x=Not allowed to use this because of security concerns.

Space Agency	Satellite	Sensor		Usage	Priority
EUMETSAT	Metop-SG A series	IASI-NG	Infrared Atmospheric Sounder Interferometer - New Generation Evolution of IASI on MetOp A to C Higher spectral resolution than IASI ($0.25\ cm^{-1}$ vs $0.50\ cm^{-1}$)	IR Radiance Reconstructed Radiance	1
		METimager	Meteorological Imager Replacing AVHRR/3 on MetOp A to C	IR Radiance Wind derivation by tracking clouds and water vapor features	1
		MWS	Micro-Wave Sounder To replace AMSU-A and MHS on MetOpA to C	MW Radiance (all-sky)	1
		RO	Radio Occultation sounder Follow-on of GRAS on MetOp A to C	Bending Angle	1
	Metop-SG B series	MWI	Micro-Wave Imager New development	MW Radiance (all-sky); microwave	1
		ICI	Ice Cloud Imager New development	MW Radiance (all-sky); sub-mm wave	2
		SCA	Scatterometer Evolution of ASCAT on MetOp A to C	Sea surface wind vector	1
		RO	Radio Occultation sounder Follow-on of GRAS on MetOp A to C	Bending Angle	1
EUMETSAT	MTG-Imager	FCI	Flexible Combined Imager Evolution of SEVIRI	IR Radiance Wind derivation by tracing clouds and water vapor features	1
	MTG-Sounder	IRS	Infra Red Sounder New development; hyperspectral	IR Radiance Wind profile derivation by tracking water vapor features	2
ESA	EarthCARE	ATLID	Atmospheric Lidar	Backscatter	3
		CPR	Cloud Profiling Radar for Earth-CARE	Reflectivity	3

Table A2. Sensors on board of EUMETSAT and ESA satellites listed in Figure A2.
Priorities: 1=Legacy sensor; 2=New sensor requiring minimal additional development (can use existing framework); 3=New sensor that requires significant scientific development; 4=Will explore depending on data quality and resource availability; x=Not allowed to use this because of security concerns.

Space Agency	Satellite	Sensor		Usage	Priority
CMA	Feng-Yun-3	MWHS-2	Micro-Wave Humidity Sounder -2	MW Radiance (all-sky)	x
		MWTS-3	Micro-Wave Temperature Sounder -3	MW Radiance (all-sky)	x
		MWRI	Micro-Wave Radiation Imager	MW Radiance (all-sky)	x
		HIRAS-2	Hyperspectral Infrared Atmospheric Sounder -2	IR Radiance	x
		GNOS-2	GNSS Radio Occultation sounder -2	Bending Angle	x
		OMS-nadir	Ozone Monitoring Suite nadir scanning unit	Ozone profile Total-column ozone	x
		OMS-limb	Ozone Monitoring Suite limb scanning unit	Stratospheric ozone profile	x
CMA	Feng-Yun-4	GIIRS	Geostationary Interferometric Infrared Sounder	IR Radiance Wind profile derivation by tracking water vapor features	x
		AGRS	Advanced Geostationary Radiation Imager	Wind profile derivation by tracking clouds and water vapor features	x

Table A3. Sensors on board of CMA satellites listed in Figure A3.
Priorities: 1=Legacy sensor; 2=New sensor requiring minimal additional development (can use existing framework); 3=New sensor that requires significant scientific development; 4=Will explore depending on data quality and resource availability; x=Not allowed to use this because of security concerns.

Space Agency	Satellite	Sensor		Usage	Priority
JAXA	GOSAT-GW	AMSR-3	Advanced Microwave Scanning Radiometer -3	MW Radiance (all-sky)	1
JMA	Himawari-8 Himawari-9	AHI	Advanced Himawari Imager	IR Radiance Wind profile derivation by tracking clouds and water vapor features	1
KMA	GEO-KOMPSAT-2A	AMI	Advanced Meteorological Imager	IR Radiance Wind profile derivation by tracking clouds and water vapor features	4
KMA	GEO-KOMPSAT-2B	GEMS	Geostationary Environmental Monitoring Spectrometer	Ozone profile and total-column	4
IRSO	OceanSat-3	OSCAT	OceanSat Scatterometer	Sea surface wind vector	1
IRSO	OceanSat-3A	OSCAT	OceanSat Scatterometer	Sea surface wind vector	1
IRSO	INSAT-3DR	IMAGER	INSAT Imager	Wind derivation by tracking clouds and water vapor features	4
IRSO	INSAT-3DR	SOUNDER	INSAT Sounder	IR Radiance	4
IRSO	INSAT-3DS	IMAGER	INSAT Imager	Wind derivation by tracking clouds and water vapor features	4
IRSO	INSAT-3DS	SOUNDER	INSAT Sounder	IR Radiance	4

Table A4. Sensors on board of Asian (non-CMA) satellites listed in Figure A3.
Priorities: 1=Legacy sensor; 2=New sensor requiring minimal additional development (can use existing framework); 3=New sensor that requires significant scientific development; 4=Will explore depending on data quality and resource availability; x=Not allowed to use this because of security concerns.

