The Alan Turing Institute

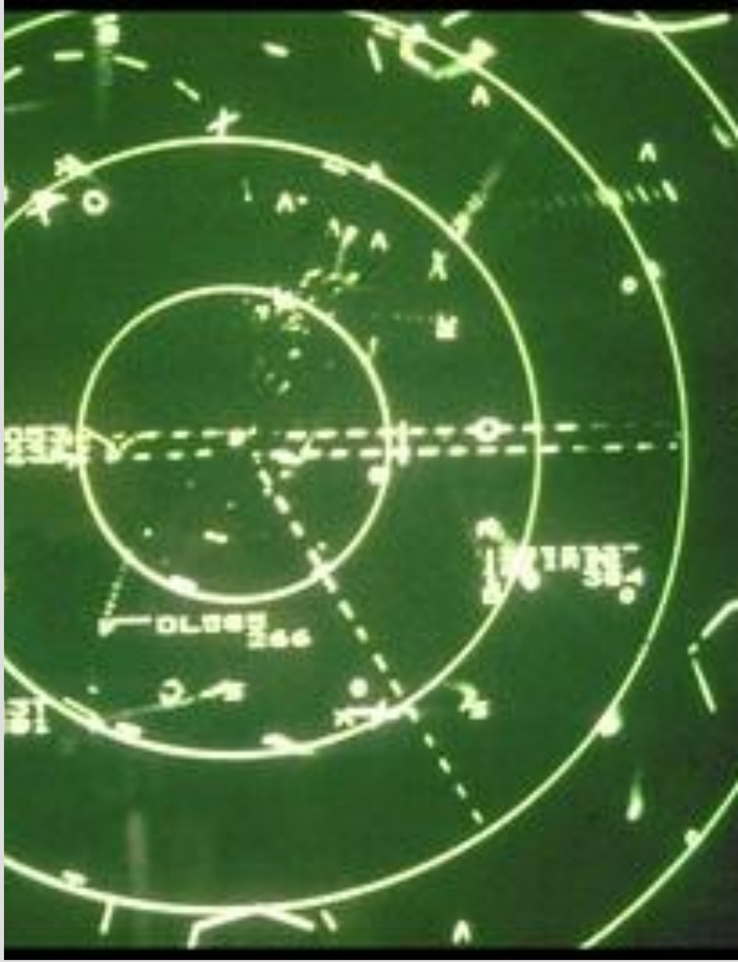
NATS

UNIVERSITY OF EXETER

Aircraft as Weather Sensors

ONLINE REFINEMENT OF WEATHER FORECASTS FOR USE IN TACTICAL AIR TRAFFIC CONTROL

Jan Povala
+ Project Bluebird



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Project Bluebird: Modernising UK airspace

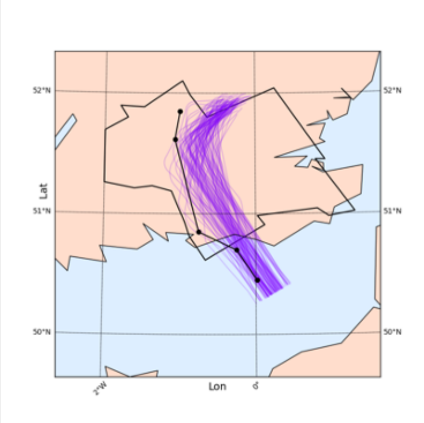
- Deliver the first AI system to work with air traffic controllers and control a section of airspace in live trials.
- Increase the throughput, and help the UK aviation industry achieve net zero carbon emissions.
- The fundamental block of the project is a high-fidelity probabilistic **Digital Twin**.

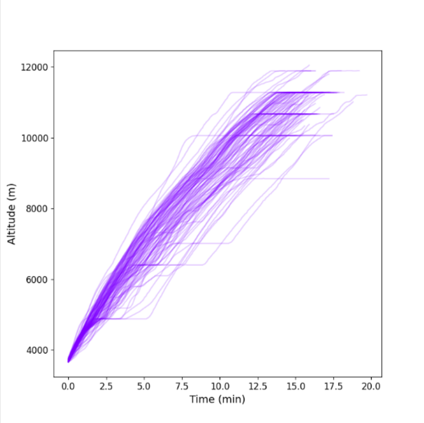
Digital Twin of UK Airspace

- A digital model of the airspace allows for:
  - Better understanding of the physical system.
  - Testing what-if scenarios — particularly useful for testing the increase in throughput.

