An Introduction to

AI for weather forecasting

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In this lecture, you will learn about:

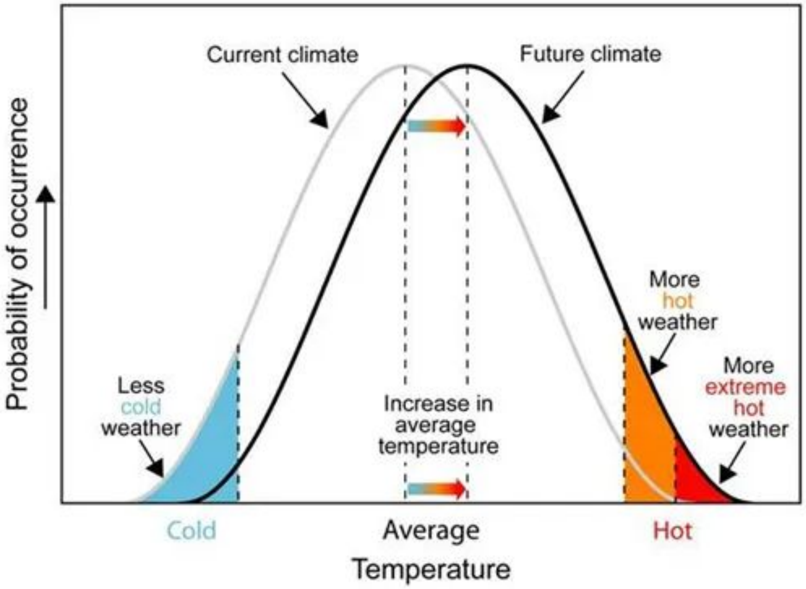
- What are short/medium-term forecasts?
  - Differences between weather and climate modeling.
  - What makes weather forecasting challenging.
  - Shortcomings of the current (conventional) approaches.
  - Why (and how) AI is playing a big role.

- A brief overview of the AI revolution in weather forecasting.
  - Demystifying AI models.

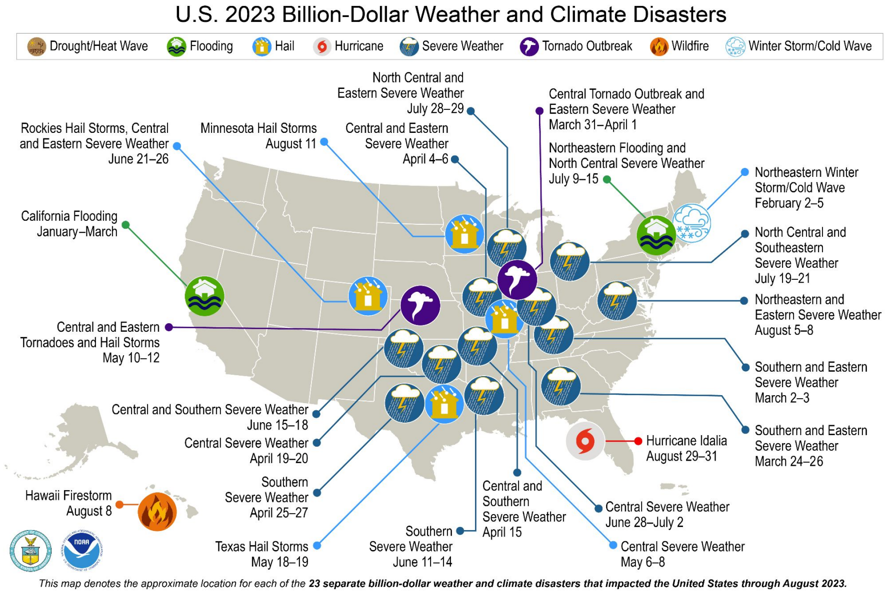
- Case studies of the use of AI in short term forecasting.
  - Extreme weather forecasting.
  - Energy forecasting.

- Open challenges, questions and opportunities.

Climate change is shifting weather patterns everywhere.

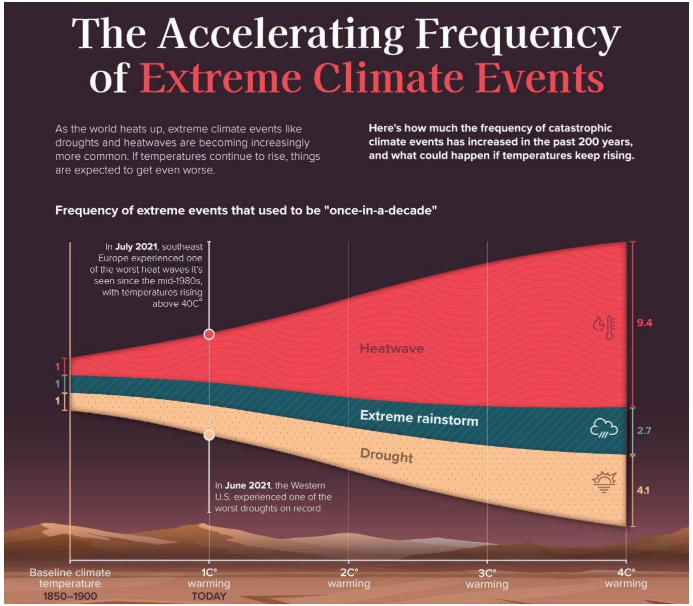


Source: Climate Desk



Source: NCEI, NOAA

Impact of changing weather on life and livelihood, is immense.



Source: IPCC

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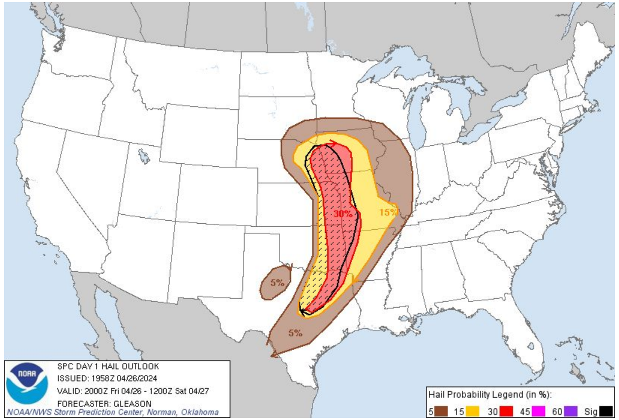
What are short or medium term weather forecasts?

- A short/medium-range weather forecast predicts weather conditions for an immediate time frame,
  - typically ranges from a few hours (nowcasts), a couple of days (short-term) upto two weeks in advance (medium-term).

