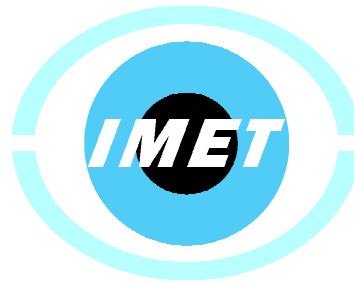


# Recommendations on trajectory selection in flight planning based on weather uncertainty



Alan Hally, Jacob Cheung, Jaap Heijstek,  
Adri Marsman, Jean-Louis Brenguier



SESAR INNOVATION DAYS, 1st-3rd  
Dec. 2015, Bologna



# Overview



## Introduction

# Overview



- **Introduction**
- **Ensemble Prediction System (EPS)**
  - **Comparison of EPSs**

# Overview



- **Introduction**
- **Ensemble Prediction System (EPS)**
  - **Comparison of EPSs**
- **Methodology (EPS + TP)**

# Overview



- **Introduction**
- **Ensemble Prediction System (EPS)**
  - **Comparison of EPSs**
- **Methodology (EPS + TP)**
- **Example Case**

# Overview



- **Introduction**
- **Ensemble Prediction System (EPS)**
  - **Comparison of EPSs**
- **Methodology (EPS + TP)**
- **Example Case**
- **Conclusions and Future Work**

## → Introduction

→ Ensemble Prediction System (EPS)

→ Comparison of EPSs

→ Methodology (EPS + TP)

→ Example Case

→ Conclusions and Future Work

# Introduction



**Trajectory Predictors** (TP) currently use deterministic meteorological (MET) forecasts

**Deterministic MET** forecasts contain uncertainties due to errors from:

- Atmospheric chaos
- Lack of observations
- Modelling errors

These uncertainties lead to **unknown uncertainty** in the **trajectory**

**Unknown uncertainty** in **flight time** and thus **fuel consumption**

# Introduction



**Trajectory Predictors** (TP) currently use deterministic meteorological (MET) forecasts

**Deterministic MET** forecasts contain uncertainties due to errors from:

- Atmospheric chaos
- Lack of observations
- Modelling errors

These uncertainties lead to **unknown uncertainty** in the **trajectory**

**Unknown uncertainty** in **flight time** and thus **fuel consumption**

## Approach?

Use **Ensemble Prediction System** + TP

# Overview



→ Introduction

→ **Ensemble Prediction System (EPS)**

→ Comparison of EPSs

→ Methodology (EPS + TP)