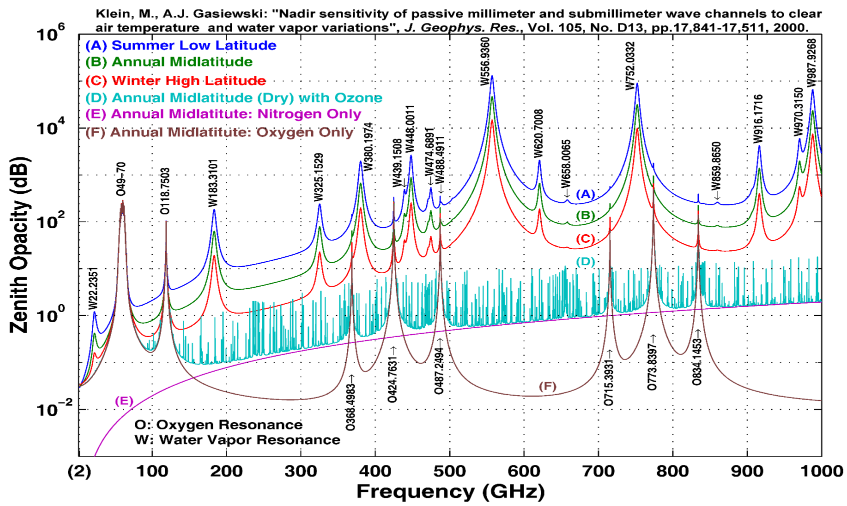

Figure A4. Atmospheric spectrum in the MW millimeter (mm) to sub-mm range. Figure adapted from Klein and Gasiewski (2000).

Channel Set GHz	Window	WV 23	Window 31	Oxygen 49-70	Window 89	Oxygen 118	Window 150-165	WV 183-190	Window 229	WV 325	WV 448	WV 658
AMSU-A (15)		23.8 V	31.4 V	50.3000 V 52.8000 V 53.5960 H 54.4000 H 54.9400 V 55.5000 H 57.2903 H (6)	89.0 V							
MHS (5)					89 V		157 V	183.31 H (2) 190.31 V				
ATMS (22)		23.8 QV	31.4 QV	50.3000 QH 51.7600 QH 52.8000 QH 53.5960 QH 53.4000 QH 54.9400 QH 55.5000 QH 57.2903 QH (6)	89.5 QV		165.5 QH	183.31 QH (5)				
GMI (13)	10.65 V 10.65 H 18.70 V 18.70 H	23.8 V	36.5 V 36.5 H		89 V 89 H		165.5 V 165.5 H	183.31 V (2)				
SSMIS (24)	19.35 V 19.35 H	22.235 V	37.0 V 37.0 H	50.300 H 52.800 H 53.596 H 54.500 H 55.500 H 57.290 RC 59.400 RC 60.792 RC (5) 63.238 RC	91.65 V 91.65 H		150 H	183.31 H (3)				
Channel Set GHz	Window	WV 23	Window 31	Oxygen 49-70	Window 89	Oxygen 118	Window 150--165	WV 183-190	Window 229	WV 325	WV 448	WV 658

Table A5. The absorption band and central frequency for **US MW sensors** available to NWP during the next few decades.

Channel Set GHz	Window	WV 23	Window 31	Oxygen 49-70	Window 89	Oxygen 118	Window 150-165	WV 183-190	Window 229	WV 325	WV 448	WV 658
MWS (24) Single Polarization (V or H)		23.8	31.4	50.3000 52.8000 53.2460 53.5960 H 53.9480 54.4000 54.9400 55.5000 57.2903 (6)	89		164-167	183.31 (5)	229			
MWI (26)	18.7 V 18.7 H	23.8 V 23.8 H	31.4 V 31.4 H	50.30 V, H 52.61 V, H 53.24 V, H 53.75 V, H	89 V 89 H	118.7503 V (4)	165.5 V	183.31 V (5)				
ICI (13)								183.31 V (3)	243 V 243 H	325 V (3)	448 V (3)	664 V 664 H
Channel Set GHz	Window	WV 23	Window 31	Oxygen 49-70	Window 89	Oxygen 118	Window 150--165	WV 183-190	Window 229	WV 325	WV 448	WV 658

Table A6. The absorption band and central frequency for **European MW sensors** available to NWP during the next few decades.