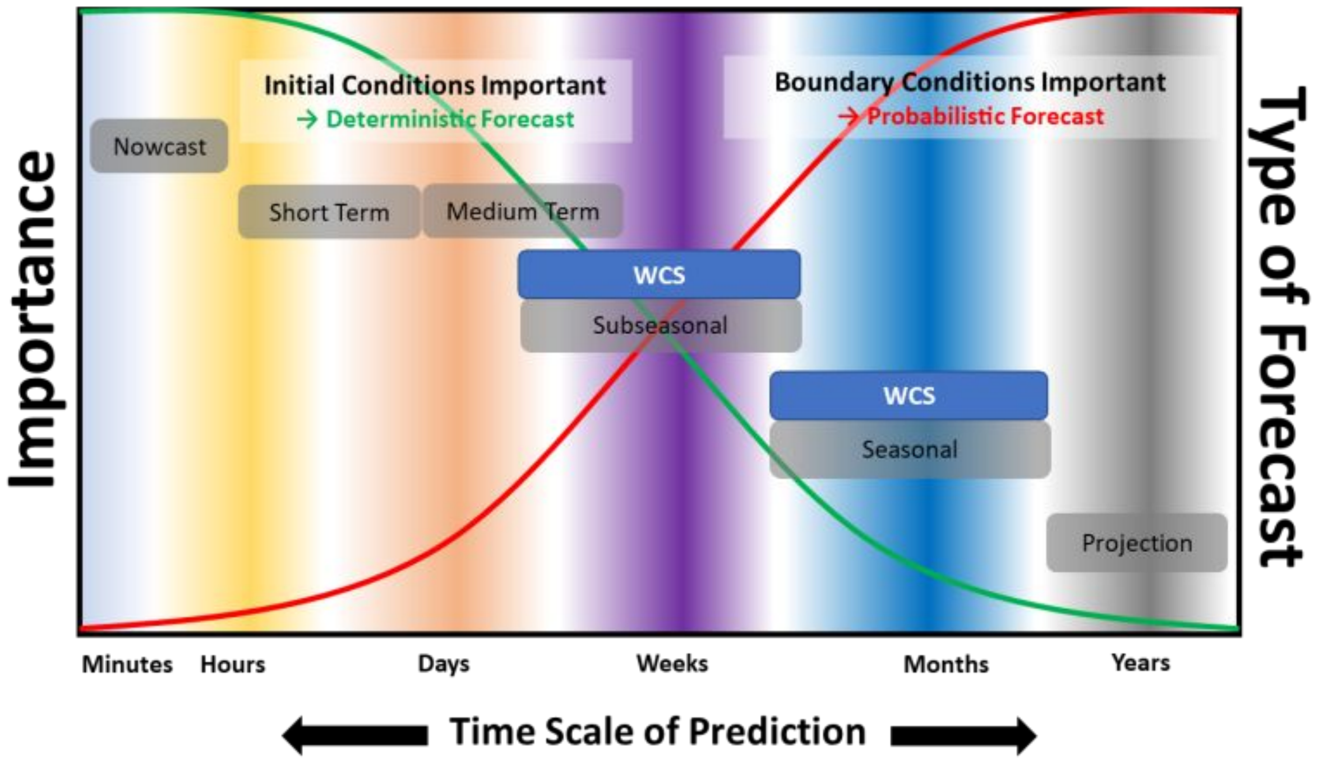
- Short-range forecasts (today, tomorrow, and the week ahead) detail information about upcoming weather patterns, changes in temperature, chance of precipitation, wind speeds, and other meteorological factors in the near future.



Source: NOAA SPC

Source: Fox Weather

How are short/medium-term forecasts (i.e. weather) different than long term forecasts (i.e. climate)?



Source: WCS

Differences in the weather and climate modeling paradigm.

Weather and climate models use same set of primitive equations, yet differ from each other in significant ways.

Weather models

- Data assimilation (e.g. satellite, in-situ observations) is a key step, initializing model predictions every few hours.
- Resolution (spatial/temporal) higher compared to climate models, e.g. 3-km regional convection allowing models like NOAA's HRRR.
- Explicitly modeling the atmosphere but representing different earth subsystems as parameterizations (e.g. hydrosphere, lithosphere).
- E.g. weather models inform when and where a storm front is located.

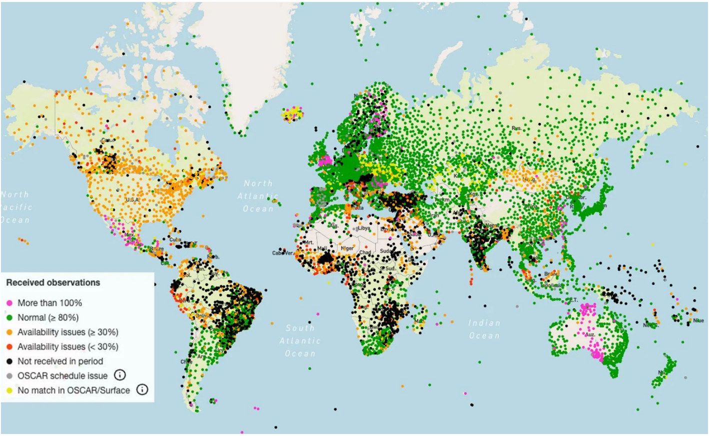
Climate models

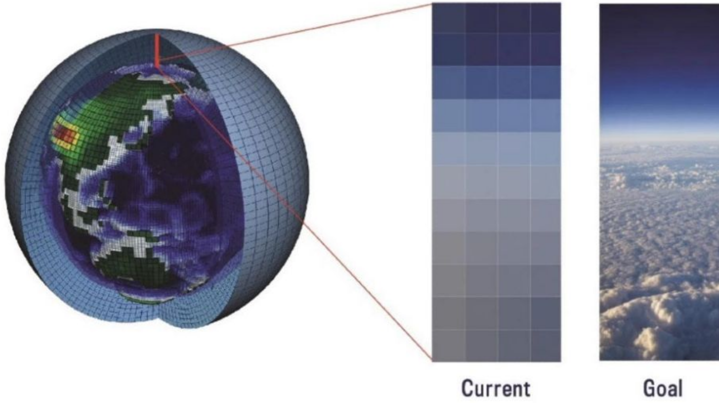
- Data assimilation occurs on a much longer timescale.
- Lower resolution means, larger number of parameterizations.
- Coupled models of the earth subsystems (e.g. atmosphere, hydrosphere, lithosphere).
- E.g., climate models inform average number of hurricanes in a given time period (typically a few decades).

How are weather forecasts made and what makes them challenging.

- Weather forecasts are made by **collecting data** about the current state of the atmosphere and using an understanding of atmospheric processes (e.g. physical laws and **parameterizations**) to predict how the atmosphere will evolve.