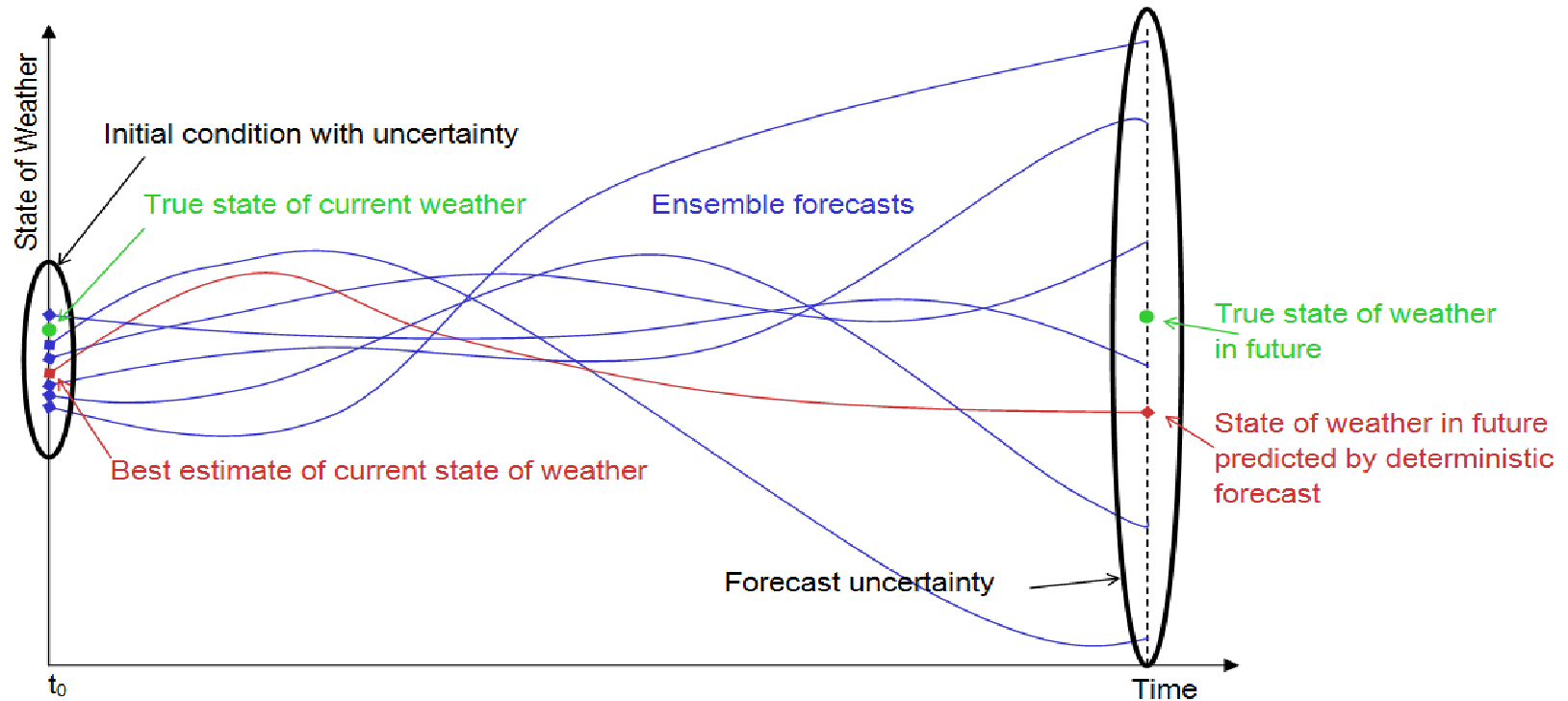
→ Example Case

→ Conclusions and Future Work

# Ensemble Prediction System (EPS)



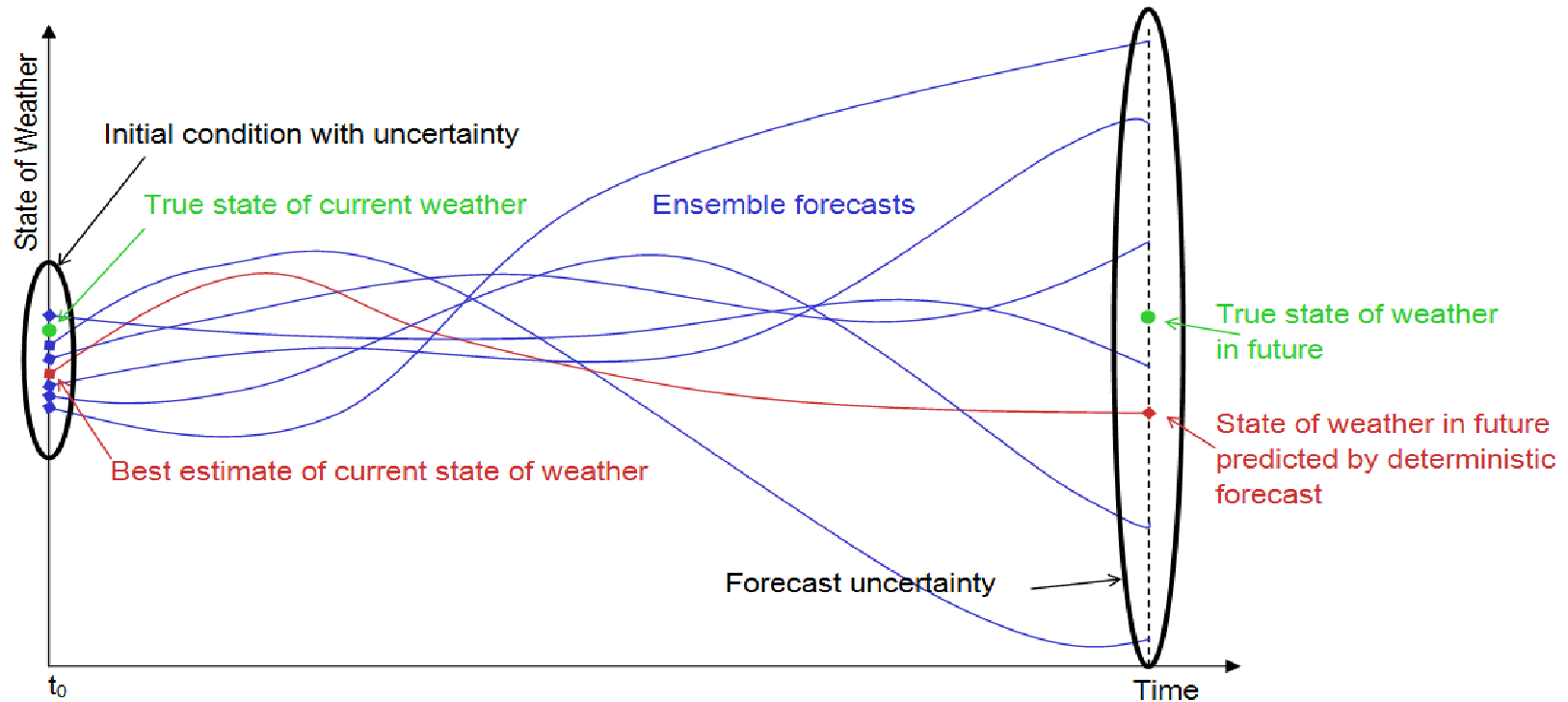
How does an EPS capture uncertainty?