Channel Set GHz	Window	WV 23	Window 31	Oxygen 49-70	Window 89	Oxygen 118	Window 150-165	WV 183-190	Window 229	WV 325	WV 448	WV 658
AMSR-2 (16)	6.900 V 6.900 H 7.300 V 7.300 H 10.650 V 10.650 H 18.700 V 18.700 H	23.8 V 23.8 H	36.5 V 36.5 H		89 A, H 89 A, V 89 B, H 89 B, V							
AMSR-3 (21)	6.925 V 6.925 H 7.300 V 7.300 H 10.250 V 10.250 H 10.650 V 10.650 H 18.700 V 18.700 H	23.8 V 23.8 H	36.5 V 36.5 H		89 A, H 89 A, V 89 B, H 89 B, V		165.5 V	183.31 V (2)				
MWTS-3 (17) Single Polarization (V or H)		23.8	31.4	50.300 51.760 52.800 53.596 (3) 54.400 54.940 55.500 57.290 (6)								
MWHS-2 (15)					89 V	118.75 H (8)	150 V	183 H (5)				
MWRI (10)	10.65 V 10.65 H 18.70 V 18.70 H	23.8 V 23.8 H	36.5 V 36.5 H		89 V 89 H							
Channel Set GHz	Window	WV 23	Window 31	Oxygen 49-70	Window 89	Oxygen 118	Window 150--165	WV 183-190	Window 229	WV 325	WV 448	WV 658

Table A7. The absorption band and central frequency for **Asian MW** sensors available to NWP during the next few decades.

Channel Set GHz	Window	WV 23	Window 31	Oxygen 49-70	Window 89	Oxygen 118	Window 150-165	WV 183-190	Window 229	WV 325	WV 448	WV 658
TEMPEST (5)					89		165	176 180 182				
TROPICS (12)					91.655	114.50 115.95 116.65 117.25 117.80 118.24 118.58		184.41 186.51 190.31 204.80				
Channel Set GHz	Window	WV 23	Window 31	Oxygen 49-70	Window 89	Oxygen 118	Window 150--165	WV 183-190	Window 229	WV 325	WV 448	WV 658

Table A8. The absorption band and central frequency for **SmallSat/CubeSat MW** sensors available to NWP during the next few decades.