Trajectory Prediction

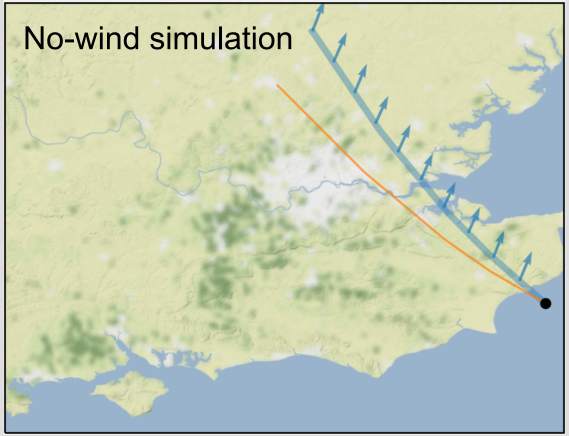
- Trajectory prediction for a given clearance/ instruction is the fundamental component of the digital twin.
- Several sources of uncertainty:
    - Unknown mass
    - Unknown controller intent
    - Pilot intent/airline procedures
    - **Meteorological conditions**

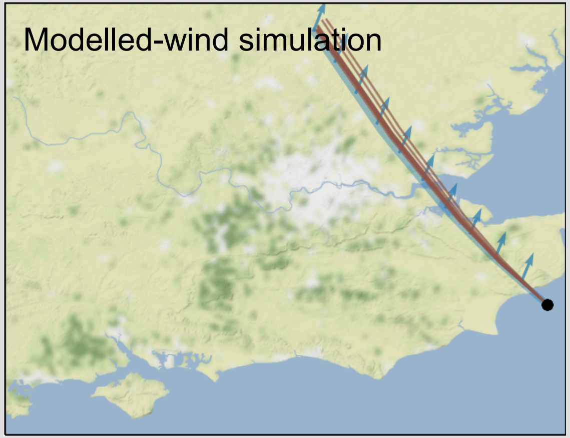




Wind

- A result of **pressure gradient** force and **Coriolis** force.
- Flow is almost completely horizontal.
- Impacts comfort/safety, time schedules, fuel consumption.
- Necessary for high-fidelity simulations of trajectories.



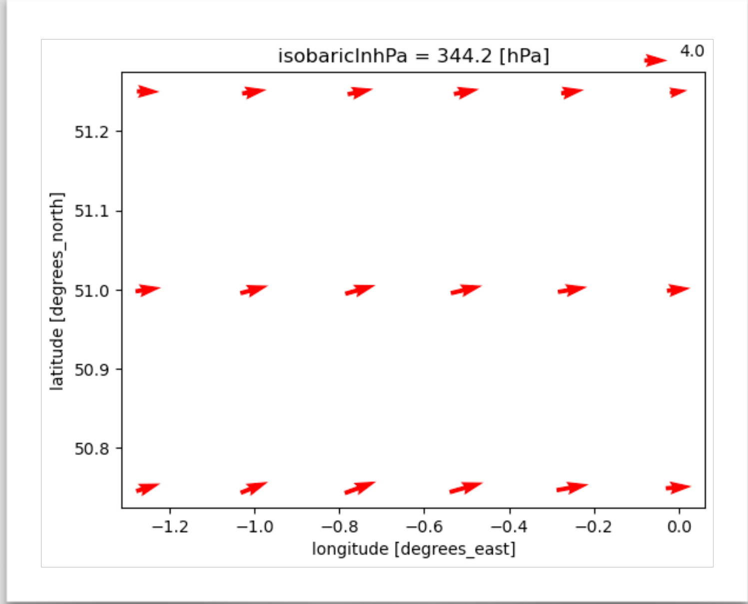


Objective

- Incorporate a representation of wind into the Digital Twin.
- Leverage different sources of information: combine **wind forecasts** from weather agencies and the **measurements of wind from airborne aircraft**.
- Note: we are not looking to capture gusts that last a few seconds.