# Ensemble Prediction System (EPS)



How does an EPS capture uncertainty?

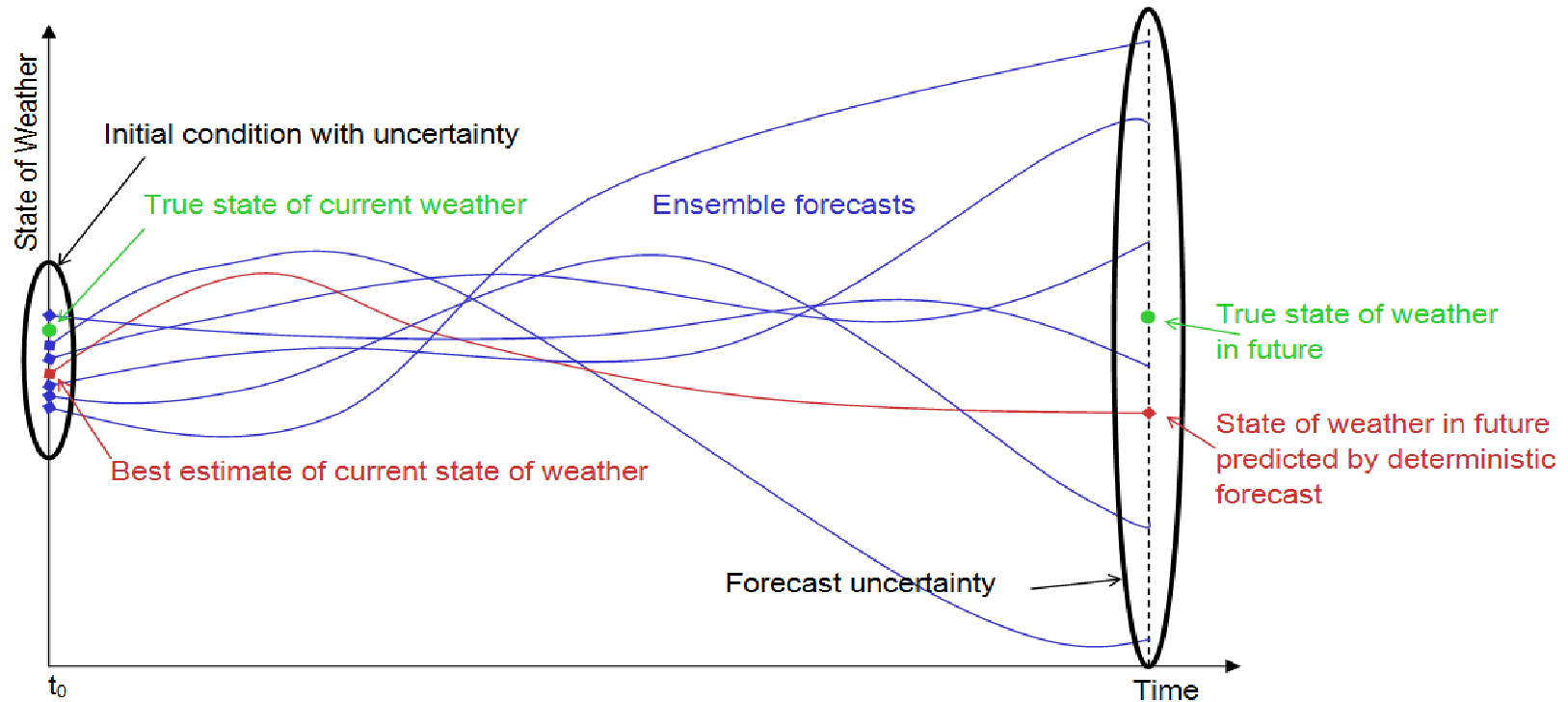


→ Maximise **spread** and thus cover whole **envelope** of **future weather scenarios**

# Ensemble Prediction System (EPS)



How does an EPS capture uncertainty?



