

Ionospheric weather models

ELECTRON DENSITY RECONSTRUCTION

DISPEC

Presented by Ivan Galkin

BOREALIS GLOBAL Designs

Chania, Greece

21 September 2026



Prelude

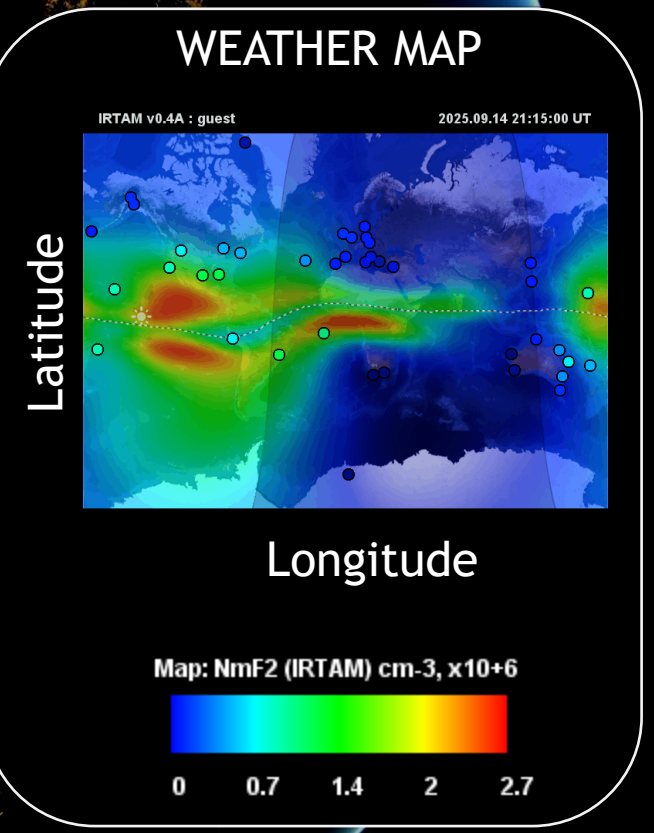
- Please consider installing GAMBIT Explorer for hand-on this afternoon

https://giro.uml.edu/GAMBIT

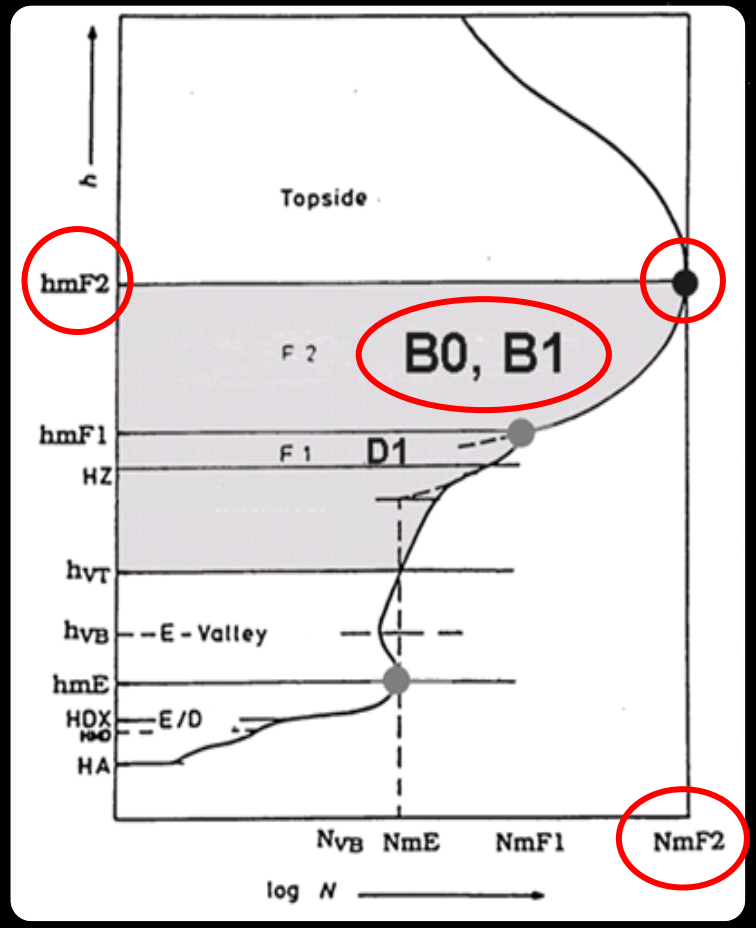
- Unzip in your user folder
- Find the text file <home>/user/gambit_info.txt
  - Line1: login name
  - Line2: password

Challenges modeling ionospheric weather

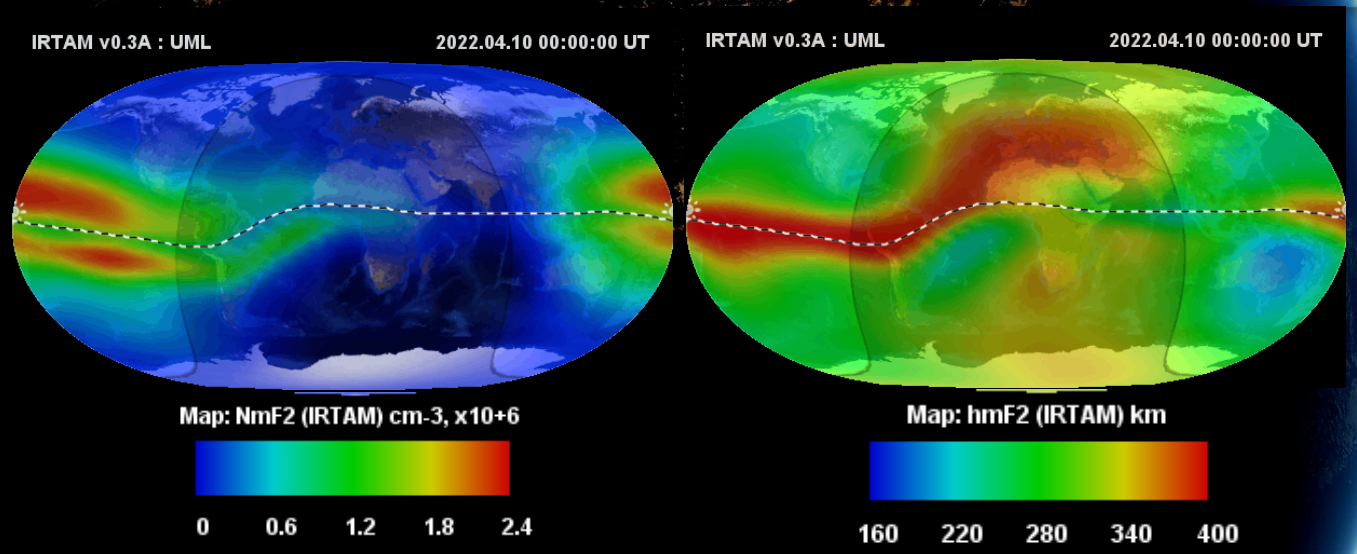
- Note: weather monitoring versus weather forecast
- Common challenges:
  - 3D volume of plasma around the Earth up to ~2,000 km
    - Needed for many applications based on ray-tracing
  - Only fragmentary 3D descriptions by a limited fleet of sensors
    - Retrospective… need a rescue effort
    - Real-time monitoring… scarce
- Weather monitoring
  - Assimilative models
    - Physics-based (NEMO… SAMI2)
    - Empirical model morphing (IRTAM)