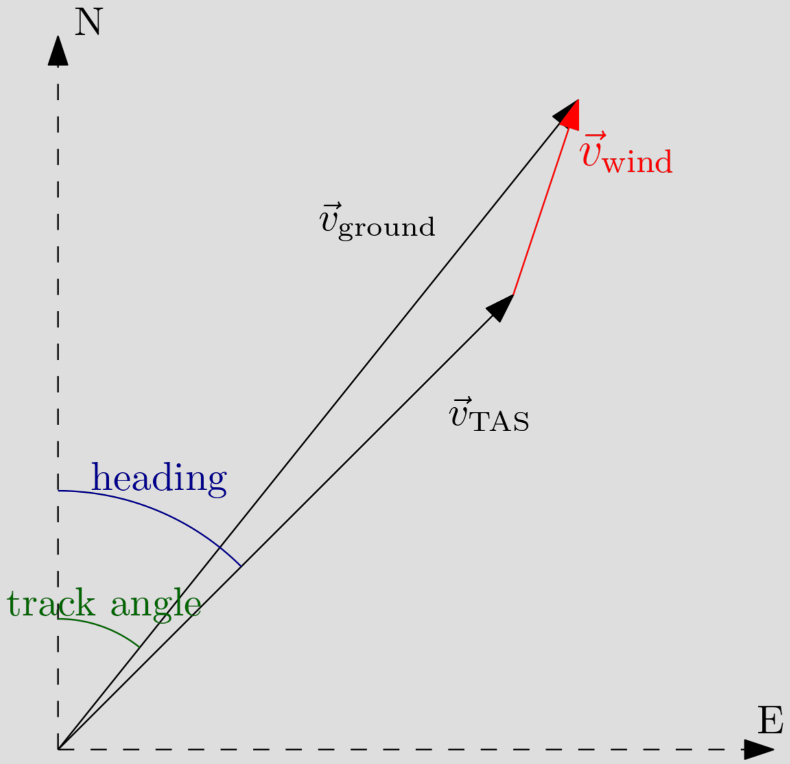
Wind: bivariate field

- The airspace is a 3D domain.
- Discretise airspace spatially (latitude, longitude) and vertically (pressure levels).
- The wind at each of the discretisation points is represented by vector components u, v.



Wind Measurements

- Compute **true airspeed** (TAS) vector from **indicated airspeed**, **heading**, and **flight level** (necessary for converting indicated airspeed to true airspeed).
- The **ground velocity** vector given by **ground speed** and the **track angle**.
- Wind vector simply follows as $\vec{v}_{\text{wind}} = \vec{v}_{\text{ground}} - \vec{v}_{\text{TAS}}$
- We discard measurements from manoeuvring aircraft (climbing, turning) and with more than 45deg crosswind.



Data Assimilation

- Weather forecasts from NOAA* are issued every 6 hours for times in the future at 6-hour multiples.
- In between, we can derive measurements of wind velocity from airborne aircraft.
- Combine wind forecasts from with measurements from the aircraft in an online manner → **filtering problem**.
- Extensive literature on this subject: Kalman Filters.

*could be other agencies, e.g., MET Office.

Filtering Formulation

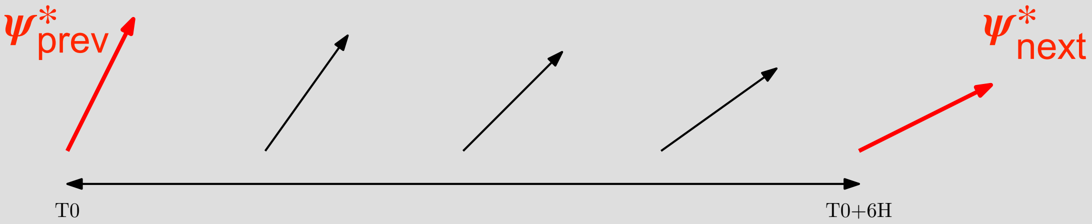
$$\boldsymbol{\psi}_k = \boldsymbol{M}_k \boldsymbol{\psi}_{k-1} + \boldsymbol{w}_k, \qquad \boldsymbol{w}_k \sim \mathcal{N}_n\left(\mathbf{0}, \boldsymbol{Q}_k\right),$$

$$\boldsymbol{y}_k = \boldsymbol{H}_k \boldsymbol{\psi}_k + \boldsymbol{v}_k, \qquad \boldsymbol{v}_k \sim \mathcal{N}_{m_k}\left(\mathbf{0}, \boldsymbol{R}_k\right),$$

- $\boldsymbol{M}_k$ is the state transition operator,
- $\boldsymbol{w}_k$ is the state transition innovation term, a **random field**,
- $\boldsymbol{H}_k$ is the observation operator mapping from state to observations at step k,
- $\boldsymbol{v}_k$ is the measurement noise,
- $\boldsymbol{Q}_k$ is the covariance matrix for the innovation term,
- $\boldsymbol{R}_k$ is the covariance matrix for the measurement noise (assumed diagonal).

State Update

- Without the knowledge of the physical process (requiring a climate model), we leverage the forecasts for the time before step k $(T0)$, and after step k $(T0+6)$, and interpolate them to obtain the expected wind at step k, based on the forecasts: $\boldsymbol{\psi}_k = w \times \boldsymbol{\psi}_{k-1} + (1-w) \times f\left(k, \boldsymbol{\psi}^*_{\text{prev}}, \boldsymbol{\psi}^*_{\text{next}}\right) + \boldsymbol{w}_k.$
- This approach guides the state update, with weight w determining the influence of the previous state, and the expected state based on forecasts.



Example $f(\cdot)$: linear interpolation.