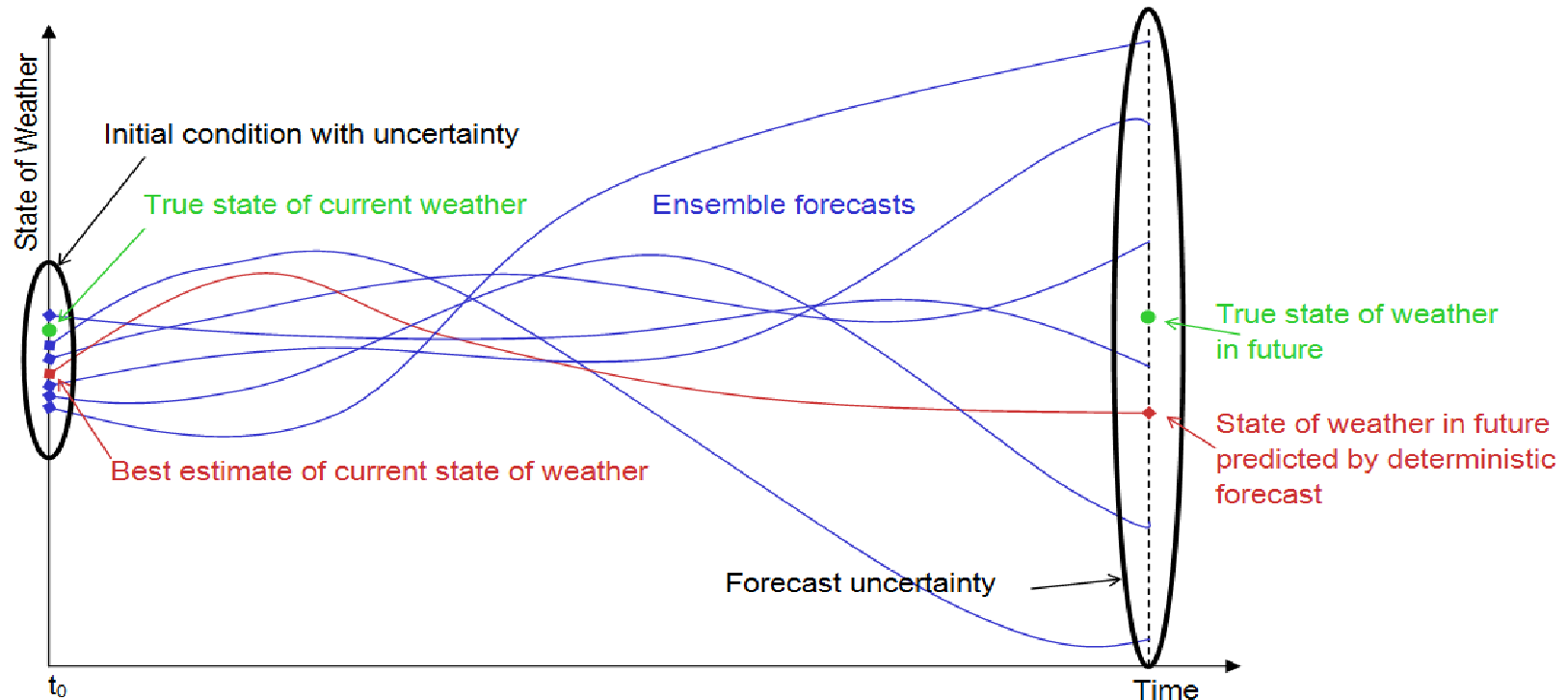
Maximise **spread** and thus cover whole **envelope** of **future weather scenarios**

Useful in nominal (**uncertainty in winds in the upper-atmosphere**) and non-nominal weather (**convection**)

# Ensemble Prediction System (EPS)



How does an EPS capture uncertainty?