- What makes weather forecasting challenging
  - Physics ⇒ The chaotic nature of the atmosphere along with the incomplete understanding of atmospheric processes is what makes forecasting difficult.
  - Parameterizations ⇒ leading source of errors
  - Data collection ⇒ major data gaps in the global south





Source: NOAA MADIS (above), NASA (below)

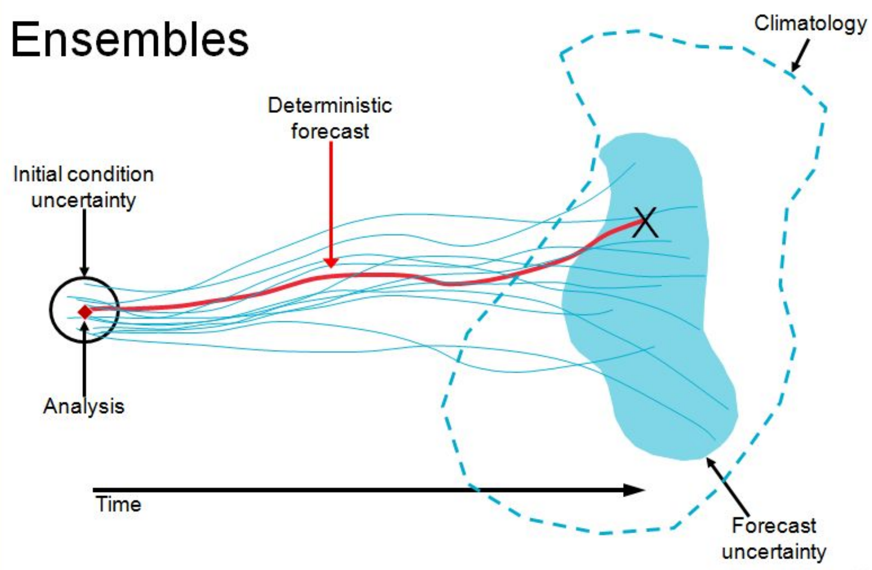
Two main types of weather forecasts

Deterministic

- Predicts one outcome based on best-estimate (guess) of initial conditions.
- Can we way off especially due to the range of possible states of the atmosphere and the uncertainties associated with 'guessing' them.

Probabilistic

- Probabilistic ensembles run many simulations accounting for all the uncertainty in the initial conditions.
- Very useful to estimate likelihood of the future weather state (e.g. heat wave, or extreme precipitation).

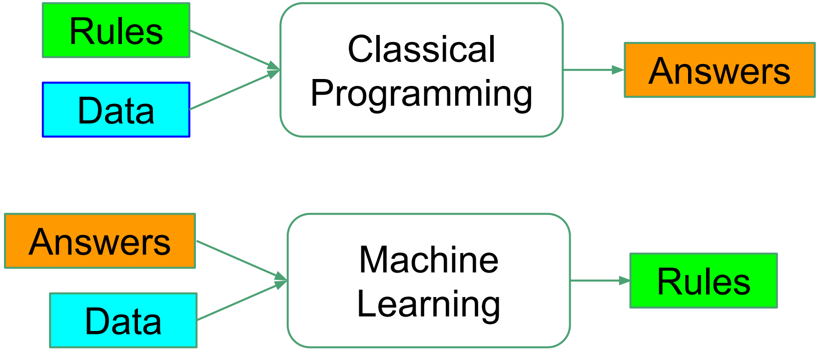


Source: UK Met Office

AI for weather forecasting

At a high level, what constitutes AI?

- **What**: To find the effective representation/mapping of input features to corresponding output, without explicitly programming instructions.
- **How**: Use training data to define ‘*decision boundaries*’.
- **Remember**: Rigorously evaluating models is very important. Badly trained models are ubiquitous!



What makes atmospheric science the next frontier for AI.

- The field of weather/atmospheric sciences generates a lot of data!
  - From more sophisticated observation platforms (space/in-situ), to improved NWPs, reanalysis products such as ERA5
    - Harder for NWPs to consume/assimilate, not so much for AI models!
  - Data is sequential in nature ➔ Large Language Models!

- Sufficient complexity for AI to learn, including local effects
  - In NWPs, large scale governing equations are well understood, yet small scale phenomenon are poorly parameterized
  - NWPs are often ‘tuned’ to data-rich regions

- Inference is orders of magnitude cheaper compared to NWPs!
  - Leads to better estimation of forecast uncertainty

Some important reminders about upcoming slides.

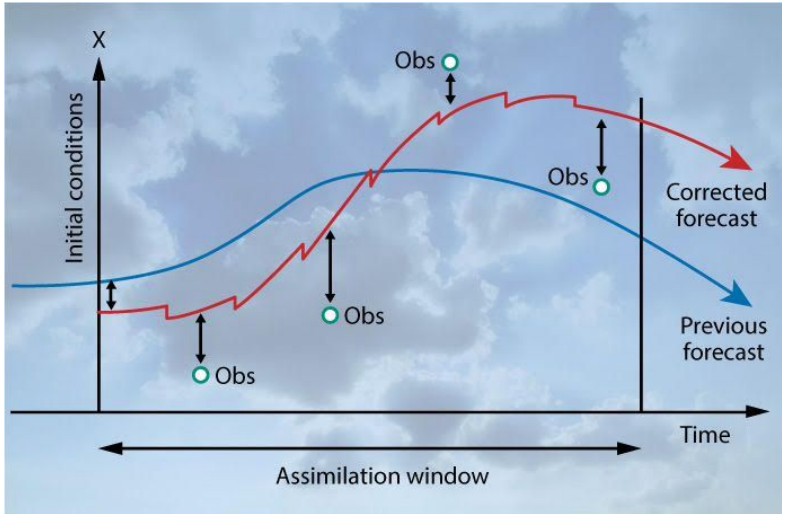
- Weather models vary widely in scope.
  - Global models (e.g. ECMWF-IFS) ⇒ lower resolution, larger timesteps (6h or longer)
  - Mesoscale models (e.g. WRF).
  - Convective allowing models (e.g. HRRR, ICON-D2) ⇒ higher resolution, smaller timesteps (1h)

Due to time limitations, our discussions on AI weather models will focus on

- AI weather emulators of global models.
- Deterministic forecasts.

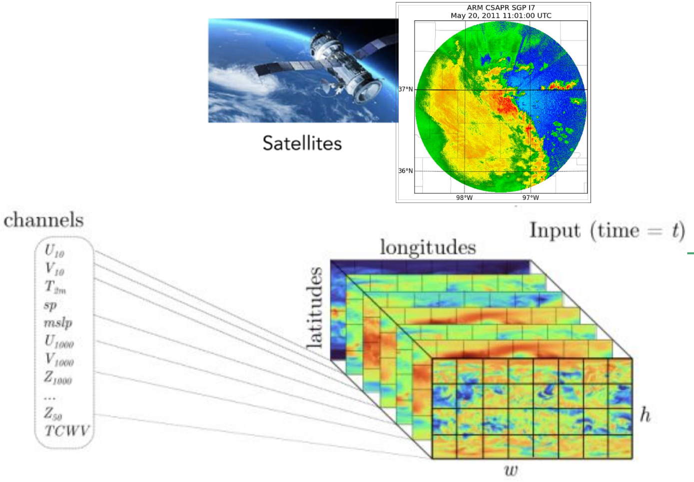
Overview of (deterministic) AI weather forecasting.