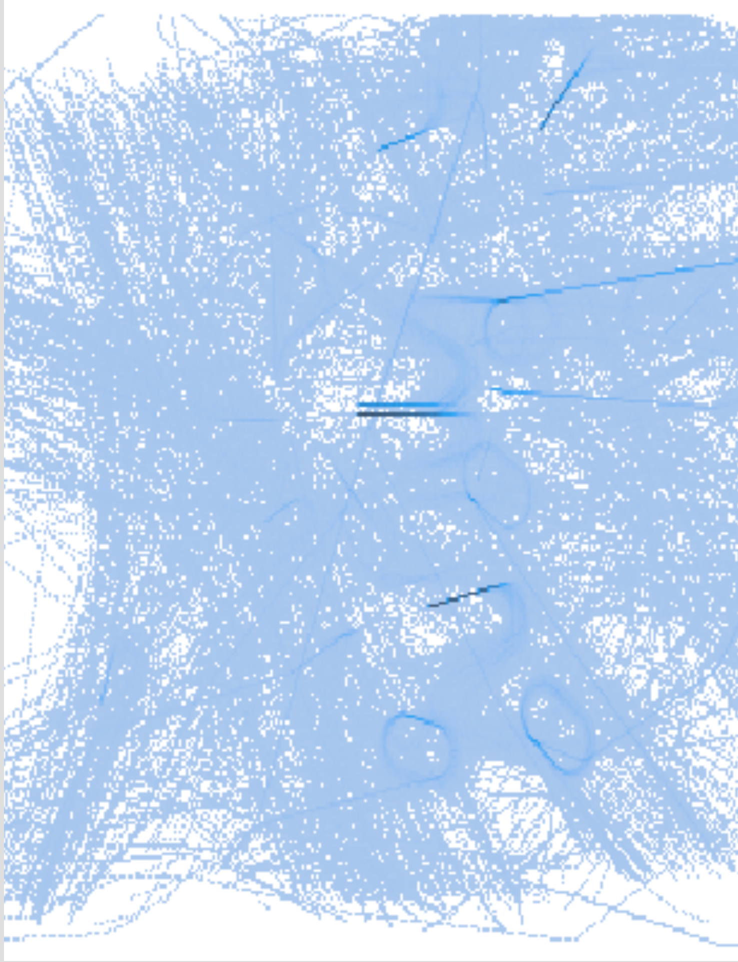
State Update continued

- Covariance matrix $\boldsymbol{Q}_k$ is a covariance matrix generated using separable covariance function $k\big([x_1, y_1, z_1], [x_2, y_2, z_2]\big) = k_{xy}\big([x_1, y_1], [x_2, y_2]\big)k_z\big(z_1, z_2\big)$.
- This allows for Kronecker factorisation: $\boldsymbol{Q}_k = \boldsymbol{K}_{xy} \otimes \boldsymbol{K}_z$
- Linear algebra cost significantly reduced, e.g., Cholesky factorisation cost goes down from $\mathcal{O}(n^3)$ to $\mathcal{O}(n^{3/2})$.

Implementation

- Due to high dimensionality of the state space, we employ **Ensemble Kalman** filter $\rightarrow$ the distribution at step k is given by an ensemble of members.
- Efficient Maximum Likelihood estimation of the parameters of the filter: lateral and vertical **length scales** of innovation term, and its **amplitude**.
- Auto-differentiation in JAX to find optimal parameters for the filtering scheme.
- Assuming separable covariance structure $\rightarrow$ efficient factorisation using **Kronecker product**.