Maximise **spread** and thus cover whole **envelope** of **future weather scenarios**

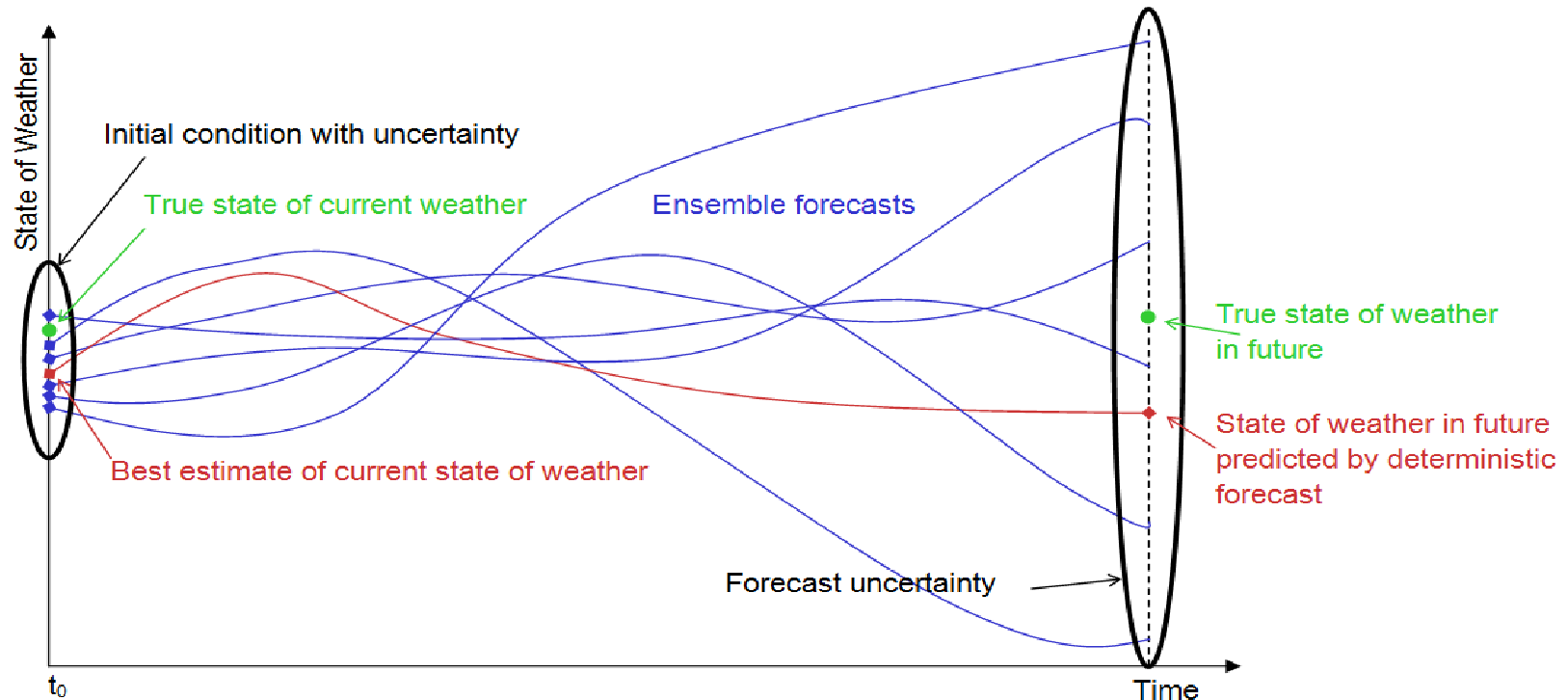
Useful in nominal (**uncertainty in winds in the upper-atmosphere**) and non-nominal weather (**convection**)

**Quantify uncertainty** in flight planning due to weather

# Ensemble Prediction System (EPS)



How does an EPS capture uncertainty?



Maximise **spread** and thus cover whole **envelope** of **future weather scenarios**

Useful in nominal (**uncertainty in winds in the upper-atmosphere**) and non-nominal weather (**convection**)

**Quantify uncertainty** in flight planning due to weather

Lead to a **more accurate** description of **extra fuel** needed for flight

# Ensemble Prediction System (EPS)



**All world-wide weather centres run EPS systems daily**

# Ensemble Prediction System (EPS)



**All world-wide weather centres run EPS systems daily**



Met Office Global and Regional Ensemble Prediction System (MOGREPS)

Global, Hor. Res. ~33 km, 70 Vert. Levels, 12 members, 00,06,12 & 18UTC

# Ensemble Prediction System (EPS)



**All world-wide weather centres run EPS systems daily**



Met Office Global and Regional Ensemble Prediction System (MOGREPS)

Global, Hor. Res. ~33 km, 70 Vert. Levels, 12 members, 00,06,12 & 18UTC



Provision Ensemble Action de Recherche Petite Échelle Grande Échelle (PEARP)

Global, Hor. Res. 15.5 km (over France), 65 Vert. Levels, 35 members, 06 & 18UTC

# Ensemble Prediction System (EPS)



**All world-wide weather centres run EPS systems daily**



Met Office Global and Regional Ensemble Prediction System (MOGREPS)

Global, Hor. Res. ~33 km, 70 Vert. