KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY

COLLEGE OF SCIENCE

DEPARTMENT OF METEOROLOGY AND CLIMATE SCIENCE

TITLE: DATA ASSIMILATION IN METEOROLOGY AND CLIMATE SCIENCE

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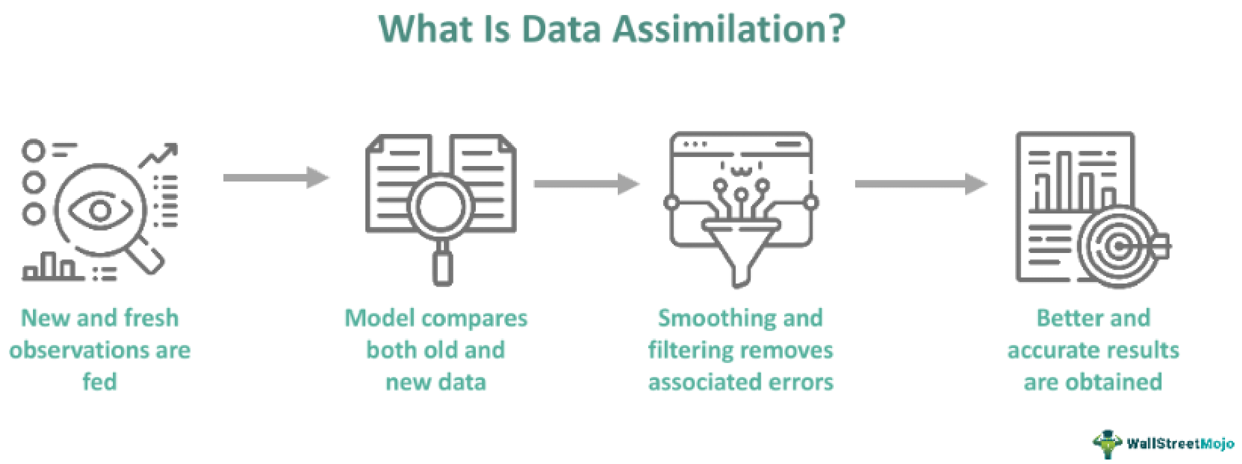
DATA ASSIMILATION

Data assimilation: refers to the process of combining observational data with numerical models to produce an accurate representation of the state of a physical system. In meteorology and climate science, data assimilation plays a crucial role in improving weather forecasts, climate projections, and our understanding of atmospheric and oceanic processes (Kalnay, 2003; Reichle, 2008).

Moreover, Data assimilation is an analysis technique in which the observed information is accumulated into the model state by taking advantage of consistency constraints with laws of time evolution and physical properties (F. Bouttier et al.,1999).



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IMPORTANCES IN METEOROLOGY AND CLIMATE SCIENCE

1. Support for Extreme Events Modeling and Forecasting: Data assimilation is necessary for improving coupled models that support extreme events modeling and forecasting. This is crucial for understanding and mitigating the impacts of extreme weather events, such as floods and storms (Centurioni et al.,2021).