3D plasma as collection of 2D maps



1D vertical profile of plasma density



N_mF2 h_mF2

One day of ionospheric dynamics



Real-Time IRI

- **Real-Time IRI Task Force**
  - concept: tweak IRI using available observations
    - To make a good model better
      - Ja Soon S. (CCMC) and GEM Challenge
- **IRTAM-3D is IRI-based Real-Time Assimilative Model**
  - 3D weather density model based on four 2D maps
    - NmF2, hmF2, B0 and B1
    - Captures [most of] the ionospheric dynamics
      - Smoothing
        - Max resolution: 4-hour order harmonic as in IRI
      - Es, D-region, and disturbance level are not included
  - Current IRTAM version 0.4A
    - Assimilates real-time data from GIRO ionosondes
    - Path forward: add assimilation of the Radio Occultation profiles



IRTAM is a physics-informed model

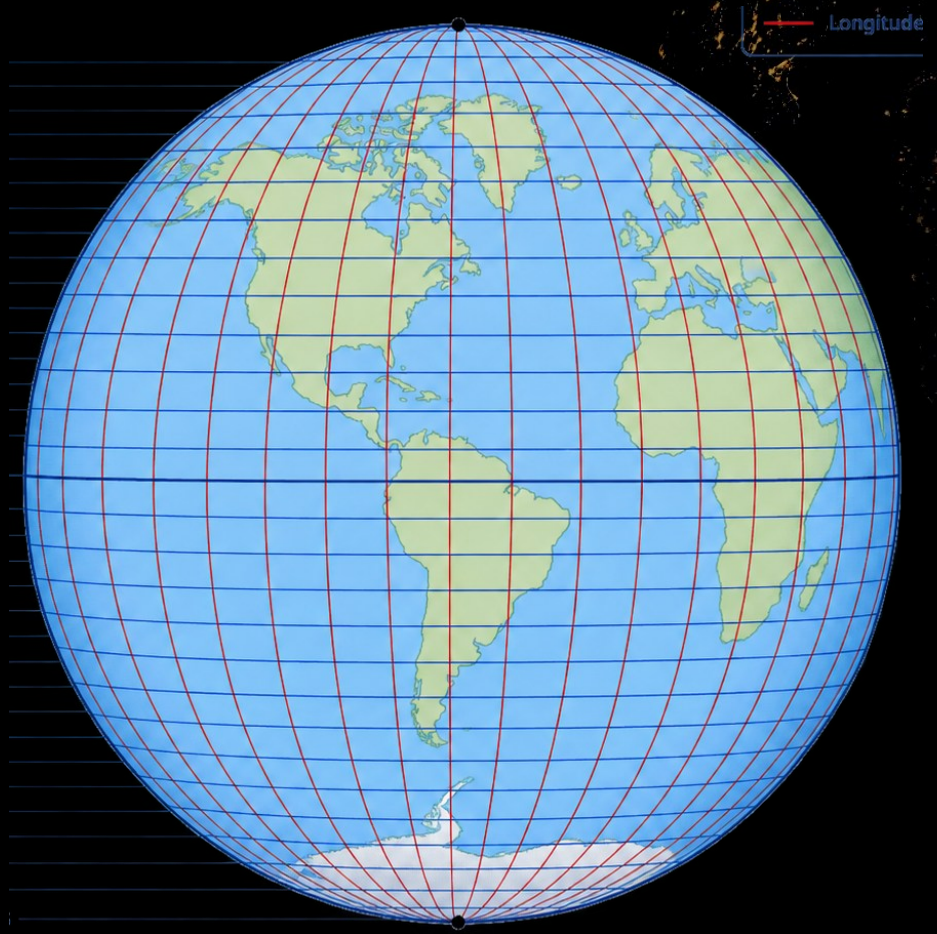
(not a theoretical white box model)

- A GRAY BOX approach
  - IRI background is responsible for capturing underlying geophysics with solar, seasonal, and geomagnetic field dependencies
  - IRTAM merely ***adjusts*** IRI background 1-DITL
    - Computes anomaly coefficients Δ_{jm} to add to the original 13 x 76 C_{jm}
- Principles of IRTAM:
  - Treat ionosphere in terms of its "disturbed" oscillations about IRI
    - Extrapolate in space when possible
    - If one GIRO site sees a wavy anomaly in time, expand this to outside the site
  - Represent 24-hour observations faithfully
    - Certain excessive smoothing effects are possible
      - Sean S. validation project confirms this smoothing effect
      - But smoothness in time and space is a valuable property
        - Assimilation of non-cooperative transmitter signals (GPSII by NWRA)
          - 2-year HFGeo Phase III project to mate GPSII and IRTAM
  - Gradually return to the background over no-sensor regions

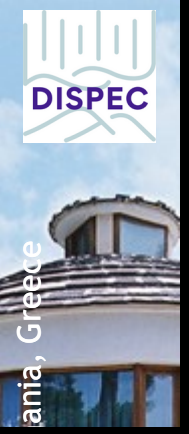
Principles of IRTAM: NECTAR Technique

- **NECTAR algorithm, original version:**
  - At each sensor site k, use 24-hour history of *deviations* from IRI, $D_k(t)$
  - Expand $D_k(t)$ into j diurnal harmonics Δ_{kj}
    - Use the same 6th order Fourier series as in IRI
    - Rumor: coefficients of the 8th order Fourier expansion are somewhere
  - Interpolate-Extrapolate Δ_{kj} to global 2D, individually for each j
    - Important! NECTAR works with harmonics of the anomaly timeline at each site
  - Expand to Jones-Gallett spatial basis m
  - Add 998 resulting corrections Δ_{jm} to 998 original IRI coefficients
- **IRTAM with a Twist**
  - A linear-trend term added to IRTAM's diurnal harmonics
    - Original IRI wraps around midnight into the same value as 24 hours ago
    - Linear trend
    - Total 1024 coefficient

24-hour 4DDA – how is this even possible?