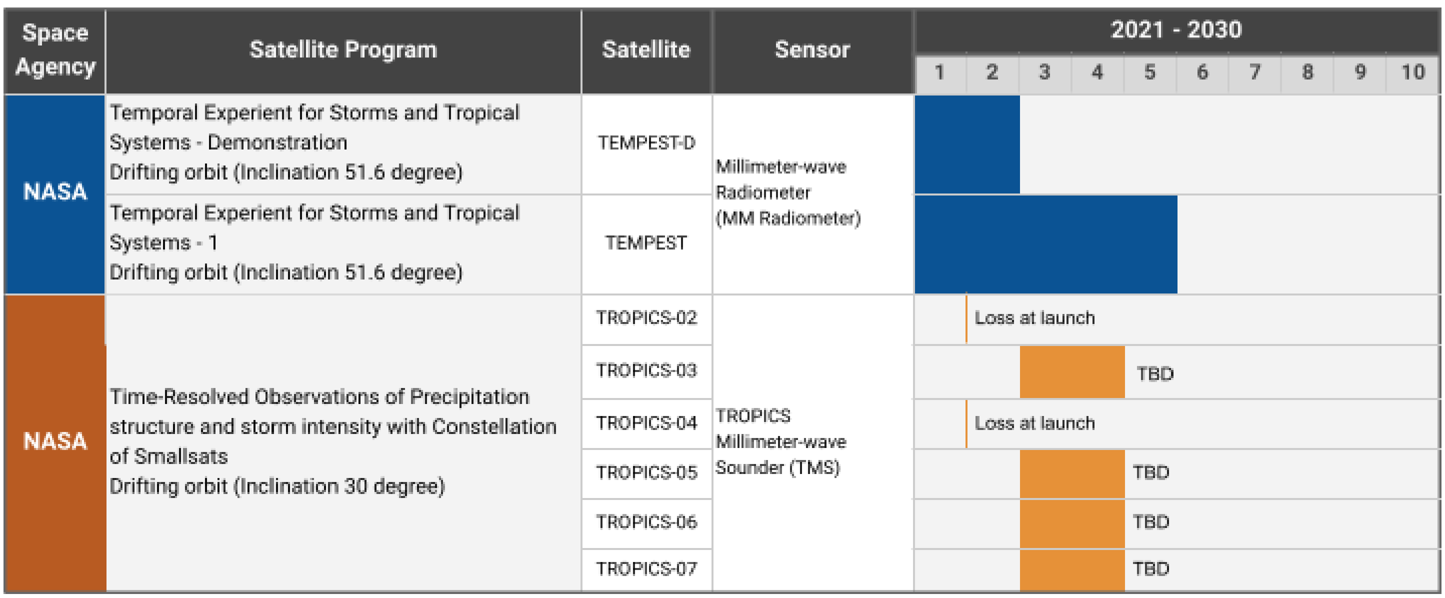

Figure A5. SmallSat/CubeSat Mission Status.

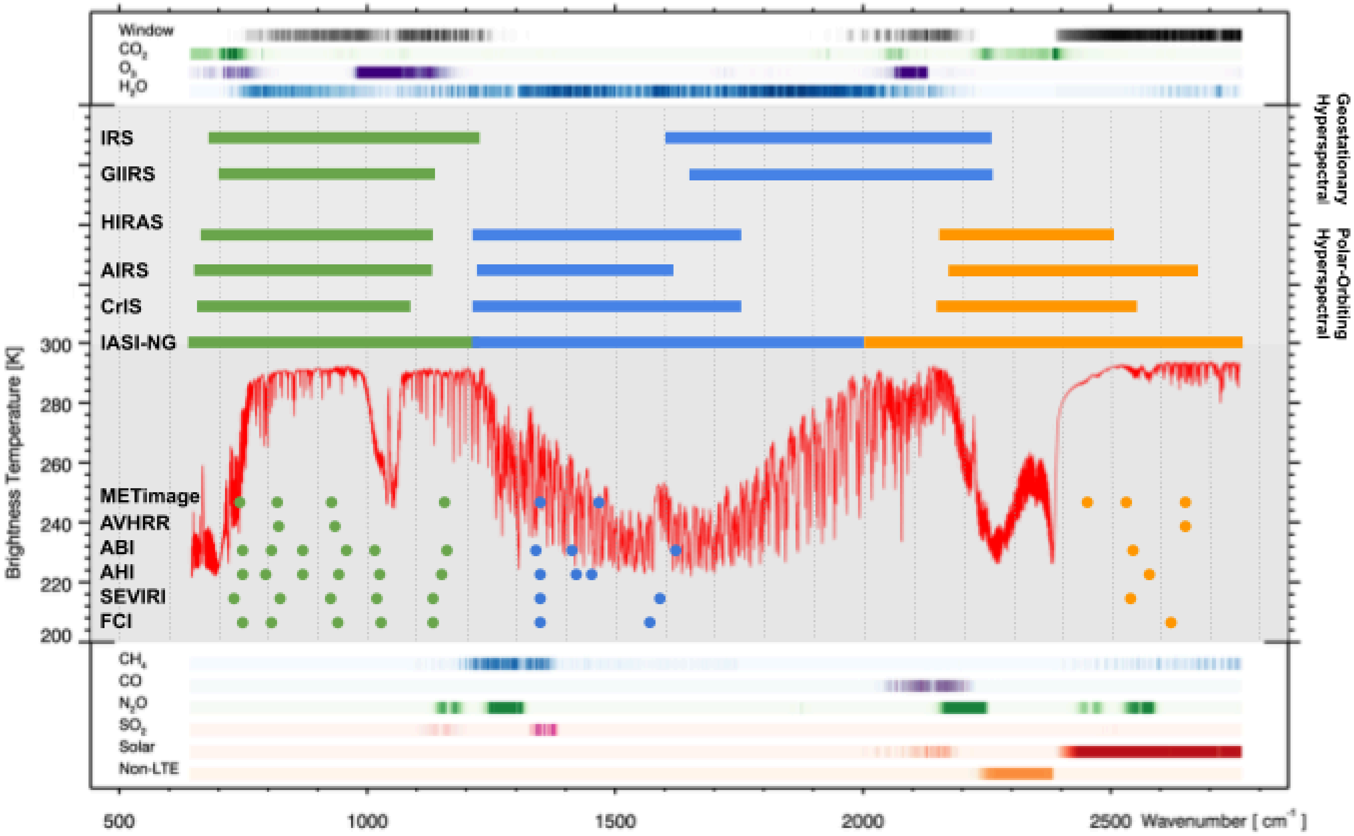

Figure A6. Spectral Coverage of satellite-based **IR sounders and imagers**. The new upcoming IR sounders are the geostationary IRS, the next generation polar-orbiting IASI. The new imagers are the polar-orbiting METimage, and the geostationary FCI.