- **Experimental design**:
  Model trained to predict next sequence of 'events' given an initial state ⇒ IVP.
  - Designed as a Markovian process.
  - Often times are autoregressive for rollouts (or 'next scene' prediction for nowcasts).
- **Data**:
  - Typically trained on high-quality renalysis products such as ERA5, or
  - observational data such as GOES-16 and MRMS (for nowcasts).
- **Characteristics**:
  - Retains core elements of conventional weather forecasting (e.g. data assimilation to initialize start states).
  - Instead of predicting the entire weather state, rollout models predict a subset of key prognostic variables.
- **Recent advances**: Recently, many new AI based techniques have been proposed
  - FourCastNet by NVIDIA, GraphCast and MetNet by Google Research/DeepMind, PanguWeather by Huawei

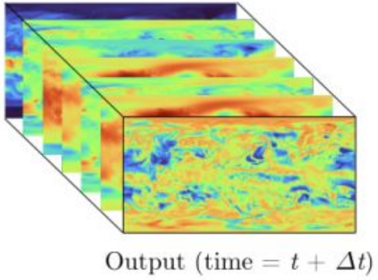


Source: ECMWF

Schematic of typical AI weather forecasting models.



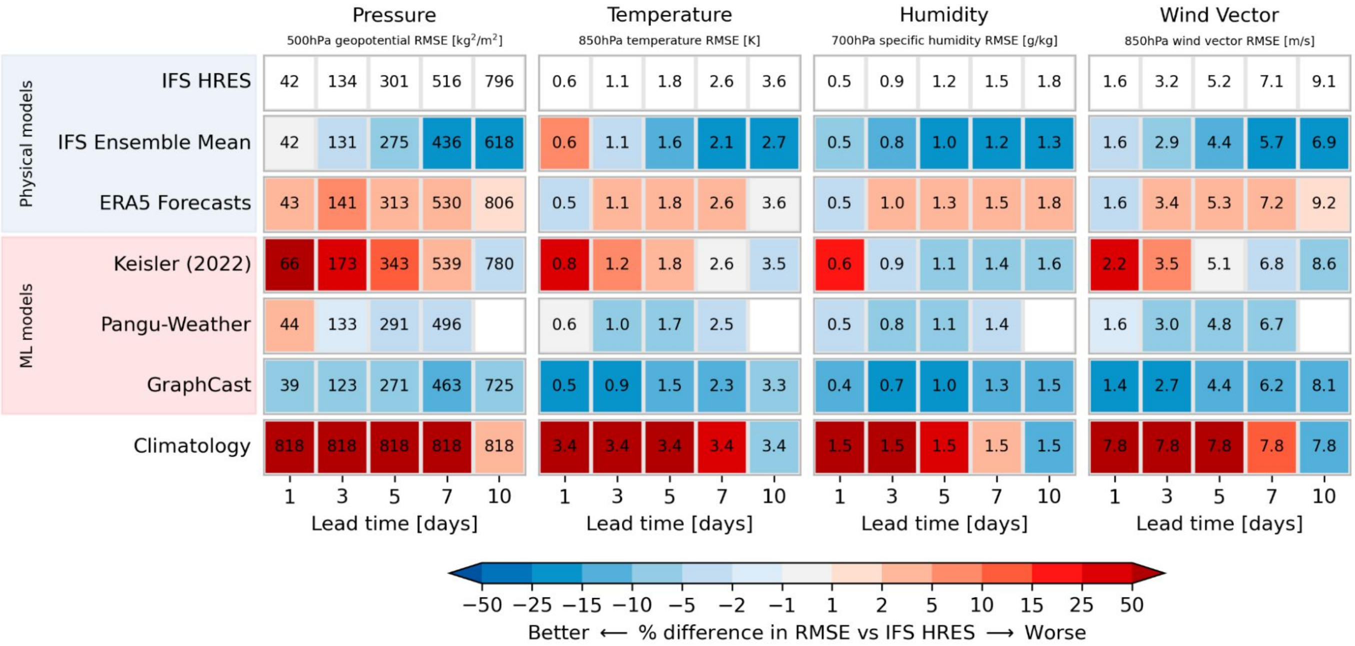
AI model (ex. Transformers, Graph Neural Networks, CNNs, Autoencoders)



Source: Pathak et al. FourCastNet (2022)

How good are these AI weather models?

Skill of different ML models compared to ECMWF's Integrated Forecast System (IFS)



Source: Google AI

Demystifying AI weather models and exploring common modes of learning

Vision Transformers (ViT): at a high level

- The Vision Transformer, or ViT, is a model for image classification that employs a Transformer-like architecture (self-attention) over patches of the image (convolution operations).

- An image is split into fixed-size patches, each of them are then linearly embedded, position embeddings are added, and the resulting sequence of vectors is fed to a standard Transformer encoder.

- **Challenges**: cost to train increases quadratically with image dimensions.

Source: IAML Distill Blog on ViT

SWIN Transformers: at a high level

- Key contribution is shifted window mechanism enabling extraction of features at variable scales and restricts computational complexity to linear!

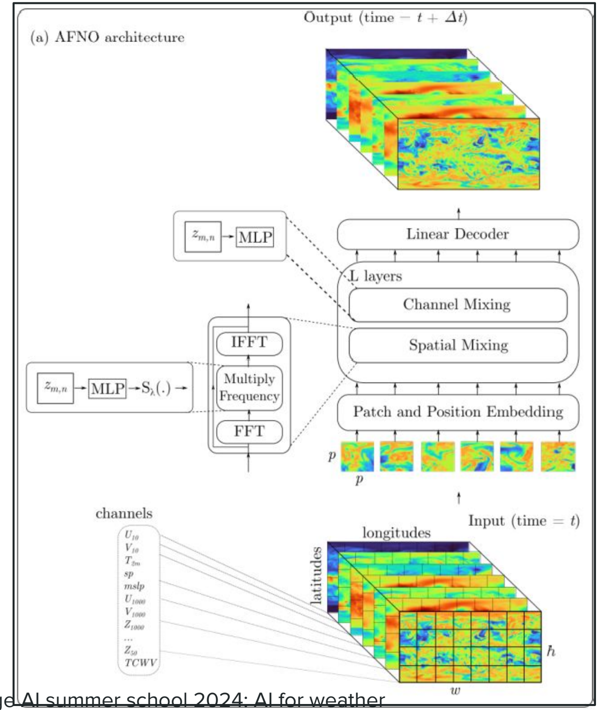
- Instead of applying global self-attention, it is applied only within each window. Shifting a window results in new window configuration to apply self-attention to.