- 43 x 42 grid
  - Not the best possible spatial resolution
  - Some ionosondes fall into the same grid
- All expansion basis terms are pre-computed, once
  - Both spatial and temporal
- Interpolation/Extrapolation using a rapid neural network evolver
- Diurnal harmonics are processed separately, then put back together
- A follow-on processing is planned to use ELO technique to improve the spatial resolution where possible

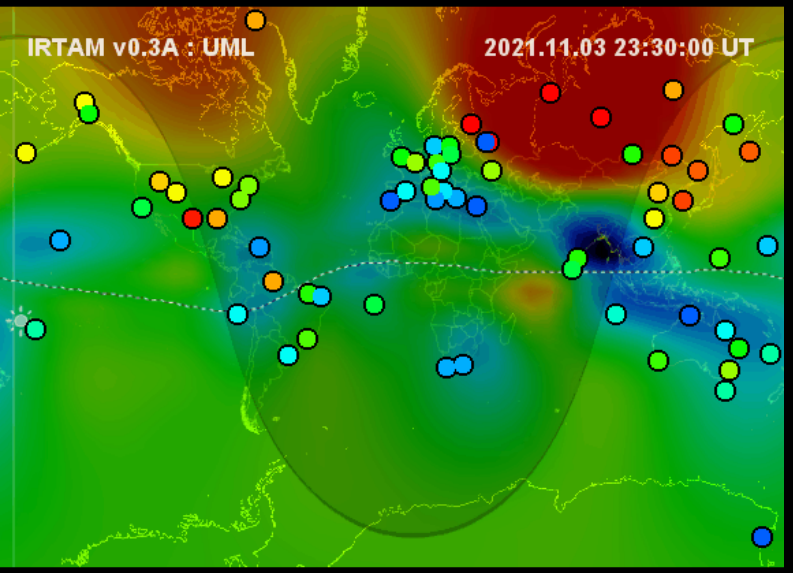


November 4, 2021 Storm, Kp ~ G3..G5

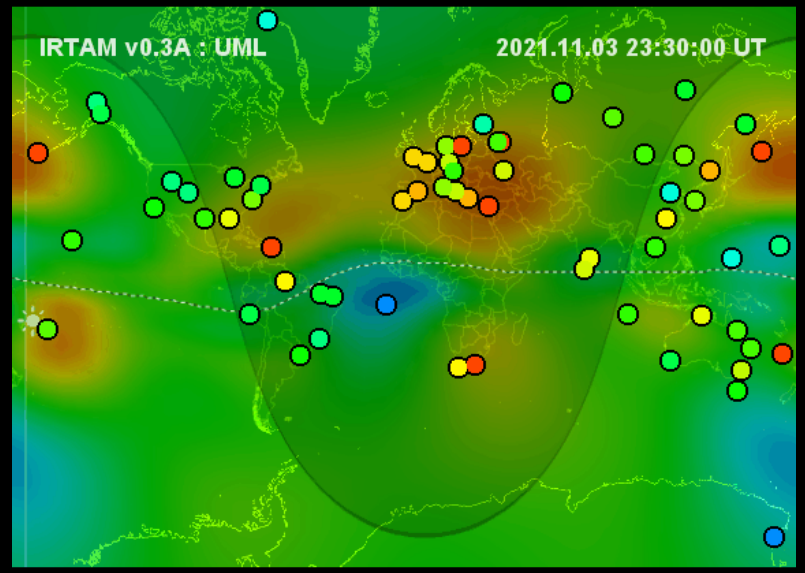
GIRO ionosondes only, IRTAM 3D assimilative model

NOT A SIMULATION!

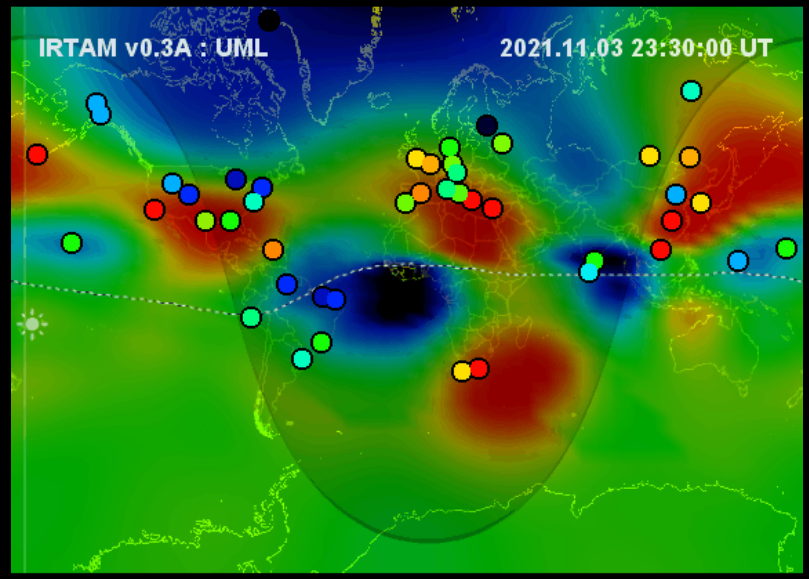
Would not it be nice to have these in 1955-2026!



Δ foF2



Δ hmF2



Δ B0



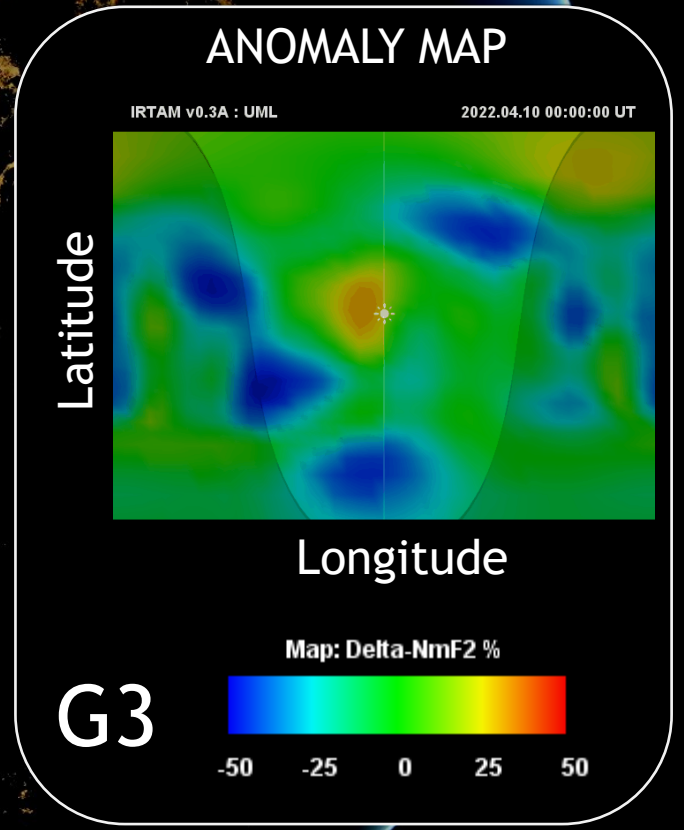
"Anomaly map" = Percent Deviation from Quiet Conditions

UMASS LOWELL

Gambit eXplorer

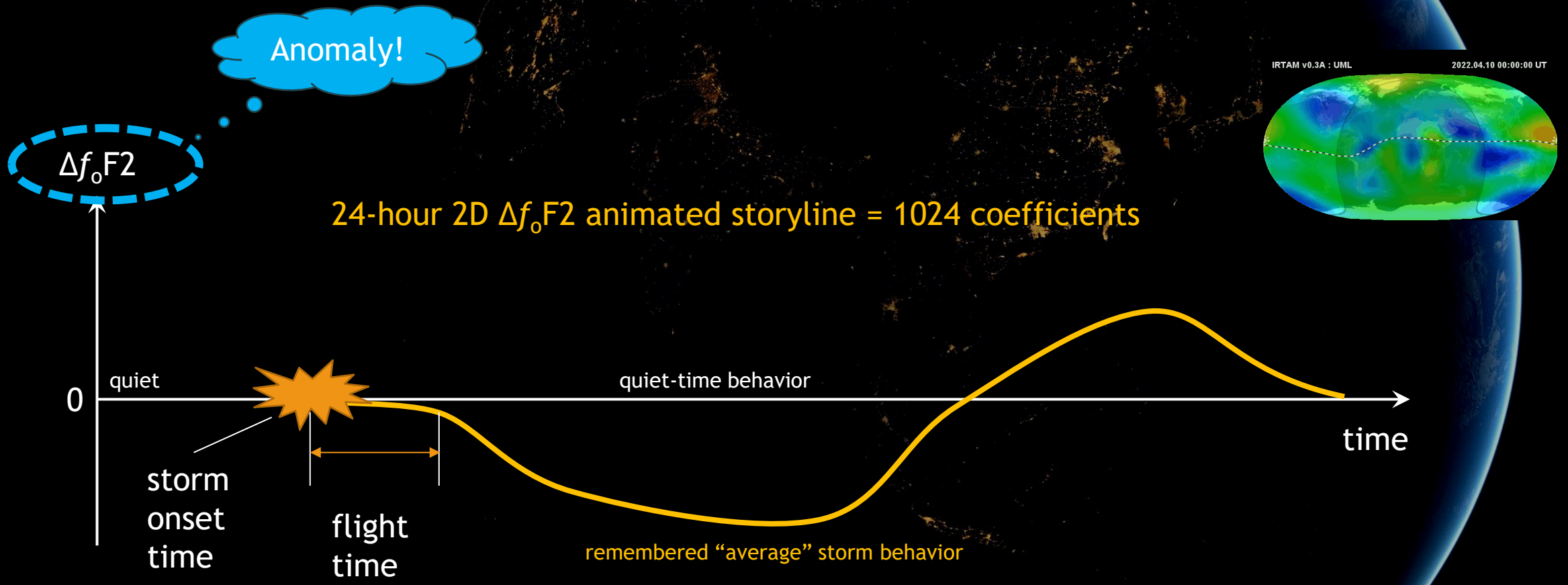
Challenges forecasting ionospheric weather

- Limited number of storms to learn them well
  - Ionosphere is mostly “quiet”
    - E.g., G3, G4, G5 geomagnetic storms are few
- When you see an ionospheric storm, you just have seen one
  - “No storms are alike”
- Prior ionospheric state does not inform its future
  - Quickly reacts for multiple forces from above and below
  - A wide context of activity in Sun-Earth system is needed
    - Interplay of multiple processes acting in different directions
    - Many processes are understood, but not their mixture



ANOMALY: weather=minus-climate deviation: how different is the ionosphere from its quiet-time expected behavior

Concept of the “Triggered” storm option



Forecast by analogy – using an average anomaly storyline

[**Fuller-Rowell *et al.***, 1999, 2000]



Capturing the ionospheric storm storylines

(mostly ideas…)