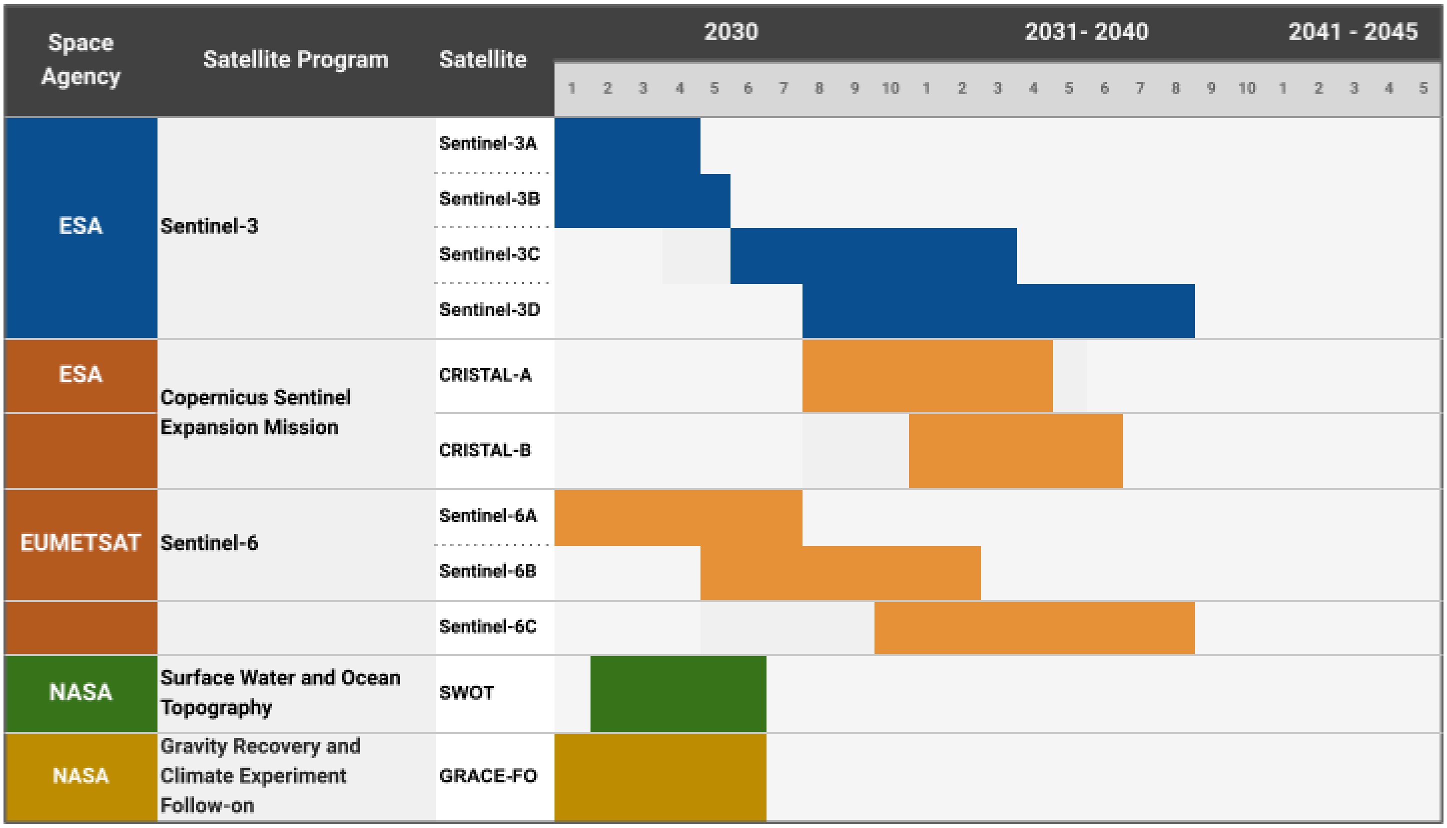

Figure A7. Operational timeline of satellites for ocean DA in the next few decades.

Space Agency	Satellite	Sensor		Usage	Priority
ESA	Sentinel-3C Sentinel-3D	SRAL	Synthetic aperture Radar Altimeter	Ocean and sea ice topography, significant wave height, wind speed on sea surface	1
	CRISTAL Copernicus polaR Ice and Snow Topography Altimeter	IRIS	Interferometric Radar altimeter for Ice and Snow	To measure and monitor the variability of ice elevation and thickness in polar regions	3
EUMETSAT	Sentinel-6A Sentinel-6B	Poseidon-4	Poseidon-4	Ocean and sea ice topography, significant wave height, wind speed on sea surface	1
NASA	SWOT	Altimeter	Altimeter	Ocean and sea ice topography, significant wave height, wind speed on sea surface, specific to sea-surface height	2
	GRACE-FO	HAIRS	High Accuracy Inter-satellite Ranging System K-band microwave-ranging link	Gravity estimated from the satellite train range rate	4

Table A9. Sensors on board of each satellite listed in Figure A7.