- **Challenges**: very long-range interactions for pixels beyond overlapping windows will be missed.

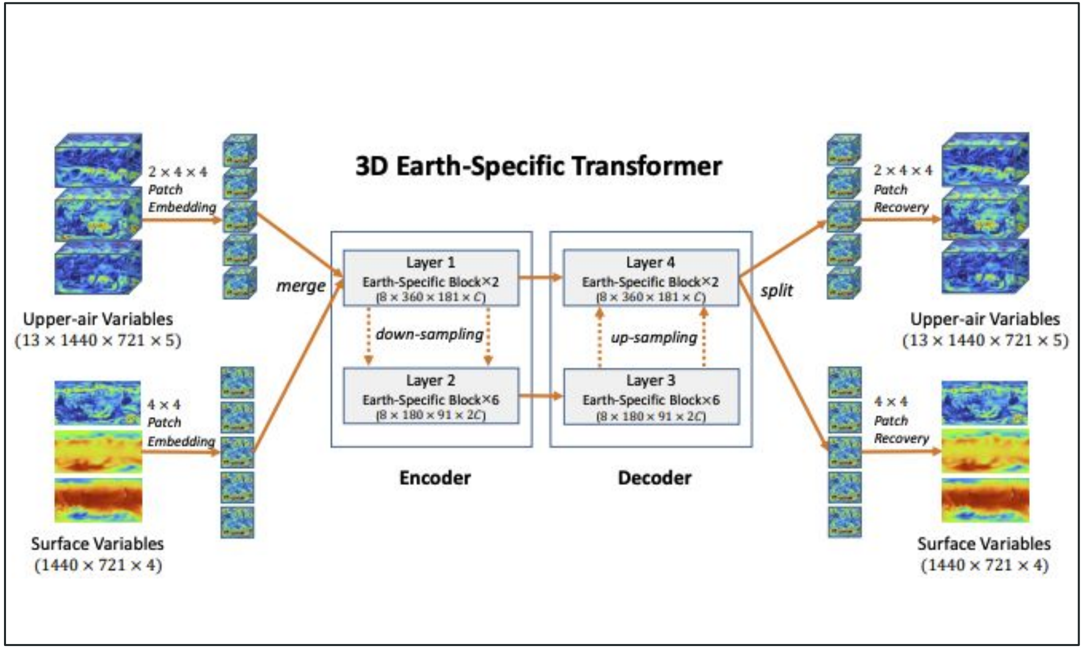
Source: Liu et al. (2021)

Examples of ViT in AI-weather forecasting

FourCastNet by Pathak et al. (2022)

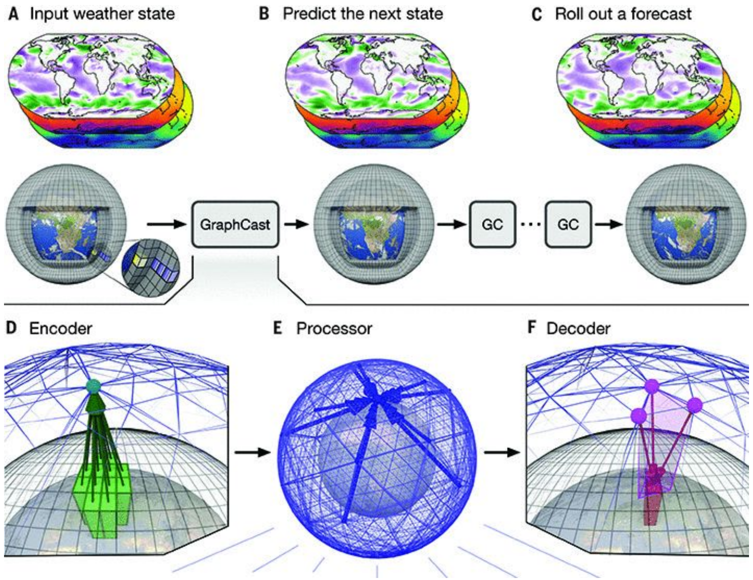


Pangu Weather by Bi et al. (2022)



Exploring common models of learning in these models

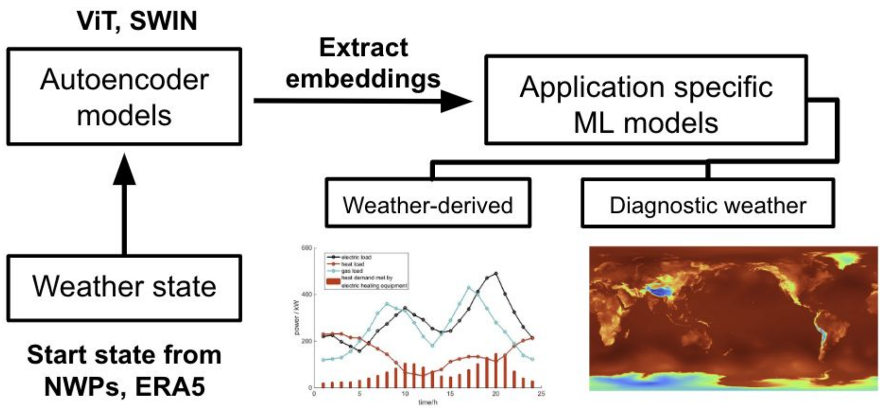
- Embeddings:
  - Patching and Positional - helps to efficiently learn from ‘near’ and ‘far’ away regions (a.ka. teleconnections).
- Encoder - Decoder block
  - Helps in efficiently learning dynamics.
  - Enc-Dec block can be composed of CNN layers, Graph NN, or attention-based models.
- Recency bias
  - Using weather state from the most recent timesteps.
- Loss functions
  - L1 / L2 are most commonly used losses.

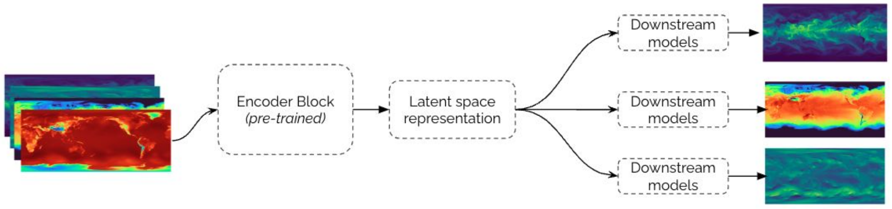


Source: Lam et al. 2022

Weather embeddings as a promising alternative

- Weather variables can be divided into prognostic and diagnostic variables.
- Build a prognostic weather embedding using ViT based autoencoders.
- **Benefits**:
    - Weather model now easily extendible to any new diagnostic variables.
    - Reduces time to train/deploy by 3-5x compared to bespoke models.
- **Challenges**:
    - Approach only limited to ‘diagnostic’ variables.





Source: Mitra et al. (2023)

Case studies for AI weather forecasting models relevant to climate change

Case studies on the use of AI-weather models: extreme events forecasting

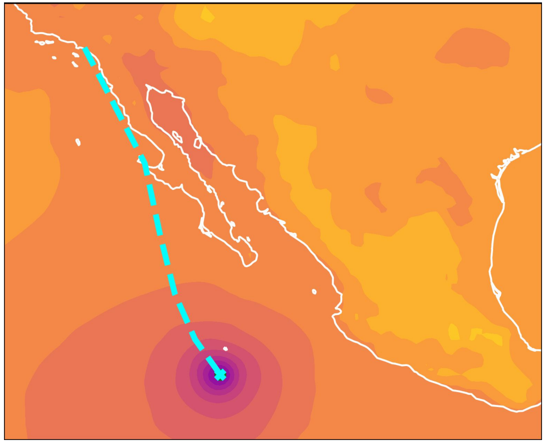
- Extreme weather
    - Rising occurrences of long-tail, high-impact weather events causing massive damage to life and property.

    - Larger ensembles (running the same model with slightly perturbed initial conditions) tend to be better at capturing these risks, something AI models are proficient at.

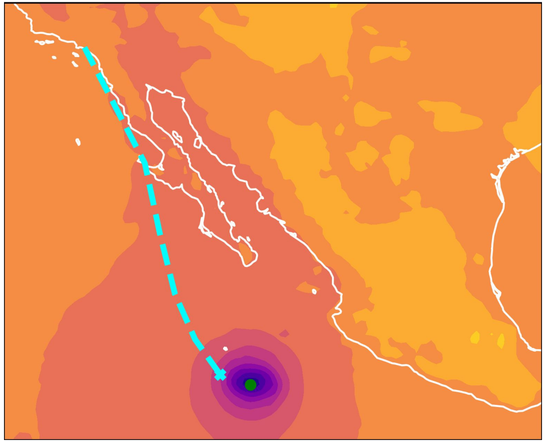
Source: Getty Images

AI models have shown to be able to accurately forecast ‘rare’ events.

Actual conditions: 2023-08-18 12:00 UTC

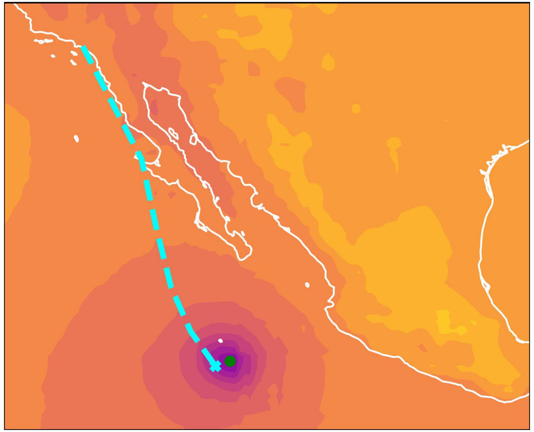


GFS: Issued 2023-08-15 00:00 UTC,
Valid 2023-08-18 12:00 UTC



AI model forecast

Valid 2023-08-18 12:00 UTC



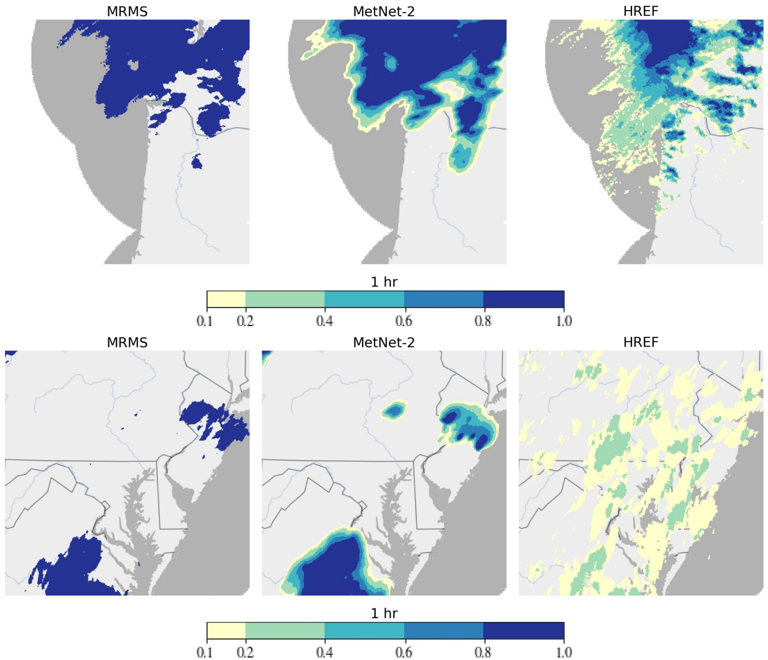
Tropical Storms and Hurricanes making landfall on the western seaboard of the CONUS are considered extremely rare

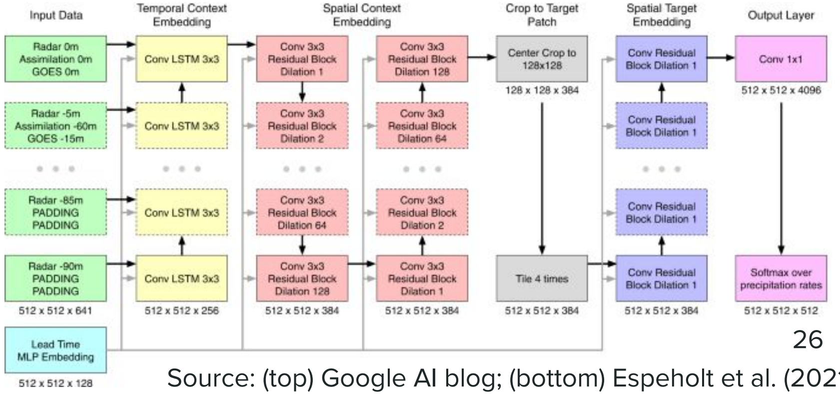
Source: Excarta blog

AI models can accurately forecast short term convective events.

- AI models (e.g. MetNet2) for nowcasting (i.e. forecasts upto 12 hours) have shown to be very proficient in forecasting severe convective events!

- What constitutes these models:
  - For example, MetNet2 is mix of convolutional and LSTM modules!

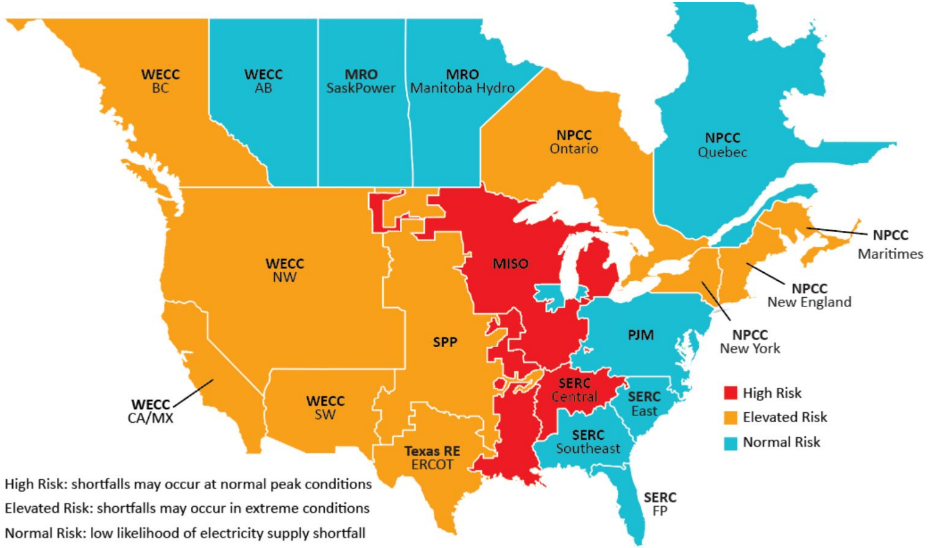




Source: (top) Google AI blog; (bottom) Espeholt et al. (2021)

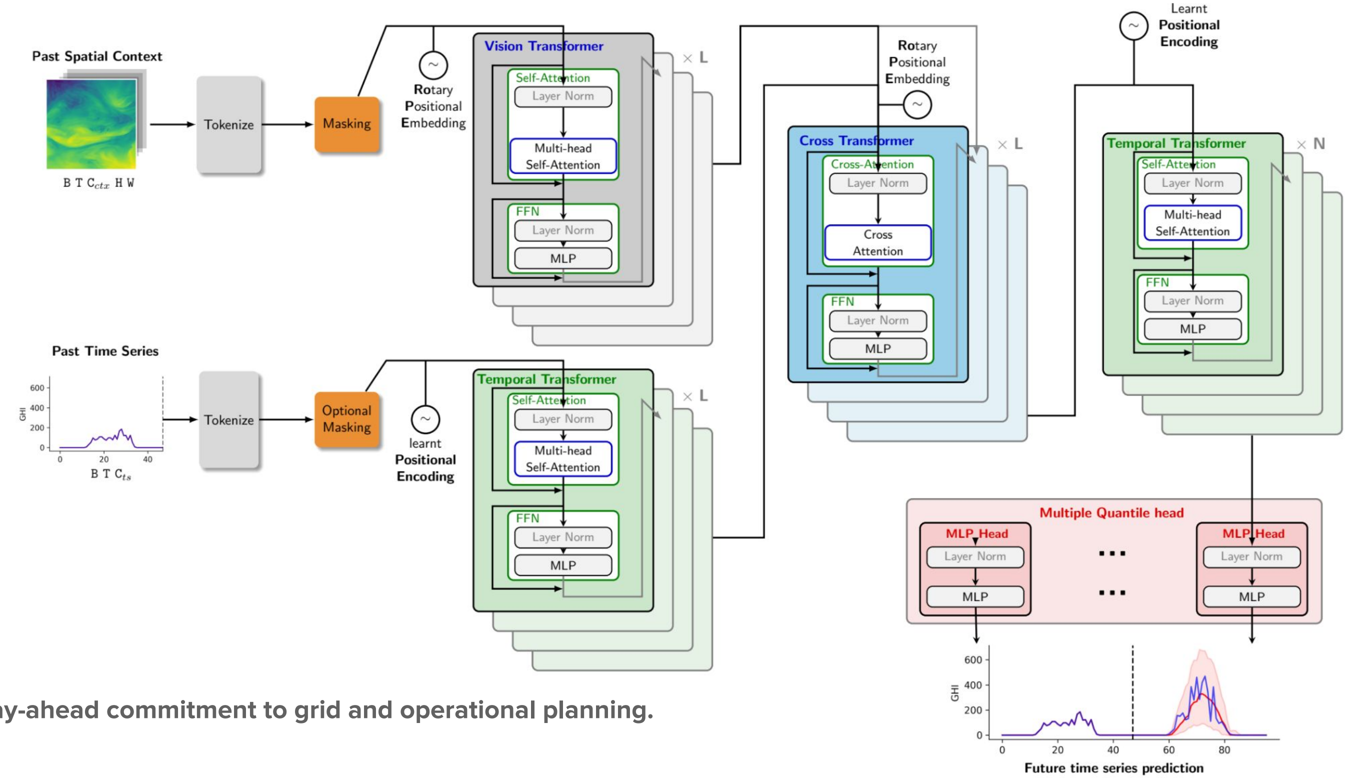
Case studies on the use of AI: energy forecasting

- AI can play an important role in building energy-resilience.
  Examples:
  - Rising occurrences of extreme weather events ⇒ exposes grid operators to higher risks of long-tail events.
  - Energy-mix shifting rapidly to low-carbon/ carbon-free alternatives ⇒ e.g. wind and solar are weather dependent, increasing energy volatility.



Source: NTEL Climate Risk Assessment report (2023)

Forecasting day-ahead solar irradiance using ViT



Critical use-case for day-ahead commitment to grid and operational planning.

Source: Boussif et al. (2023)

Better long-tail risk estimation

AI can generate faster, and larger ensembles creating a better estimate of tail-risk events

Source: Google AI blog on SEEDS

Some thoughts on the rapidly evolving AI-weather paradigm.

- AI weather models (i.e. nowcasting to medium range) has shown great promise yet they cannot fully replace NWPs.
  - AI weather model start states are often obtained from assimilation which comes from NWPs.

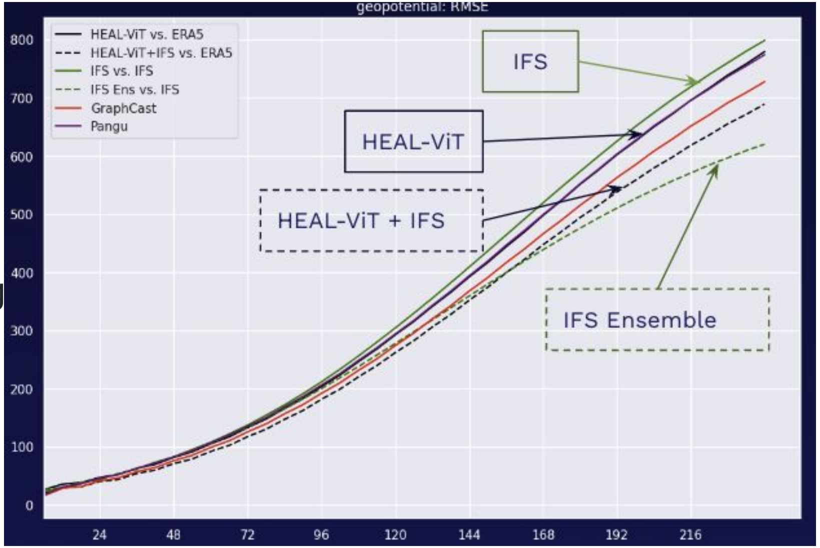
- New AIWPs are being proposed every few weeks by small research groups ⇒ Much faster rate than conventional NWP development timeline (a few months to years) by large scientific teams.