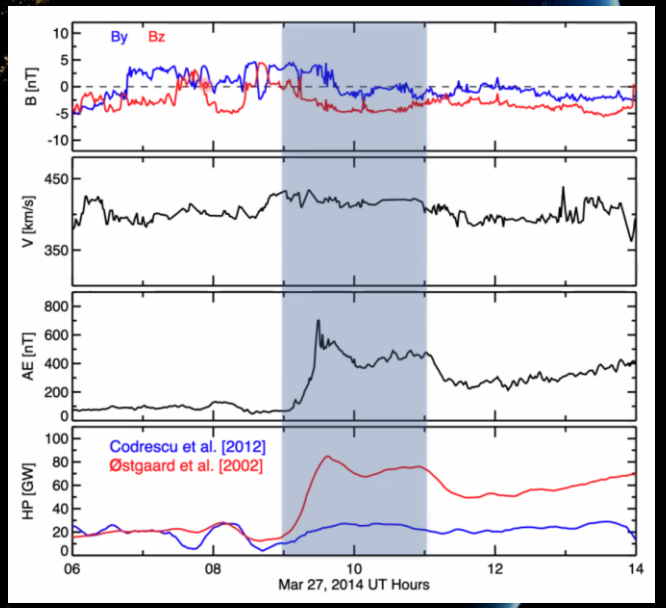
- 3D storyline = collection of several 2D-map storylines
- Each storyline is a 72-hour anomaly animation
- Concept: Natural Language Processor (as in the voice assistants)
- "Hey Google, play me Yesterday by The Beatles"
  - "Hey Google" = storm onset time
  - "Play me" = which storm library to use
  - "Yesterday by The Beatles" = activity context
  - The song = the storm storyline
- Need ideas for the library of standard storm storylines and search-most-relevant-storm algorithm

Onset time and type of storm is a separate research

Next step: Library of the storm storylines

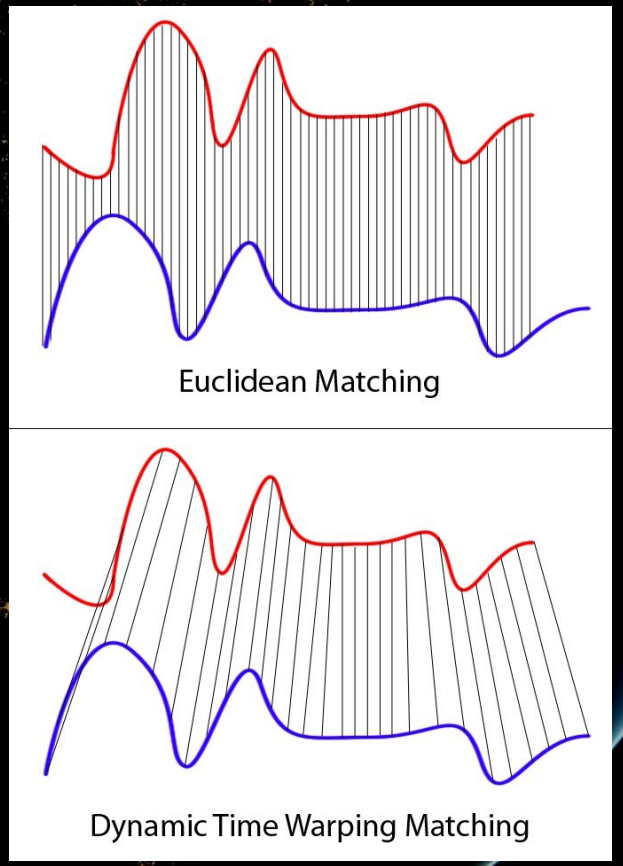
instead of the “average storm timeline”

- Instead of an “typical” storm (as in IRI storm option), keep a library of previous storm storylines of ΔNmF2
  - To forecast, just find the most relevant storm in the library
- “Most Relevant”?
  - Each storyline must be remembered in the context of the activity in the Sun-Earth environment (forcing from below and above)
- IDEAS
  - Store fixed-local-noon *demagnetized* anomaly animation
  - Standard pace of the stories with DTW (dynamic time warping) – a.k.a. *natural* speaker pace
    - i.e., recognize access and speech pace
  - Associative memory for each activity indicator to restore time series from initial fragment
  - Re-warp, estimate arrival time LT, re-magnetize, apply Δ to current state, generate report



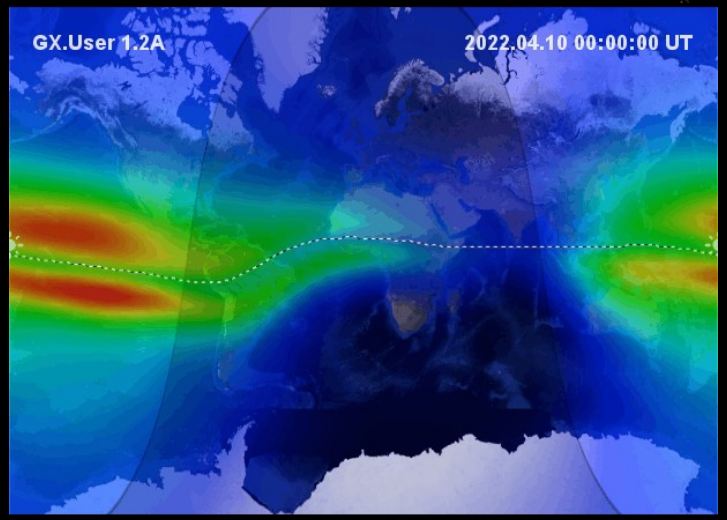
Dynamic Time Warping (DTW)

- Warp library-provided storm storyline
  - DTW finds similarity between 2 storylines
  - Driver storylines may be indicative of *how different* the actual storm timing is from the Library copy
  - Corresponding time warping shall be applied to the correction ΔNmF2