Priorities: 1=Legacy sensor; 2=New sensor requiring minimal additional development (can use existing framework); 3=New sensor that requires significant scientific development; 4=Will explore depending on data quality; x=Not allowed to use this because of security concerns.

Appendix B: JEDI Components and Design

The Joint Effort for Data assimilation Integration (JEDI) project is the next-generation DA system being developed by the JCSDA and its partners, including NOAA. A key concept for modern software development for complex systems such as JEDI is the idea of separation of concerns. This means that when a complete codebase becomes too large or complex for one person or group to be experts in, it is broken down into pieces that are more focused and allow developers to become experts in their relevant areas of the system. Through this separation of concerns also comes modularity, and with the inclusion of object-oriented programming, JEDI can create a series of applications from a combined set of separate, but complementary, libraries.

At the center of JEDI is the Object Oriented Prediction System, or OOPS. This is the high level driver that contains all the generic code for running a DA system. OOPS includes code for variational and ensemble solvers, utilities such as time manipulation, and other high-level codes to be utilized by final applications. There are two key components that deal with observations, for I/O and storage, as well as their use. The Interface for Observational Data Access, or IODA, library deals with the reading, writing, and access of observational data in memory (including distribution). IODA includes file backends (such as netCDF) in order to read data from disk and write out model-space diagnostics. The Unified Forward Operator (UFO) library contains all aspects of the use of observations. This includes the forward, tangent linear, and adjoint operators for observations, and quality control filters and error assignment procedures. There are other model-agnostic key libraries included in JEDI. The System Agnostic Background Error Representation, or SABER, library, provides generic tools for computing and working with the background error covariance matrix, a key component of DA. Finally, the VAriable DErivation Repository, or VADER, provides generic routines for deriving variables from other variables using a set of recipes.

These libraries form the shared codebase of a JEDI application, but most JEDI applications require a model interface to be included. Each modeling system that is supported by JEDI requires a model interface library to be developed. For FV3 based models, there is FV3-JEDI, for MPAS, MPAS-JEDI, for MOM6 and CICE6 there is the Sea-Ice, Ocean, and Coupled Assimilation, or SOCA, interface. Each of these interfaces provide the connection between the model specific implementation and the generic JEDI libraries for a DA application. A variational DA application for FV3 or MPAS, for example, would share the majority of the same codebase from the agnostic libraries, and would only differ in their model specific interface code. This allows for more rapid development of DA systems for other models, as only the model interface needs to be developed, all other components (the solver, the observation operators, etc.) are already ready to be linked to at compile time. The end result of building JEDI is a series of executables that are a combination of the generic libraries in JEDI and the model interface(s) that the user requires for their prediction system. A brief overview diagram is shown in Fig. B1.