- Best AIWP approach is not obvious, as different AIWPs behave differently from each other, and from NWPs.

- Many ML techniques work ‘out of the box’ but domain-awareness is lacking.

Opportunities with AI-weather models.

- AIWPs offer novel information, not just ‘emulate’ NWPs.
- Many proficient AIWPs codebases are publicly available ⇒ so easier to get started!
- More local observational data coming online making AIWPs primed to take advantage!
- Generative models such as diffusion are showing great promise for probabilistic forecasts, useful for extreme weather outliers.



Credit: Ramavajjala et al. (2024)

Challenges to be aware of in operationalizing these forecasts.

- Models are trained on data that is heavily skewed towards the developed world ⇒ leads to poorer performance in the global south.

- More thorough benchmarks are needed[1]. In absence of standard benchmarks, each model defines its own.
    - FourCastNet: improves RMSE.
    - PanguWeather: cyclone track prediction (only strong ones).
    - WeatherBench2 is a good start for standardizing evals.

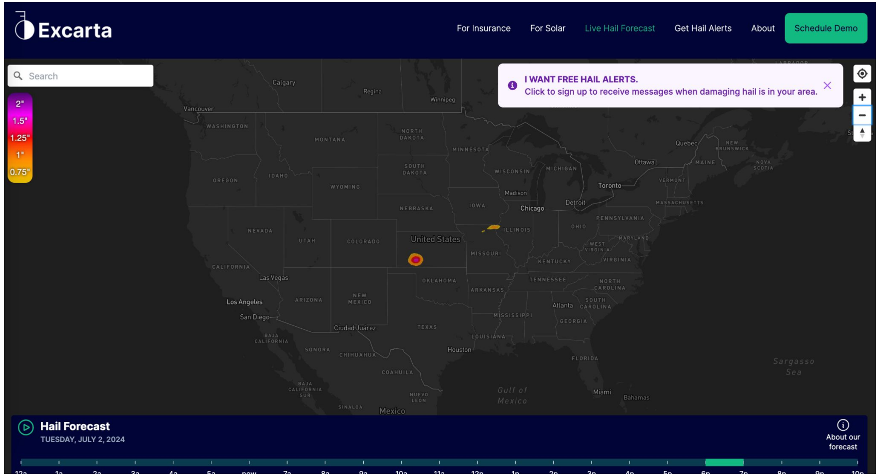
- AI weather models are dependent on initialization from NWPs, carry their biases into forecasts.

- Domain experts need to be incorporated into model design.

- Robust train ➜ test ➜ deploy ➜ monitor pipeline necessary to keep up with rapid evolution.

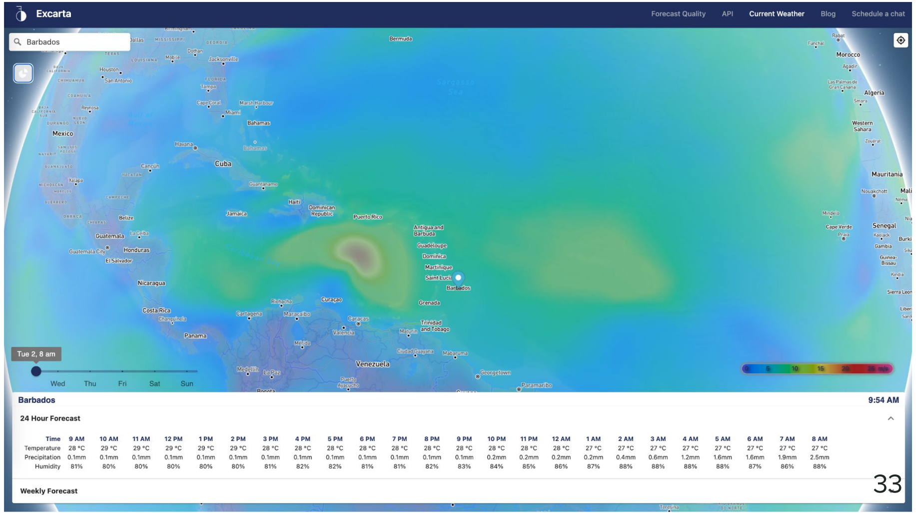
[1]credit: Ramavajjala (2024)

Finally: what does an operational AI weather forecast look like?



https://hail.excarta.io/forecast

https://app.excarta.io/map



Resources to continue your learning

Papers

- AI weather forecasts
  - FourCastNet
  - GraphCast
  - PanguWeather
  - HEAL-ViT
  - AI weather embeddings
- Nowcasting applications for extreme precipitation
  - MetNet
  - DGMR
- Foundational models
  - ClimaX

Blogs

- ECMWF:
  - how physics-based forecasts can be improved using AI
  - AI Forecasting System (ECMWF AI model) blog

Code Repositories (open-sourced)

- ECMWF ai-models package: https://github.com/ecmwf-lab/ai-models
- NVIDIA: https://github.com/NVlabs/FourCastNet
- Deepmind: https://github.com/google-deepmind/graphcast

Data Repositories (open-sourced)

- ERA5:
  - Google Research: https://github.com/google-research/arco-era5
  - Copernicus Data Store: https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=overview
- MADIS (observations):
  - https://madis.ncep.noaa.gov/
  - https://huggingface.co/datasets/excarta/madis2020

Thank you for your time!

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Extras

Challenges in using conventional ways of weather forecasting

- Numerical weather predictions, or NWPs are computationally expensive and slow!
  - Requires solving physics based equations on discrete grids using large supercomputers
- Weather forecasts are improving slowly!
  - Some estimates suggest at the average of one day a decade since 1981!
  - Limitations:
    - Not able to fully leverage extensive observations
- The dynamical scales too small to be resolvable
  - For example, many complicated yet important processes are modeled using simplistic approximations
    - Leads to uncertainties in predictions

What are some of the key challenges

- Data:
    - Multiscale, multimodal/heterogenous, high-dimensional, sparse, noisy, class imbalance (for example in case of extreme weather events), and shifting distributions
    - Physical laws <u>that need to be respected</u> *and* unknown physics that <u>needs to be discovered</u>!
        - Models should **respect or incorporate physical laws**, constraints, and other domain knowledge!
    - In discovery-oriented tasks, **ground truth is unknown** and benchmark data sets are unavailable.

- Algorithmic/Interpretability:
    - Robust methods and and ability to quantify uncertainty are required for scientific rigor
    - Extracting new scientific insights from data requires **human-interpretable** models or outputs.