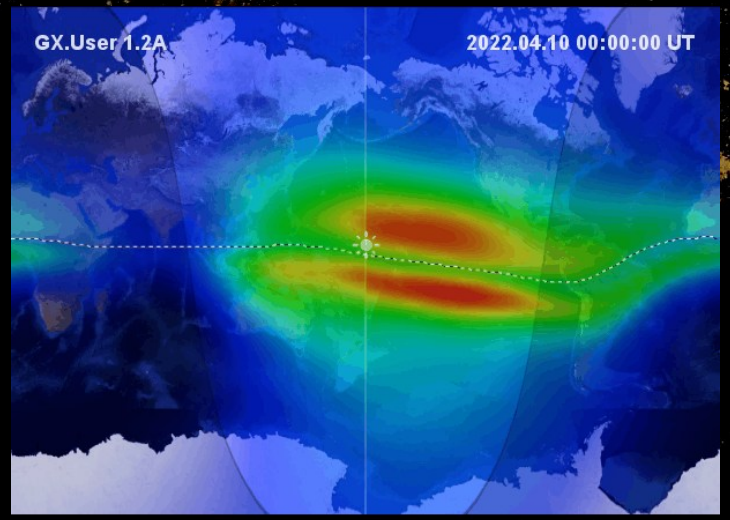


Library of storms in longitude-neutral form

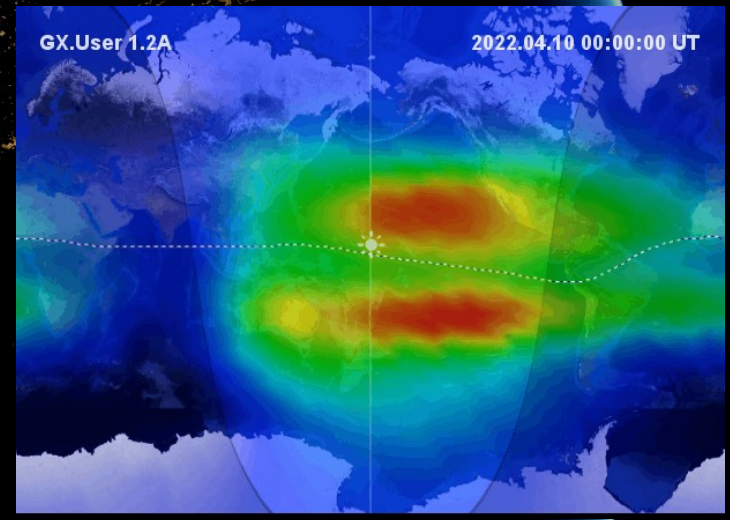
"Classic" view of NmF2



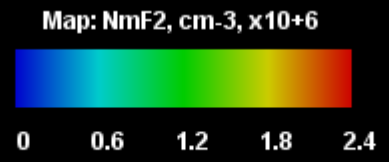
Local Time Noon view of NmF2



De-magnetized view of NmF2

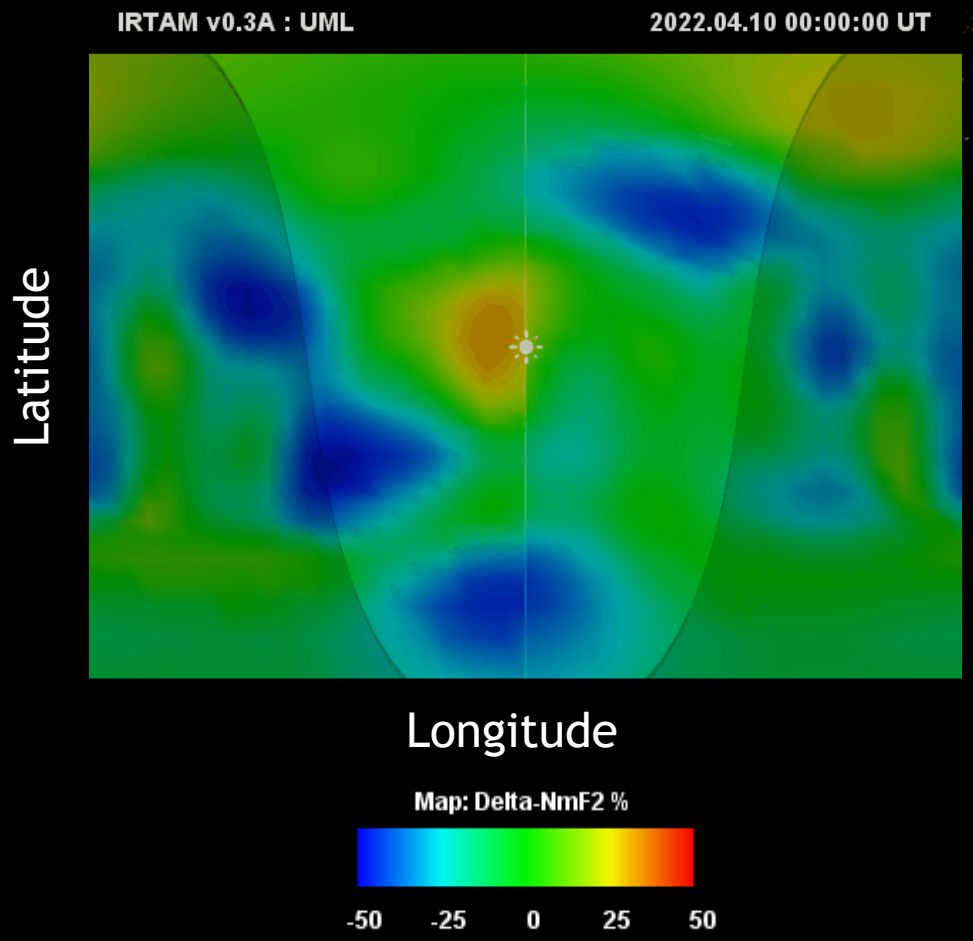


"Fish in the bowl"

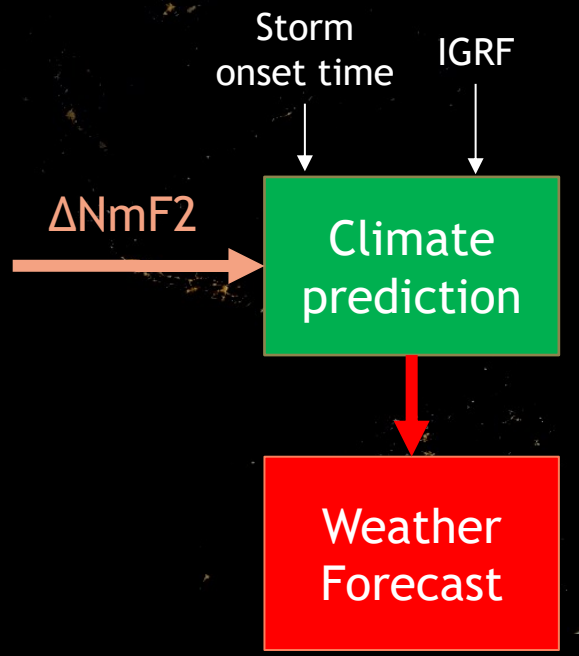


THIS CONCEPT IS APPLIED TO ANIMATED ANOMALY MAP

Encoding library storylines of ΔNmF2



- Total 1024 coefficients to store 24 hour global animated 2D maps
- Can be expanded to 2048 coefficients to store 2-day storyline



The IGRF model of the Earth magnetic field is needed to re-magnetize the retrieved library

Summary

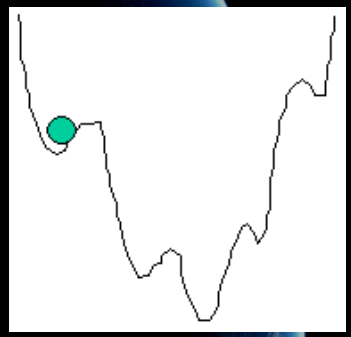
- Deep Learning “Ice-Break” is ongoing in NN-based forecasting
  - DL learns the system from its previous behavior
- A concept study of DL-based forecast of the ionospheric storm storylines:
  - Forecast deviation timeline of the disturbed ionosphere
    - Deviation from the quiet-time LT-centered/demagnetized ionosphere
  - Sync the deviation timeline to the actual/definitive storm onset time (Alexa!)
  - Use Dynamic Time Warping to maintain a smaller vocabulary of the storm behavior
  - Deep Learning to describe ionosphere timeline in the context of key storm driver timelines
  - For each activity driver, use associative memories to retrieve a full-length storyline from the initially observed fragment
- Procedure:
  - Detect storm onset, obtain full-length driver storylines
  - Take 30-day median current ionosphere, LT-center, de-magnetize,
  - Retrieve deviation storyline from the storm library, time-warp to current activity
  - Apply deviation to the median, position at reference LT, re-magnetize.

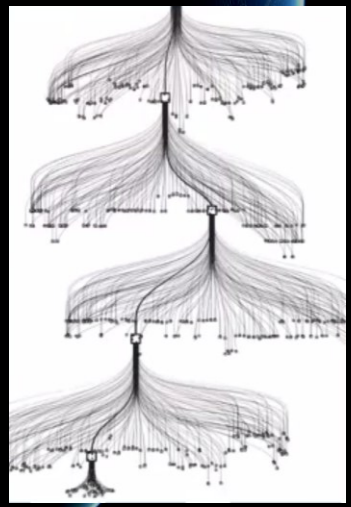


BACKUP SLIDES

Hey Google, play Yesterday by The Beatles

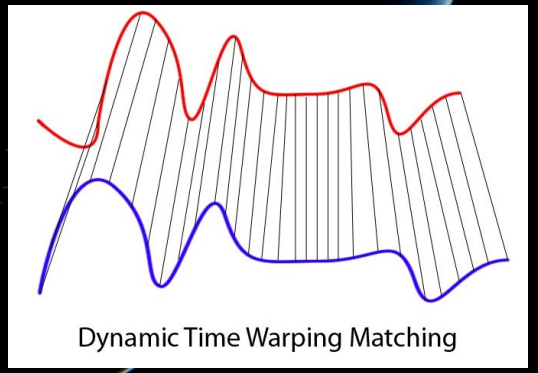
- "Hey Google" is a storm onset time
  - Multiple international teams working on this onset time forecast
    - Use dedicated spacecraft fleet in the Sun-Earth space
    - Current uncertainty is poor, but things will improve
- "Play" is the library selector
  - Different categories of ionospheric storms
- The rest of the input to forecast retrieval is CONTEXT
    - Context: reports of ongoing Sun-Earth activity
      - **But only an initial fragment is available**
      - Associative memory: restore full storyline from its fragment
        - Given AAABBA, find AAABBACCDDFBAAAA
        - This task is much easier!.. Just a timeline of activity indicator
          - Encouraging results with Kp index
        - Quality of restoration improves as the initial segment becomes longer
    - Output: given AAABBACCDDFBAAAA, fetch the storm storyline
      - Storylines are coefficients for 24-, 48-, 72-hour dynamics of Δ
        - 1024 values per 24 hours per 2D map



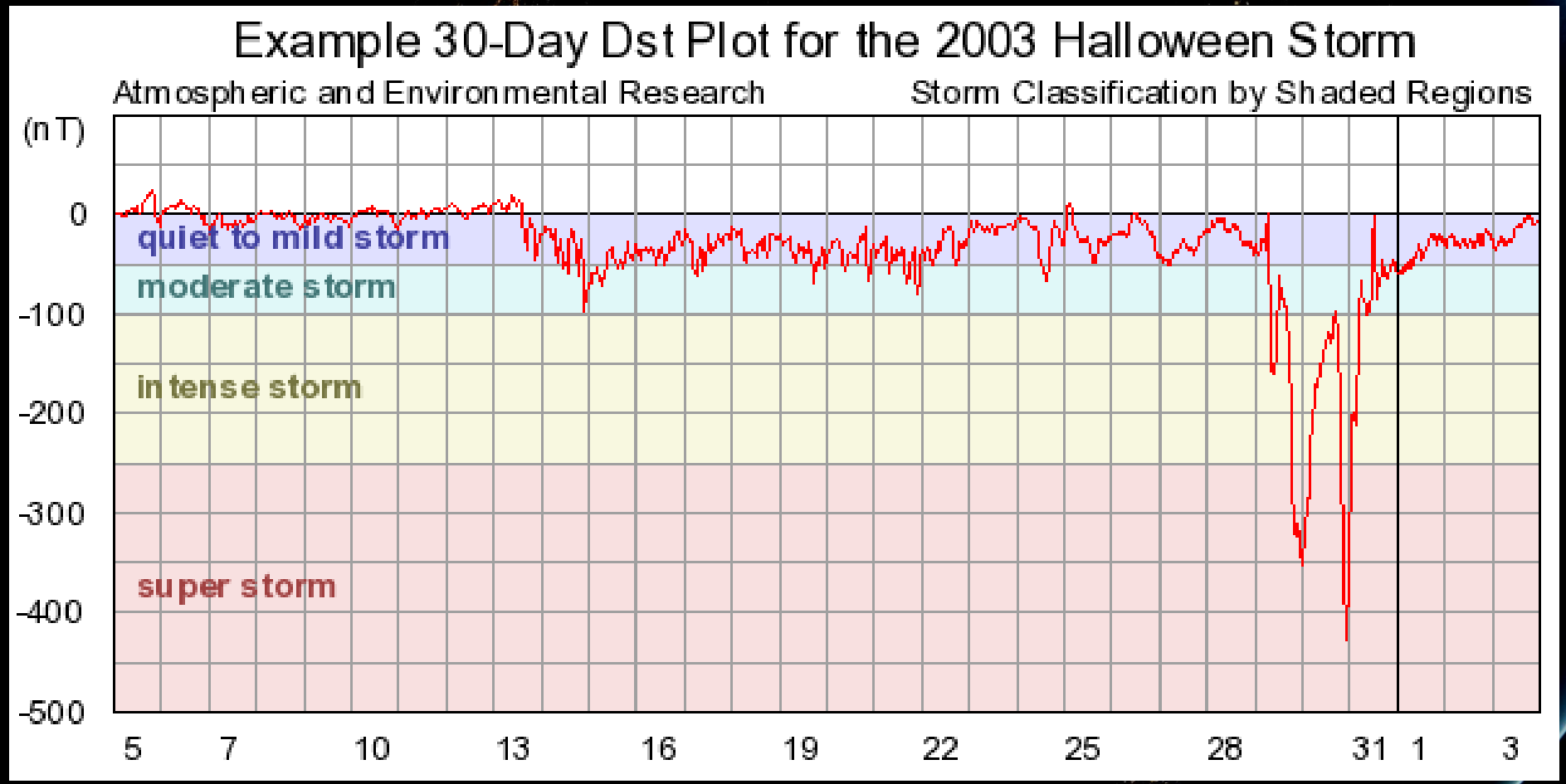


Standard Library of Ionospheric Storms

- Not easy to accept the idea
  - "No storms are alike" is prevailing argument
  - Many SWx scientists tried to find a way to generalize storms
- In support of our concept:
  - Use "anomaly" instead of "property"
    - i.e., use ΔNmF2 instead of NmF2 itself
    - "Training" will not be confused by underlying climatology dynamics
      - Excellent climatology models are out there, we use IRI
  - Record each library entry (*song*) together with the context storyline
  - Use NLP and DTW to scale storylines to a standard "pace"
    - NLP: find vowels/consonants/syllables in input speech
    - DL: use relative, not absolute representation of time series
    - DTW: allow inexact matches
  - Additionally standardize ionospheric dynamics
    - Use LT noon as reference
    - Demagnetize 2D maps before storing in the library

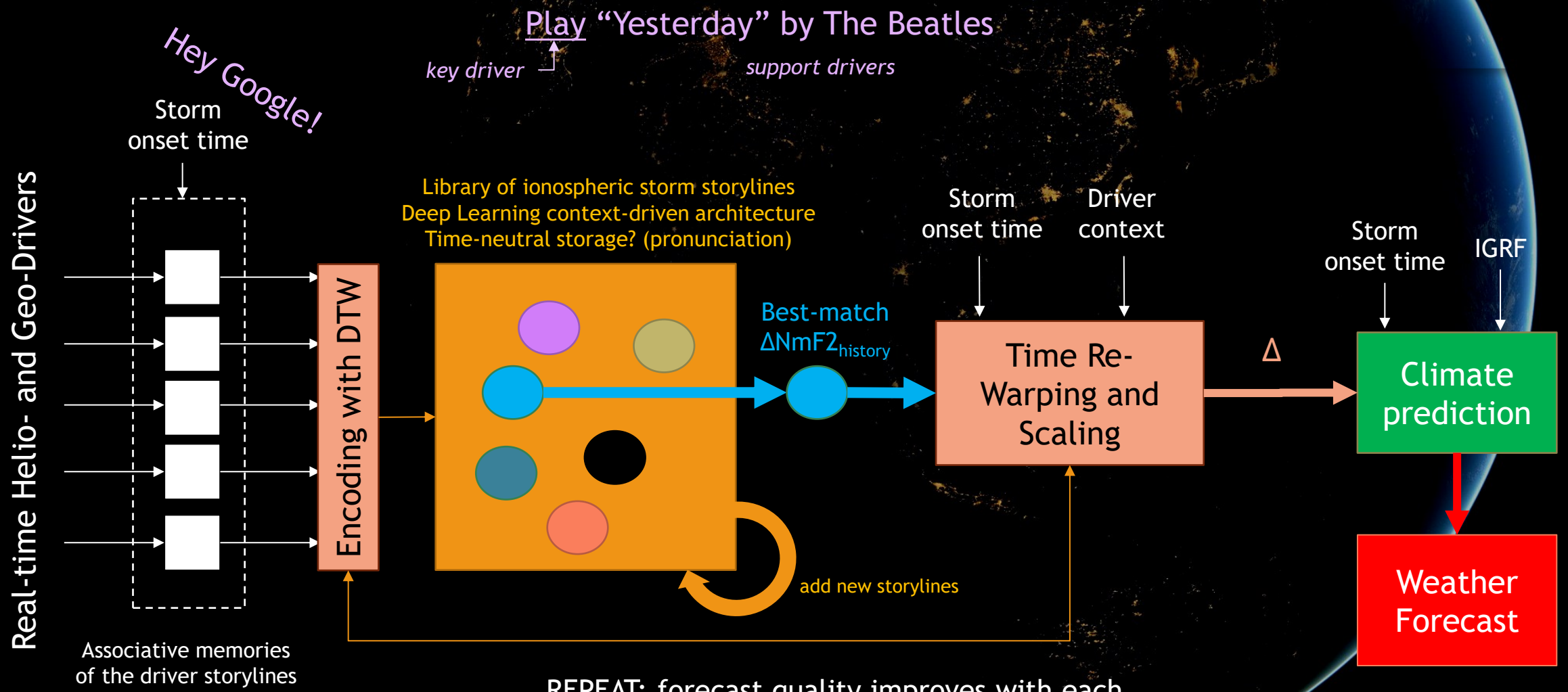


Natural Language Processing as DTW example



----------AAABBCBBBBBBBBBBCBBBBBBBCBBBECGCBAAAAA

Forecast Architecture





Forecasting by context-driven memory

- NOT to build a least-square regression on 1024 unknowns
- NOT to build a back-prop feed-forward NN with 1024 outputs
- Just memorize them, *cleverly*
  - Associate the timeline of ionospheric dynamics with timelines of ionospheric state drivers
    - DL: placing the storm vocabulary into the context of a “sentence” of ongoing geospace activity
    - Rely on NN superior inductive bias to build the context
    - Plus other tricks:
      - Dynamic Time Warping (DTW)
      - Associative memory (AM)
        - Restore a driver’s full storm timeline from its initial observed fragment