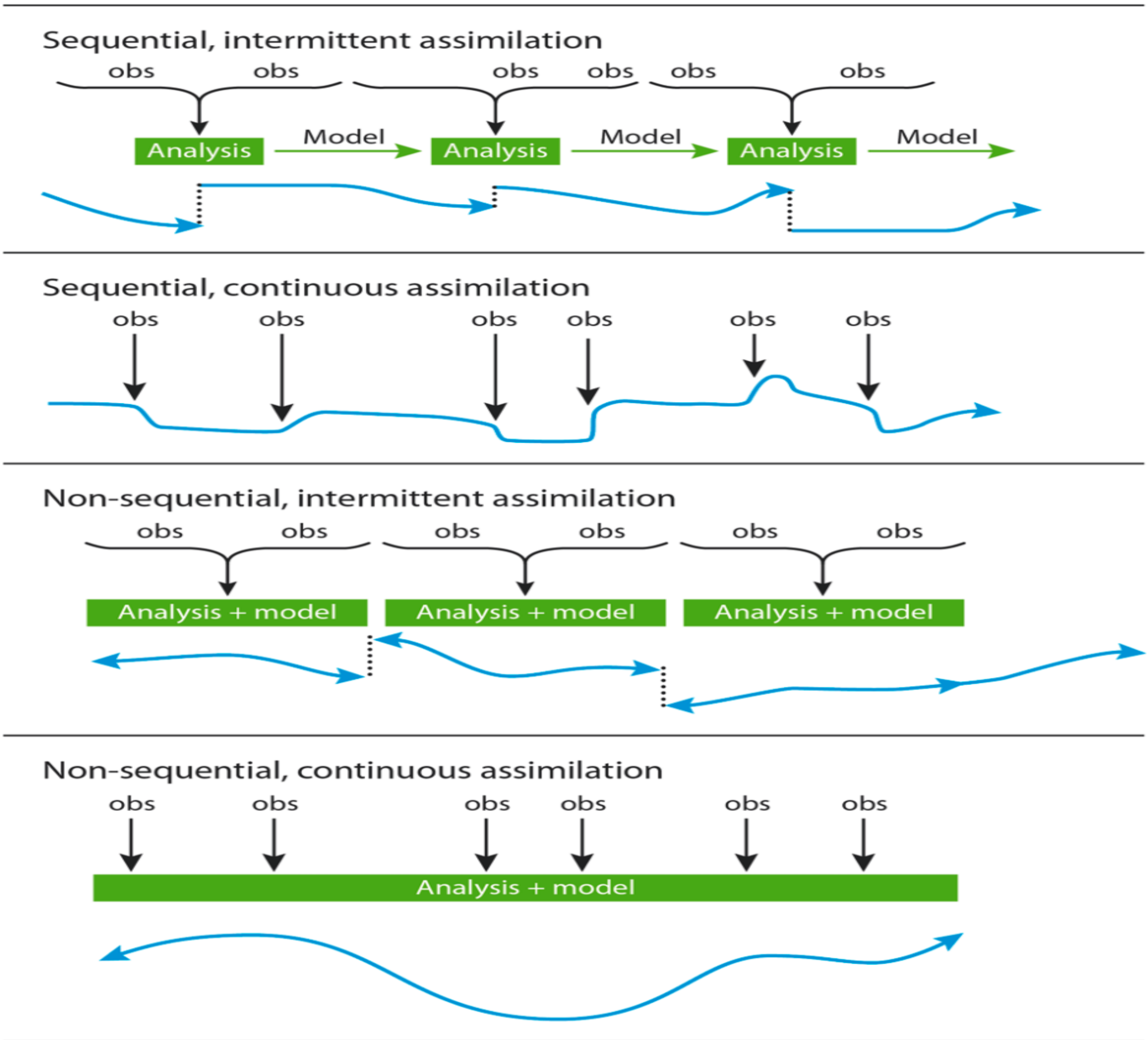
2. Enhanced Understanding of Complex Systems: Data assimilation helps in understanding the interactions between the atmosphere and the ocean, which is crucial for climate science. By combining observations with models, researchers can better comprehend the dynamics of the coupled system and improve their predictive capabilities (Bamzai, A. 2020).

3. Support for Climate Modeling: Data assimilation is essential for climate modeling, as it allows for the integration of observational data with models to better understand and predict climate patterns. This is critical for understanding and mitigating the impacts of climate change (Brasseur et al.,2013).

BASIC CONCEPT OF DATA ASSIMILATION

The basic concept of data assimilation is to combine real observations with dynamic models using estimation theory. This process is crucial in various fields such as meteorology, geophysics, engineering, and physical oceanography, particularly in understanding the role of the ocean in a global change perspective (Brasseur et al.,2013). Data assimilation involves integrating real data with models to improve the accuracy of predictions and enhance our understanding of complex systems.

There are two basic approaches to data assimilation: sequential assimilation, that only considers observation made in the past until the time of analysis, which is the case of real-time assimilation systems, and non-sequential, or retrospective assimilation, where observation from the future can be used, for instance in a reanalysis exercise (F. Bouttier et al.,1999).



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DATA ASSIMILATIONS METHODS

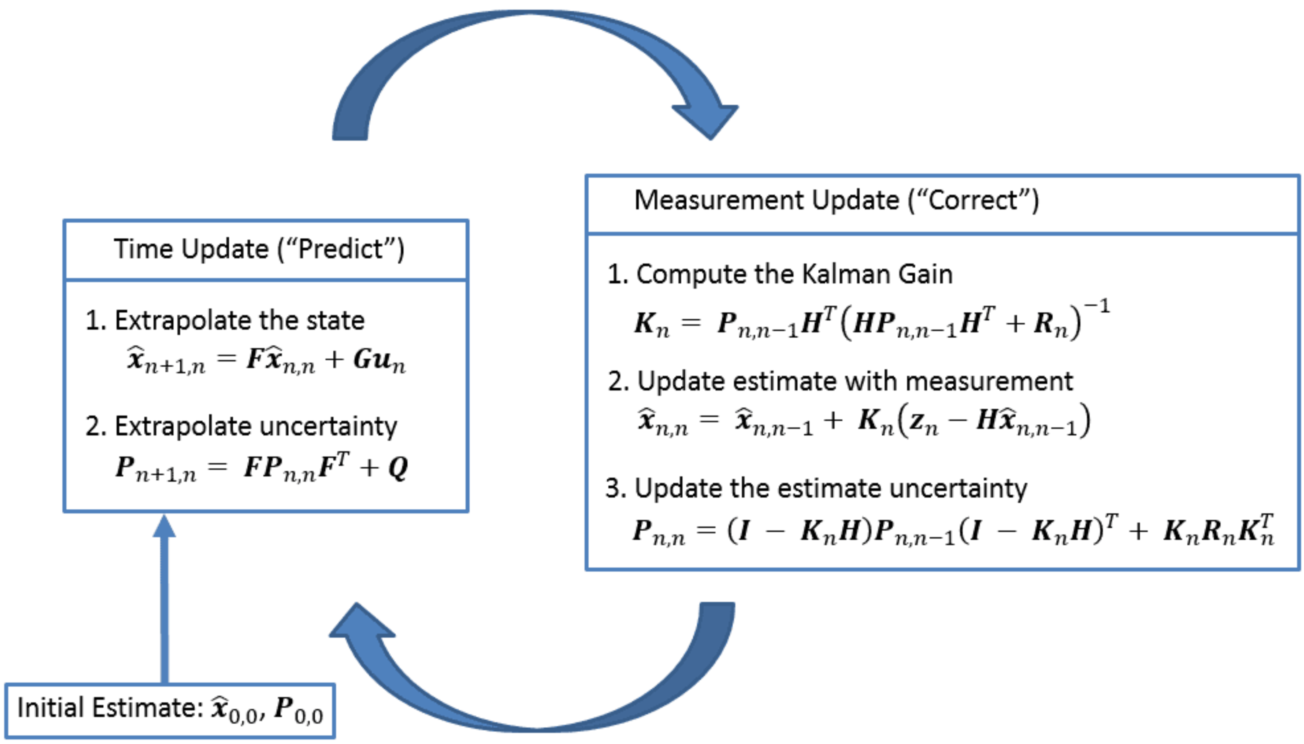
KALMAN FILTER: The Kalman Filter is a recursive algorithm that estimates the state of a dynamical system from a series of noisy observations (Kalman, 1960). It works by propagating the state estimate and the associated uncertainty forward in time using the system's dynamics, and then updating the estimate by incorporating new observations. Moreover, The Kalman Filter is a recursive algorithm that estimates the state of a dynamic system from a series of measurements. It is optimal for linear systems with Gaussian error statistics (Neef et al.,2007).

The qualities of the Kalman Channel incorporate its: Effortlessness, Computational productivity, Capacity to deal with ongoing applications, Computationally effective for little frameworks.

The weakness of the Kalman Filter include its:

1. It's restricted to straight frameworks and Gaussian blunder circulations (Jardak et al.,2010).

2. proves to be computationally expensive for frameworks with several layers.



Source: kalmanfilter.net

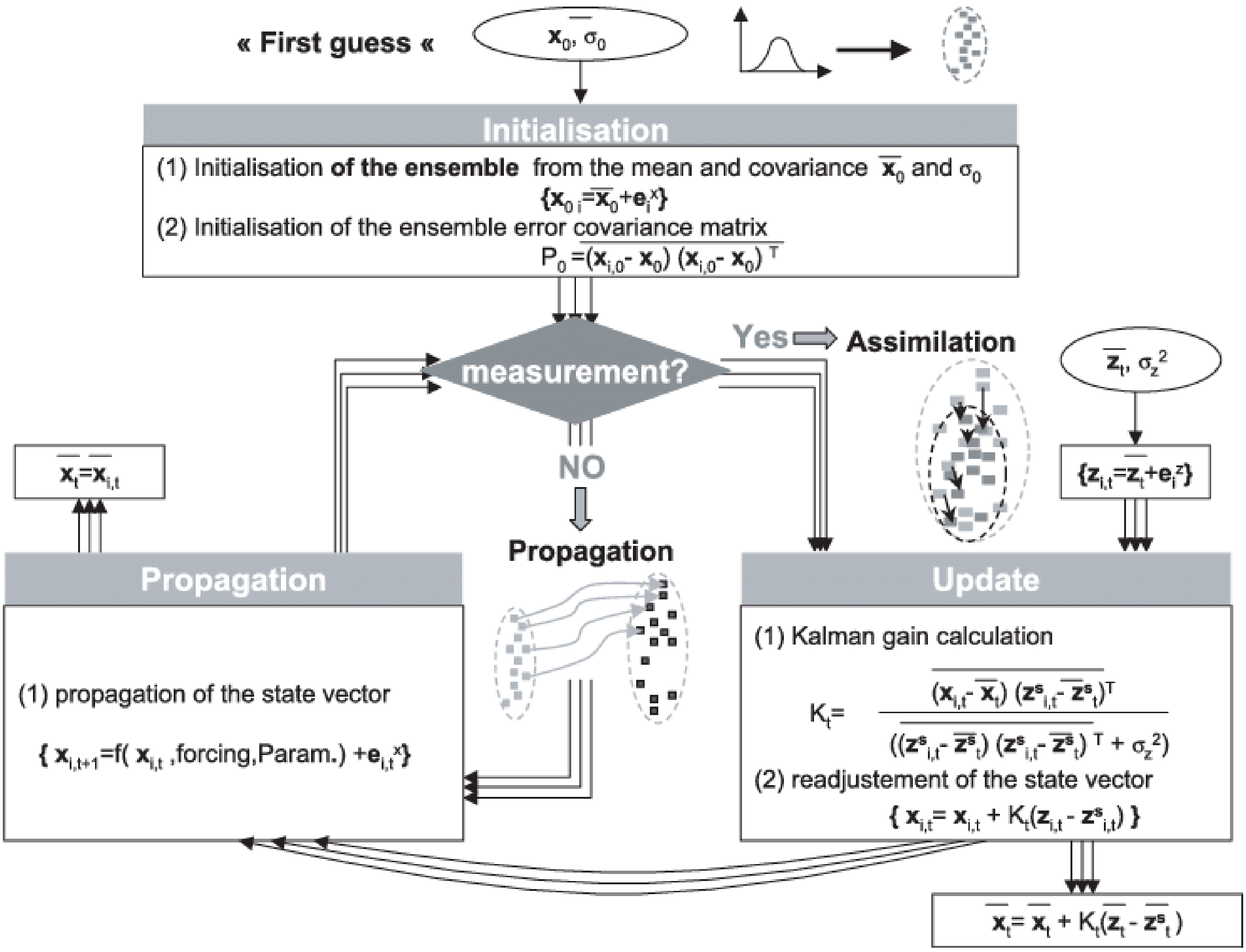
ENSEMBLE KALMAN FILTER (EnKF): The Ensemble Kalman Filter is an extension of the Kalman Filter for nonlinear systems (Evensen, 2003). It uses an ensemble of model runs to represent the uncertainty in the state estimate and to approximate the error covariances. However, Kalman Filter uses an ensemble of model states to estimate the error covariances. It can handle nonlinear systems and non-Gaussian error distributions (Jardak et al.,2010).

The strengths of the Ensemble Kalman Filter include its: computationally efficient, Provides an estimate of the uncertainty in the state estimate, handle nonlinear systems and can be easily parallelized.

The weakness of the Ensemble Kalman Filter include its:

1. Assumes that the error statistics are Gaussian and can suffer from filter divergence if the ensemble size is too small (Oke et al.,2013).

2.May suffer from filter divergence and ensemble collapse in highly nonlinear systems.



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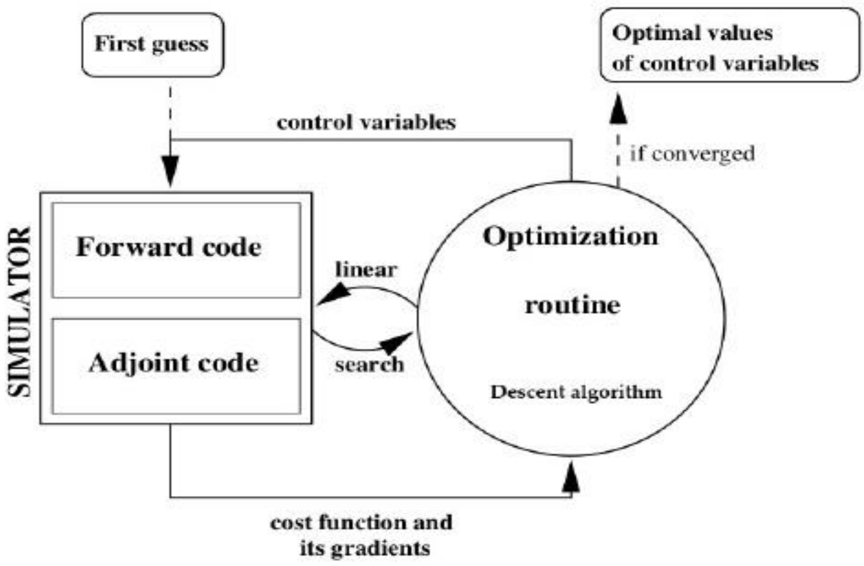
THREE-DIMENSIONAL VARIATIONAL ANALYSIS (3D-VAR):

Three-dimensional variational analysis (3D-VAR) is a data assimilation method used to combine model forecasts with observational data to improve the accuracy of weather forecasts and climate models. It is particularly useful for handling complex systems and non-linear dynamics. Nevertheless, The 3D-Var method finds the analysis state that minimizes a cost function measuring the distance from the background (model forecast) and the observations, subject to certain constraints (Courtier et al., 1994).

Strengths: handling complex systems, non-linear dynamics, and multiple types of data. It provides a robust and accurate method for data assimilation (Liu et al.,2010; XIEHongqin et al.,2004). Provides a consistent analysis by combining observations and background information.

Weakness: computationally intensive and may require significant computational resources. Additionally, the choice of background fields and observation operators can impact the accuracy of the assimilation (Liu et al.,2010). Assumes that the background and observation errors are Gaussian and uncorrelated in time.



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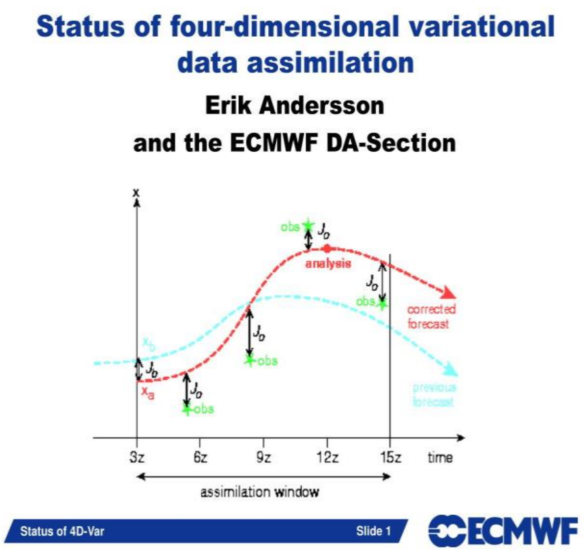
FOUR-DIMENSIONAL VARIATIONAL ASSIMILATION (4D-VAR): it's a powerful data assimilation technique used to combine observational data with numerical models over a time window. It is particularly effective in handling complex systems with non-linear dynamics. The 4D-Var method is an extension of 3D-Var that takes into account the temporal evolution of the system by minimizing the cost function over a time window, rather than at a single time step (Rabier et al., 2000).

Strengths: capable of handling a variety of information types, non-direct components, and complicated frameworks. It provides an effective and precise information osmosis technique (Daescu, D.N. 2008; Shutyaev et al., 2023). Integrates model elements to provide a more predictable research over time.

Weakness: The technique can be computationally escalated, particularly while managing enormous scope models. It requires the advancement of adjoint models, which can be testing and tedious (Daescu, D.N. 2008). Requires an adjoint model for effective minimization of the expense capability.



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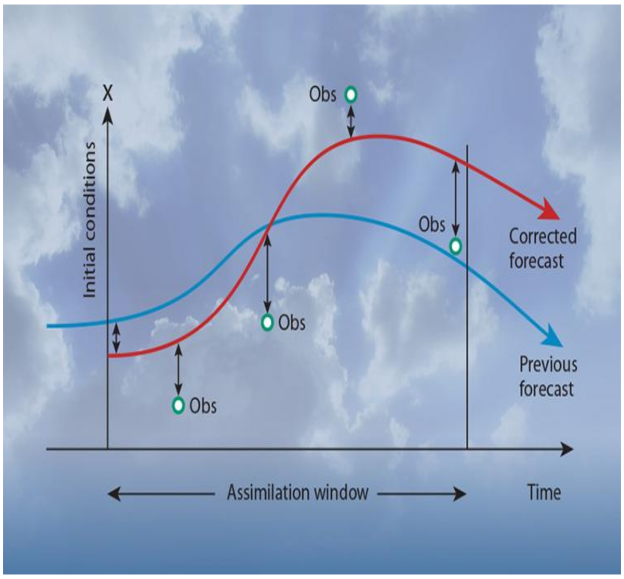

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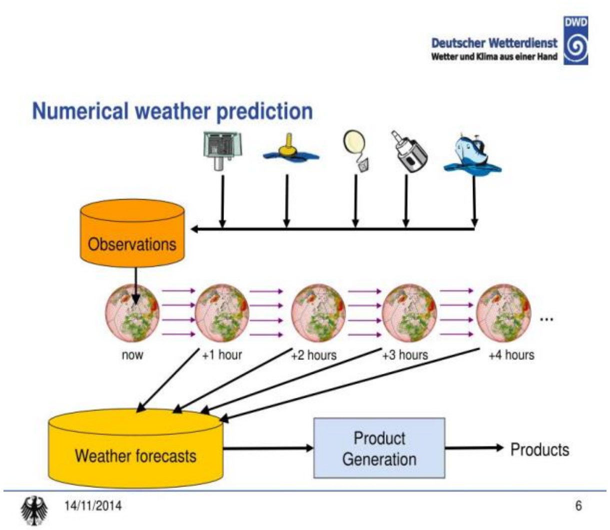
APPLICATIONS OF DATA ASSIMILATIONS IN WEATHER FORECASTING AND CLIMATE MODELLING

1. **Weather Forecasting**:

Numerical Weather Prediction (NWP) models rely heavily on data assimilation to incorporate observational data from various sources, such as ground-based weather stations, weather balloons, satellites, and radar systems (Bauer et al., 2015). Data assimilation techniques are used to initialize the NWP models with the best estimate of the current state of the atmosphere, which serves as the starting point for forecasting future weather conditions (Kalnay, 2003).

For example, the European Centre for Medium-Range Weather Forecasts (ECMWF) and the National Centers for Environmental Prediction (NCEP) use advanced data assimilation systems, such as 4D-Var and hybrid ensemble-variational methods, to produce global weather forecasts (Rabier et al., 2000; Kleist et al., 2009).

GPS Radio Occultation (RO) Data Assimilation: In order to create a practical Worldwide Information Digestion Framework, the Public Communities for Ecological Expectation (NCEP) combined GPS RO profiles from the Star grouping Noticing Framework for Meteorology, Ionosphere, and Environment (Inestimable) mission. By providing more information on the thermodynamic state of the environment, this has effectively improved the model's level of knowledge (Cucurull, L. 2010).



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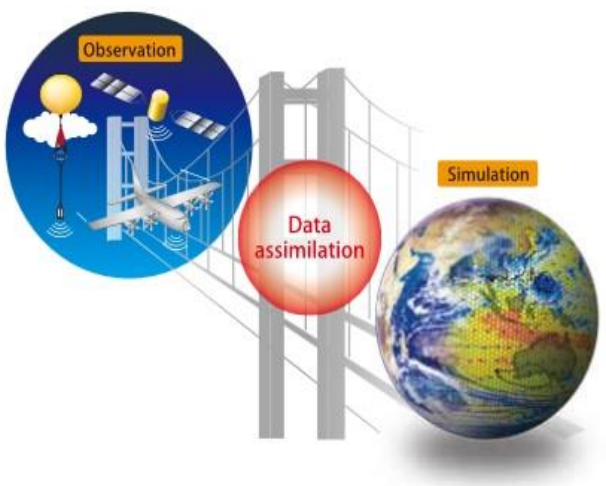
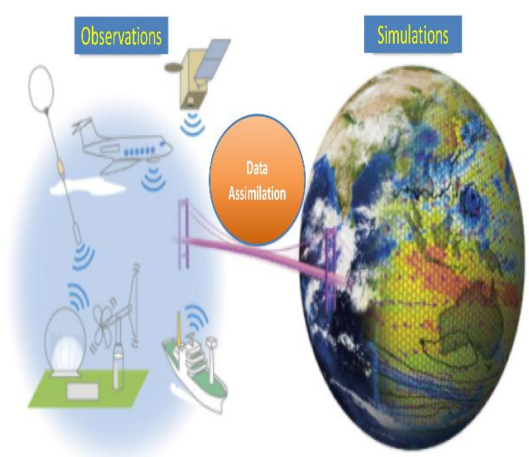
2. **Climate Modeling:**
   - When modeling climate change, data assimilation techniques are used to limit model simulations using observable data and to establish beginning conditions (Bannister, 2017).
   - Research initiatives such as the Environment Figure Framework Reanalysis (CFSR) and the Advanced Time Review Examination for Exploration and Applications (MERRA) use information osmosis to provide consistent global datasets of air and maritime conditions over several years (Rienecker et al., 2011; Saha et al., 2010).
   - These reanalysis datasets are widely used in climate research, monitoring, and model evaluation, providing valuable insights into long-term climate trends and variability.

   - Snow Data Assimilation: Blending ways to deal with approval and procedures of snow estimating rehearses, instrumentation, calculations, and information digestion strategies was the objective of the European Collaboration in Science and Innovation (COST) Activity ES1404 "HarmoSnow." This work has shown the advantages of snow information osmosis for climate and hydrological guaging, propelling its application in mathematical climate expectation (NWP) and hydrological models (Helmert, et al. 2018).





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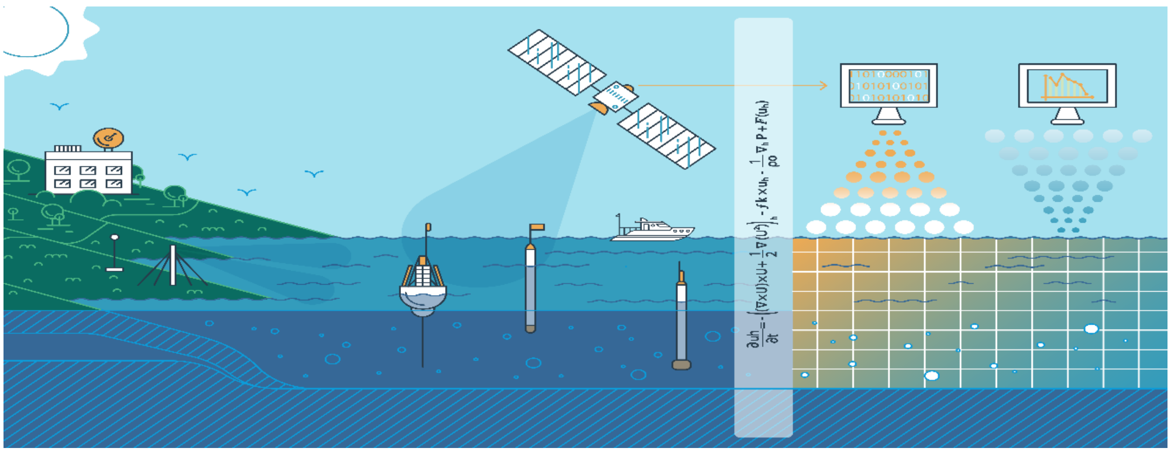
3. **Ocean and Environmental Monitoring**:
   - Sea and natural checking frameworks use information digestion to combine observations from satellites, floats, and other devices with sea and climate models (Cummings and Smedstad, 2013).

   - Examples include the Hybrid Coordinate Ocean Model (HYCOM) and the Global Ocean Data Assimilation System (GODAS), which assimilate data to produce estimates of ocean currents, temperatures, and other properties for applications such as marine forecasting and ecosystem management (Chassignet et al., 2007; Behringer, 2007).

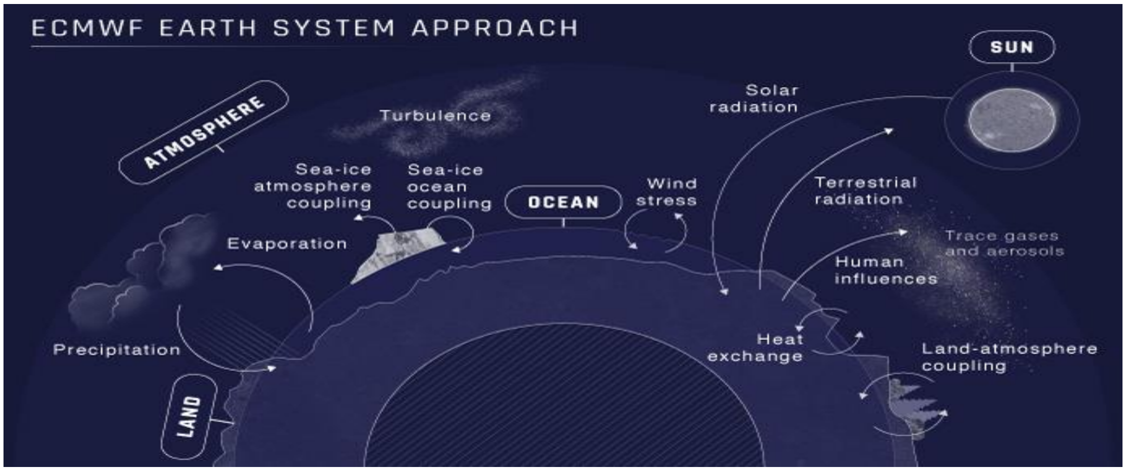


Source: marine.copernicus.eu

4. **Coupled Earth System Modeling:**

- Coordinating perceptions from the air, oceans, land surface, and cryosphere will be conceivable with the improvement of coupled information absorption frameworks (Penny et al., 2017).

- These structures expect to give a more extensive and predictable portrayal of the worldwide climate by zeroing in on how we could grasp data sources and correspondences across various parts (Zhang et al., 2014).



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CHALLENGES AND FUTURE DIRECTIONS

1. Handling Model Errors and Biases:
    - Due to approximations and imperfect representations of physical processes, numerical models frequently contain systematic biases and inaccuracies (Dee, 2005).
    - A current topic of research is creating methods to take into account and reduce model errors, such as online model error estimation and bias correction (Carrassi et al., 2018).
2. Assimilating New Observational Data Types:

- There are issues in coordinating numerous information sources into digestion frameworks when new observational stages and instrumentation, as worked on satellite sensors and publicly supported information from individual weather conditions stations, are created (Lahoz and Schneider, 2014).
- It is necessary to have techniques for handling diverse information sources, handling information quality management, and developing administrators that create appropriate perceptions.

3. Coupled Data Assimilation for Earth System Modeling:
    - It remains a major test to incorporate information osmosis across many regions of the Earth framework, such as the environment, seas, land surface, and cryosphere (Penny et al., 2017).
    - Research is currently being finished on creating connected information osmosis frameworks that regard the interconnections and actual limitations between different parts.
4. Ensemble-based Data Assimilation and Uncertainty Quantification:

- Gathering-based techniques, such as the Troupe Kalman Channel, provide a way to identify and evaluate the digestion cycle's vulnerabilities (Evensen, 2003).
- Progressing research centers around upgrading outfit age techniques, taking care of issues, for example, gathering breakdown, and ascertaining vulnerabilities in convoluted frameworks.

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