Experiments



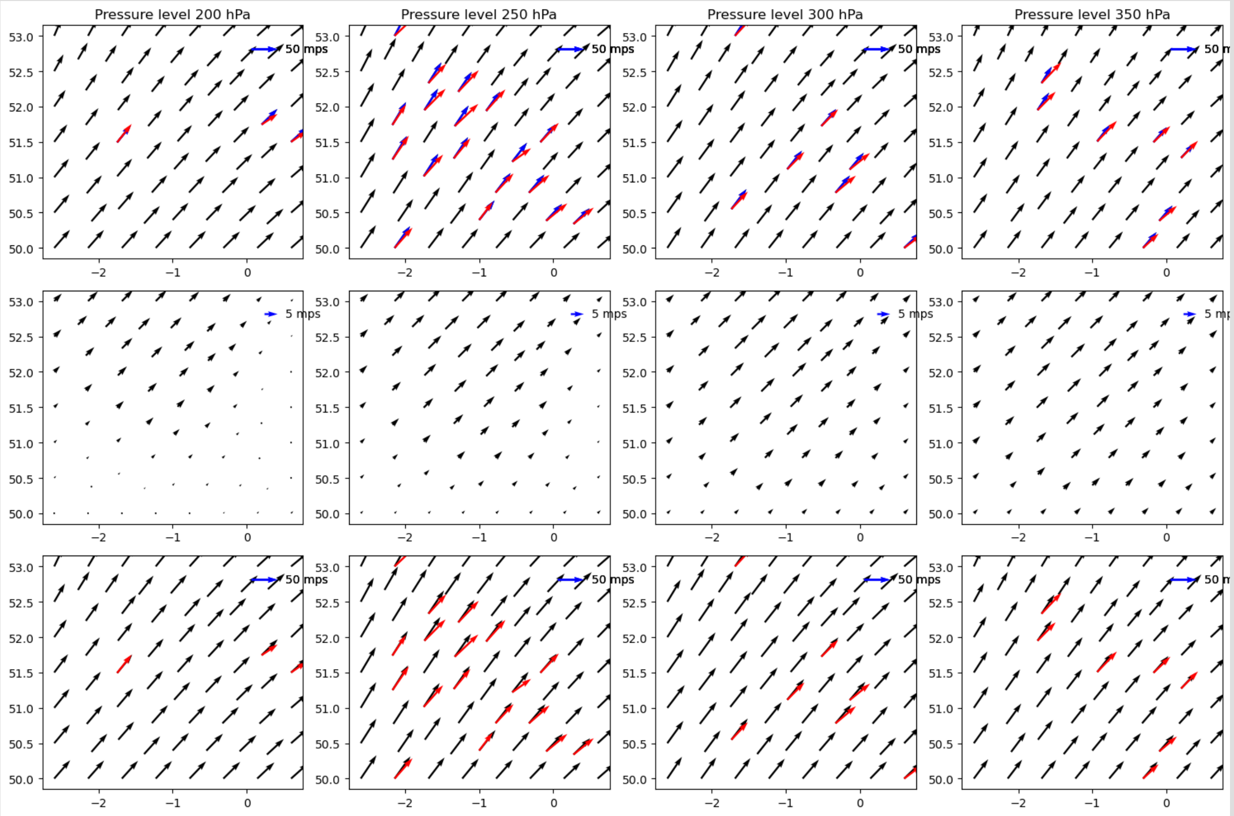
Density of radar blips in a 6H window in SE England

Wind Field Updates

$\mathbb{E}[\boldsymbol{\psi}_{k-1}]$

$\mathbb{E}[\boldsymbol{\psi}_{k}] - \mathbb{E}[\boldsymbol{\psi}_{k-1}]$

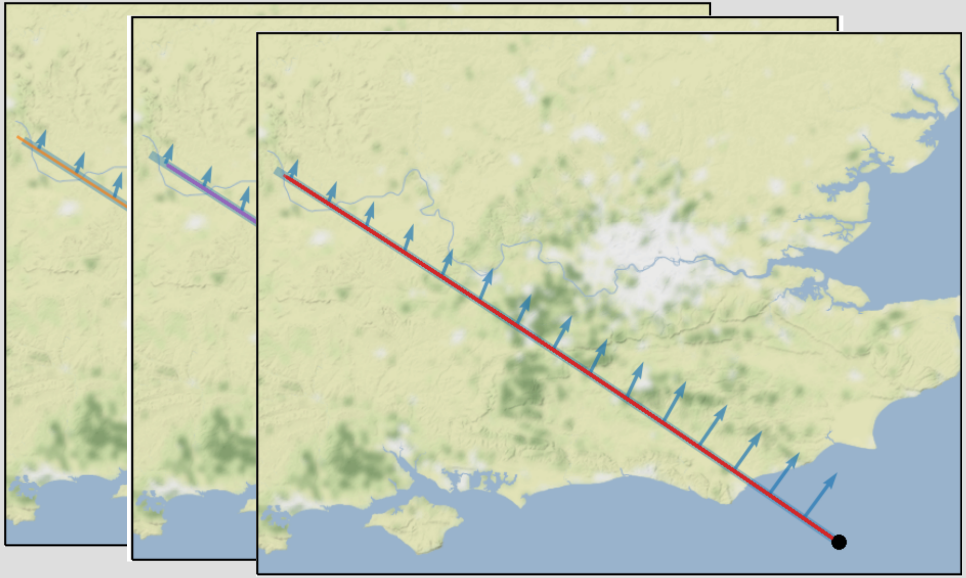
$\mathbb{E}[\boldsymbol{\psi}_{k}]$



Evaluation

- Ground truth of wind is sparse:
  - Reanalysis data from weather agencies comes at hourly resolution and is averaged.
  - Radiosonde weather balloon measurements are sparse spatially.
  - End-to-end validation with a simulator and comparing against the radar: we simulate real-life instructions from the controllers and compare to the radar data.