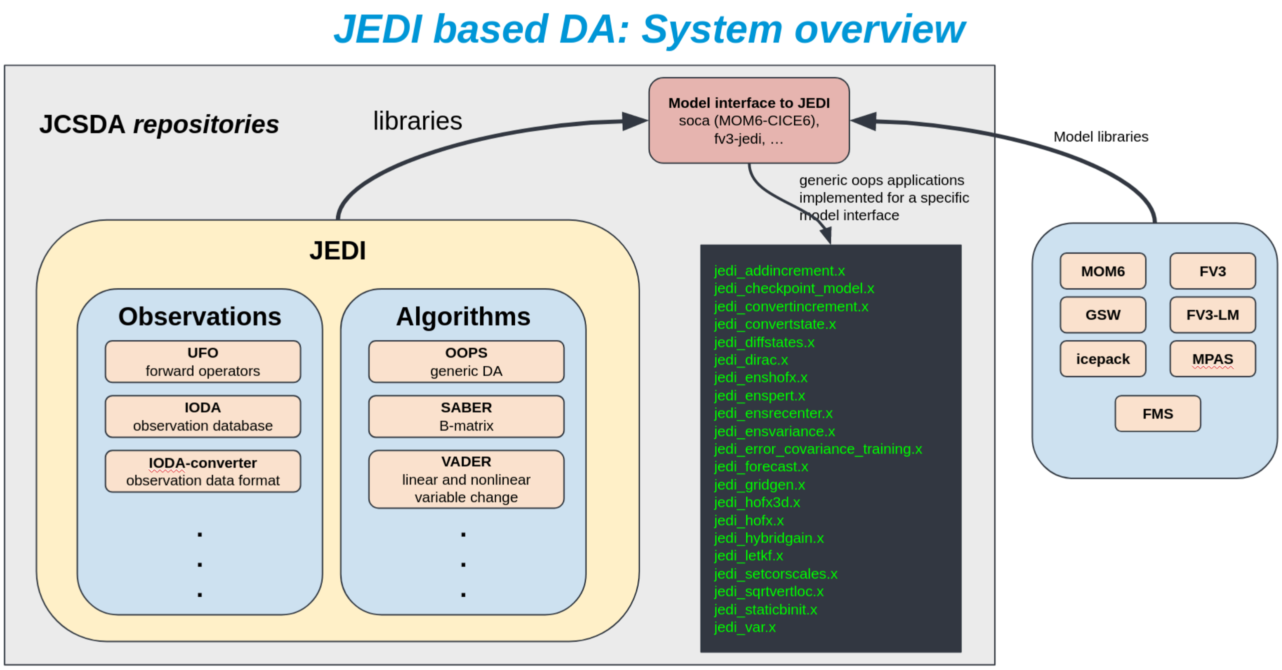

Figure B1. Overview of the JEDI-Based DA infrastructure and components.

Appendix C: Abbreviations, Acronyms, and Terminology

3DVar	Three-Dimensional Variational
3DEnVar	Three-Dimensional Ensemble Variational
4DVar	Four-Dimensional Variational
4DEnVar	Four-Dimensional Ensemble Variational
ABI	Advanced Baseline Imager
AD	Adjoint
AHI	Advanced Himawari Imager
ALADIN	Atmospheric Laser Doppler Instrument
AI	Artificial intelligence
AIRS	Atmospheric Infrared Sounder
AMS	American Meteorological Society
AMSR	Advanced Microwave Scanning Radiometer
AMSR-E	Advanced Microwave Scanning Radiometer-EOS
AMSU-A	Advanced Microwave Sounding Unit - A
AMV	Atmospheric Motion Vector
AOD	Aerosol Optical Depth
ATMS	Advanced Technology Microwave Sounder
AVHRR	Advanced Very High Resolution Radiometer
BUFR	Binary Universal Form for the Representation of meteorological data
BUMP	Background error on an Unstructured Mesh Package
CALIPSO	Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation
CD	Continuous Deployment
CFS	Climate Forecast System
CFSR	Climate Forecast System Reanalysis
CI	Continuous Integration
CONUS	Contiguous United States
COSMIC	Constellation Observing System for Meteorology, Ionosphere, and Climate
CPU	Central Processing Unit
CRIS	Cross-track Infrared Sounder
CRISTAL	Copernicus Polar Ice and Snow Topography Altimeter
CRTM	Community Radiative Transfer Model
CYGNSS	Cyclone Global Navigation Satellite System
DA	Data Assimilation
DFI	Digital Filter Initialization
DTC	Developmental Testbed Center
ECMWF	European Centre for Medium-Range Weather Forecasts
EDA	Ensembles of Data Assimilation
EMC	Environmental Modeling Center
ENKF	Ensemble Kalman Filter
EnVar	Ensemble-Variational
EPIC	Earth Prediction Innovation Center
ESA	European Space Agency
EUMETSAT	European Organisation for the Exploitation of Meteorological Satellites
FCI	Flexible Combined Imager

FLOPS	Floating Point Operations
FSOI	Forecast Sensitivity to Observations Impact
FV3	Finite-Volume Cubed-Sphere dynamical core
GDAS	Global Data Assimilation System
GEFS	Global Ensemble Forecasting System
GEMS	Geostationary Environment Monitoring Spectrometer
GEO	Geostationary Orbit
GEO-XO	Geostationary Extended Observations
GFS	Global Forecast System
GHG	Greenhouse Gas
GIIRS	Geostationary Interferometric Infrared Sounder
GMI	Global Precipitation Measurement Microwave Imager
GNSS	Global Navigation Satellite System
GNSS-R	Global Navigation Satellite System-Reflectometry
GNSS-RO	Global Navigation Satellite System-Radio Occultation
GODAS	Global Ocean Data Assimilation System
GOES	Geostationary Operational Environmental Satellites
GPU	Graphics Processing Unit
GRACE	Gravity Recovery and Climate Experiment
GSI	Gridpoint Statistical Interpolation analysis system
GTS	Global Telecommunication System
HAFS	Hurricane Analysis and Forecasting System
HFIP	Hurricane Forecast Improvement Program
HWRF	Hurricane Weather Research and Forecasting Model
IODA	Interface for Observational Data Access
IoT	Internet of Things
HPC	High performance computing
HRRR	High Resolution Rapid Refresh
I/O	Input/Output
IASI	Infrared Atmospheric Sounding Interferometer
IAU	Incremental Analysis Update
ICI	Ice Cloud Imager
IR	Infrared
IRS	Infrared Sounder
JCSDA	Joint Center for Satellite Data Assimilation
JEDI	Joint Effort for Data assimilation Integration
JPSS	Joint Polar Satellite System
LEO	Low Earth Orbit
LETLM	Local Ensemble Tangent-Linear Model
LIDAR	Light Detection and Ranging
LMAI	Language model Artificial Intelligence
MET	Model Evaluation Tools
METEOSAT	Meteorological Satellite (EUMETSAT Geo)
METOP	Meteorological Operational satellite (EUMETSAT Leo)
MHS	Microwave Humidity Sounding
ML	Machine learning
MRW	Medium Range Weather

MTG	Meteosat Third Generation
MW	Microwave
MWI	Microwave Imager
MWS	Microwave Sounder
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environmental Prediction
NCL	NCAR Command Language
NCO	NWS Central Operations
NDVI	Normalized Difference Vegetation Index
NEON	NOAA's Near Earth Orbit Network
NEXRAD	Next-generation weather radar
NGGM	Next Generation Gravity Mission
NGGPS	Next Generation Global Prediction System
NOAA	National Oceanic and Atmospheric Administration
NSST	Nea-Surface Sea Temperature
NWP	Numerical weather prediction
NWS	National Weather Service
NWSSP	National Weather Service Strategic Plan
O2R	Operations to Research
OAR	Oceanic and Atmospheric Research
OMI	Ozone Monitoring Instrument
OMPS	Ozone Mapping and Profiler Suite
OOPS	Object-Oriented Prediction System
OSCAR	Observing Systems Capability Analysis and Review
OSE	Observing System Experiment
PACE	Plankton, Aerosol, Cloud, ocean Ecosystems mission
PDA	Product Distribution and Access
PWR	Report on Priorities for Weather Research
QC	Quality Control
R&DVA	Research and Development Vision Areas
R2D2	Research Repository for Data and Diagnostics
R2O	Research to Operations
RAP	Rapid Refresh (system)
RDHPCS	Research and Development High Performance Computing System
RL	Readiness Level
RMS	Root Mean Square
RRFS	Rapid Refresh Forecast System
RTMA	Real-Time Mesoscale Analysis
RTOFS	Real Time Ocean Forecast System
RTTOV	Radiative Transfer for TOVS
S2S	Subseasonal to Seasonal
SDL	Scale-dependent Localization
SEVIRI	Spinning Enhanced Visible Infra-Red Imager
SFS	Seasonal Forecasting System
SOCA	Sea-ice Ocean and Coupled Assimilation
SMBA	Sounder for Microwave-Based Applications
SSI	Spectral Statistical Interpolation analysis system

SSMIS	Special Sensor Microwave - Imager/Sounder
SST	Sea Surface Temperature
STI	Science and Technology Integration
SWOT	Surface Water and Ocean Topography
TAC	Traditional Alphanumeric Codes
TDCF	Table Driven Code Forms
TDR	Tail Doppler Radar
TDWR	Terminal Doppler Weather Radar
TEC	Total Electron Content
TEMPEST	Temporal Experiment for Storms and Tropical Systems
TEMPO	Tropospheric Emissions: Monitoring Pollution
TIROS	Television InfraRed Observation Satellite
TL	Tangent-Linear
TLNMC	Tangent-Linear Normal Mode Constraint
TOVS	TIROS Operational Vertical Sounder
TROPICS	Time-Resolved Observations of Precipitation structure and storm Intensity with a Constellation of Smallsats
TROPOMI	Tropospheric Monitoring Instrument
UAS	Uncrewed Aircraft System or Uncrewed Autonomous System
UFO	Unified Forward Operator
UFS	Unified Forecast System
VAD	Velocity-Azimuthal Display
VARQC	Variational Quality Control
VIIRS	Visible/Infrared Imager Radiometer Suite
VOC	Volatile Organic Compound
WCOSS	Weather and Climate Operational Supercomputing System
WAM-IPE	Whole Atmosphere Model-Ionosphere Plasmasphere Electrodynamics
WDAS	Whole atmosphere Data Assimilation System
WDQMS	WIGOS Data Quality Monitoring System
WIGOS	WMO Integrated Observing System
WMO	World Meteorological Organization
WPO	Weather Program Office
WSR-88D	Weather Surveillance Radar-1988
ZTD	Zenith Total Delay