End-to-end Simulation: route-following



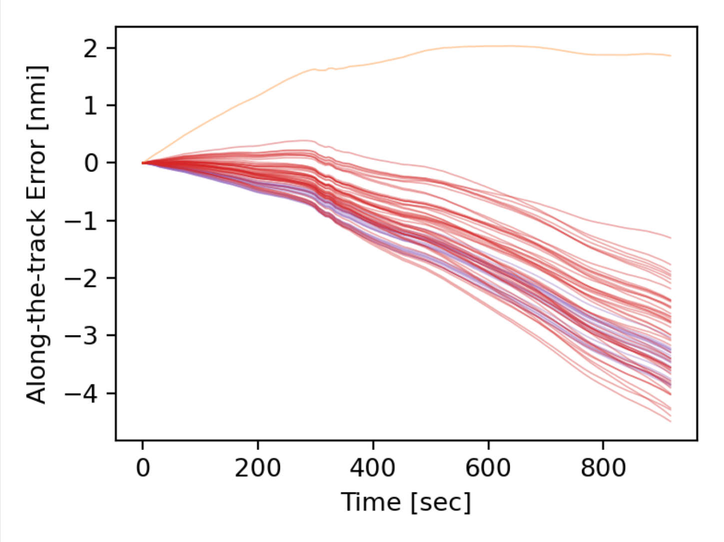
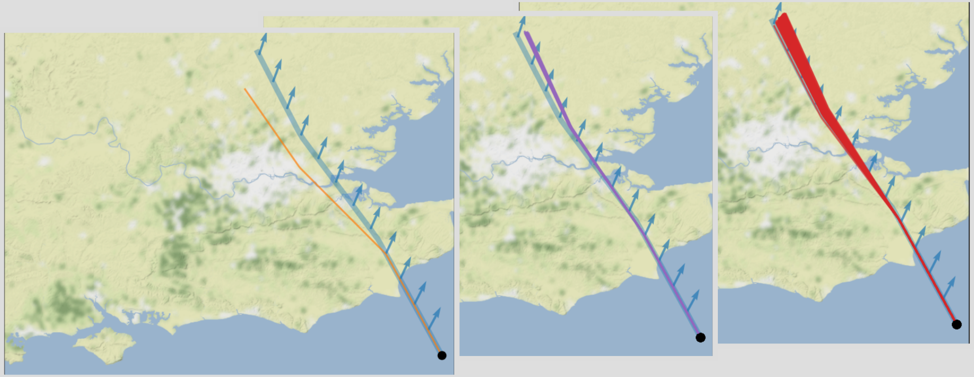


Fig: Trajectories and the corresponding error: no-wind (orange), interpolated wind (purple), filtered wind (red)

Using filtered wind reduced the along-the track distance error, compared to the wind given by interpolating two forecasts (which are 6hr apart).

End-to-end Simulation: on-heading aircraft



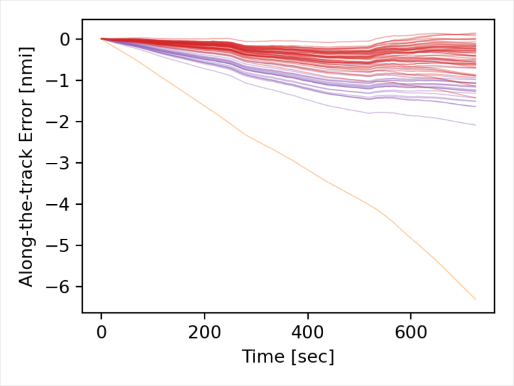
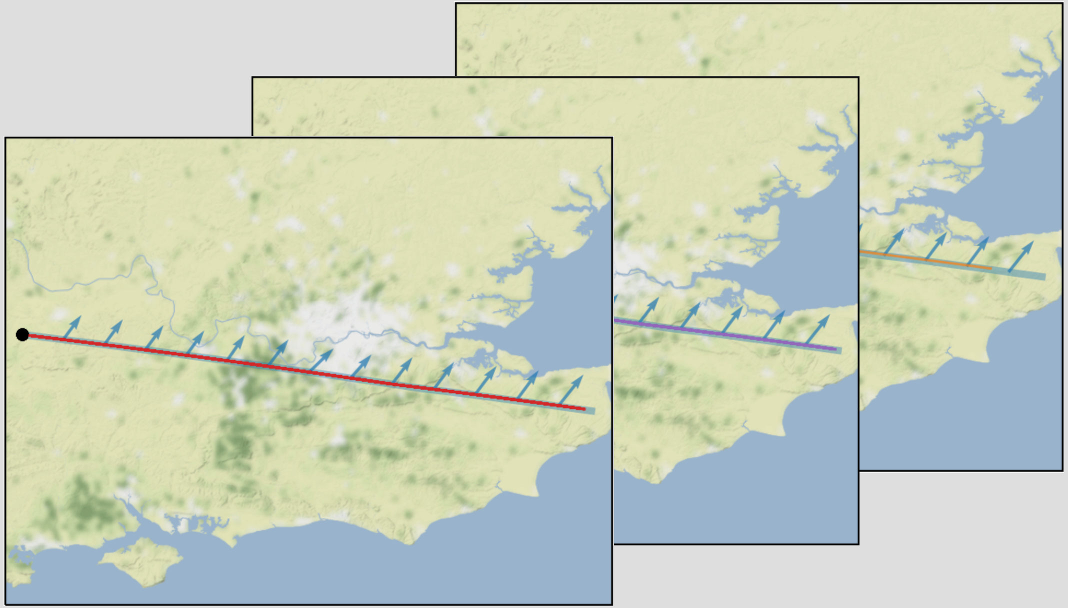


Fig: Trajectories and the corresponding error: no-wind (orange), interpolated wind (purple), filtered wind (red)

- The error gets more pronounced for on-heading aircraft.
- Filtering reduces along-the-track error.

End-to-end Simulation: a bad case



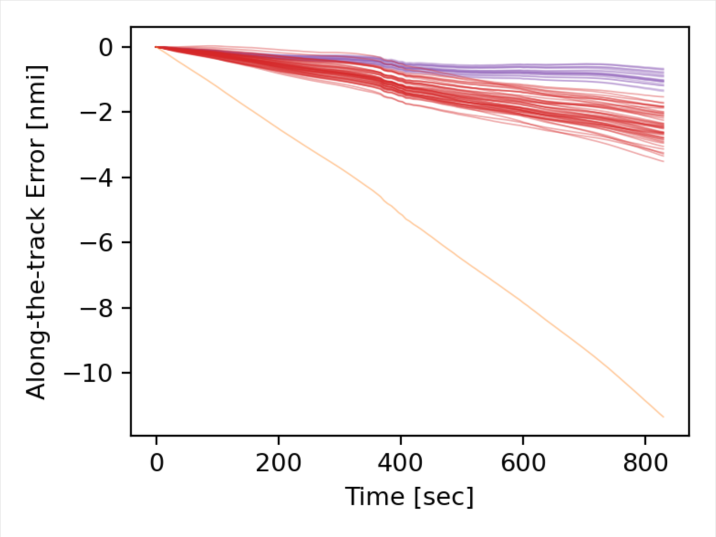
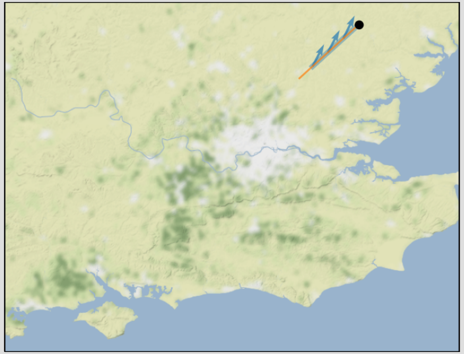
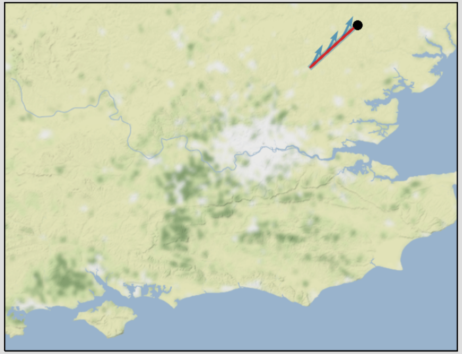


Fig: Trajectories and the corresponding error: no-wind (orange), interpolated wind (purple), filtered wind (red)

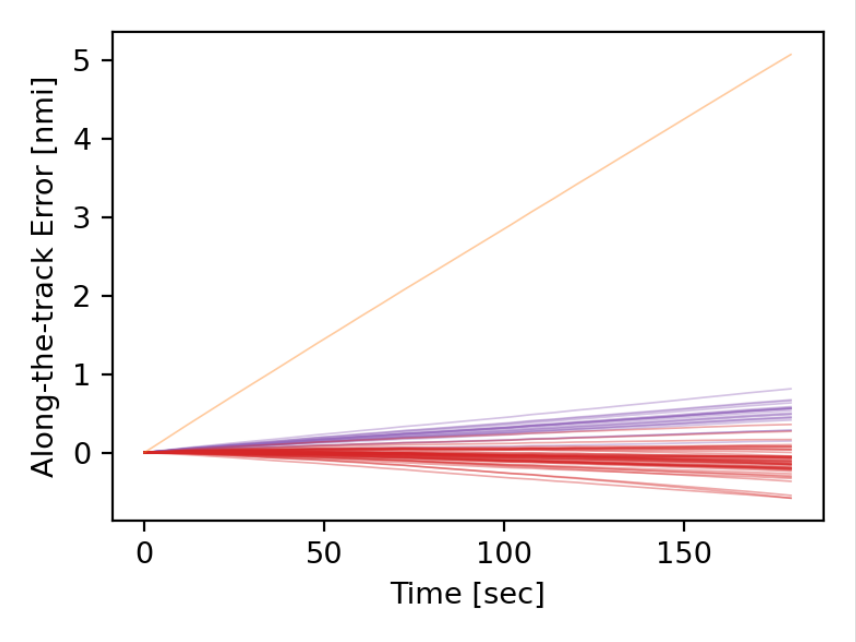
End-to-end Simulation: short segment



No-wind simulation

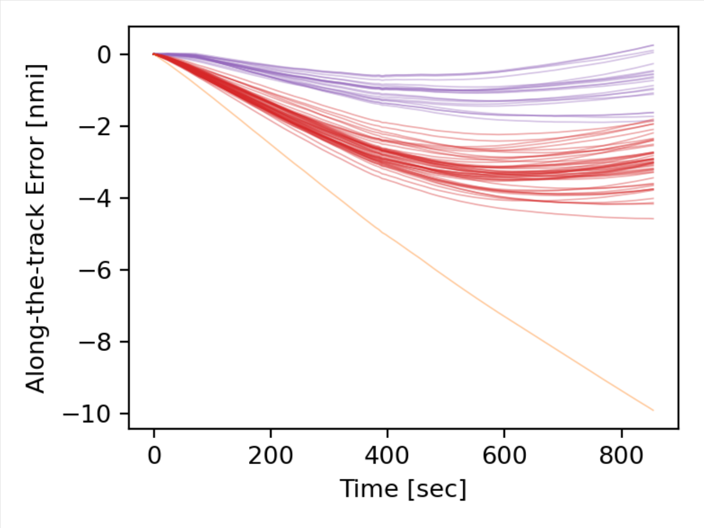


Filtered-wind simulation

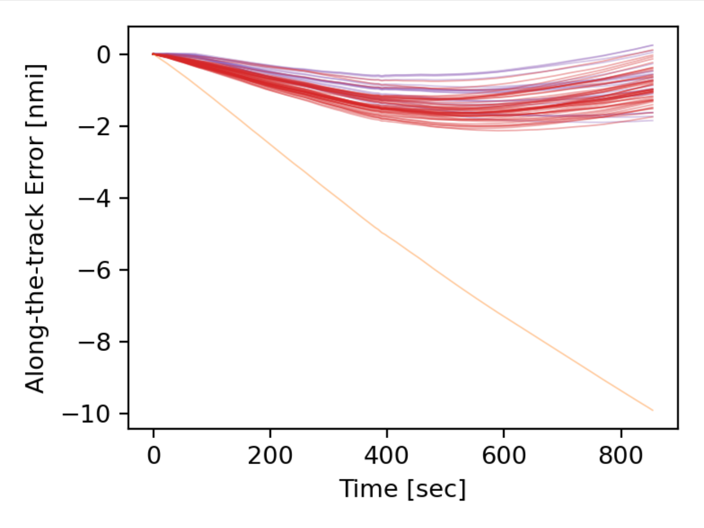


Error: forecast interpolation (purple), filtered wind (red), no-wind (orange)

State update sensitivity



$w = 0.5$



$w = 0.75$

Fig: along-the-track error: no-wind (orange), interpolated wind (purple), filtered wind (red)

Conclusions

- Not including wind conditions in the digital twin can result in up to 10nm in along-the-track distance for a 20-min flight.
- Filtering methods are a natural choice for assimilating wind measurements from the aircraft.
- Using random fields allows for enforcing the smooth changes in wind velocity.
- The state transition step leverages forecasts to guide the filtering distribution.
- By assuming separability of the horizontal dimension from the vertical dimension in the innovation term, this method scales up to 1000’s of discretisation points.
- Hard to verify usefulness of the algorithm as ground truth data measurements are sparse.
- We have employed end-to-end simulation replicating aircraft trajectories and compared to radar data, with promising results.

Next steps

- A suite of experiments covering more aircraft.
- Assessing the covariance separability assumption.
- Assessing the stationarity assumption of the covariance function (the covariance is only dependent on distances, rather than locations).

Thank you!

Questions?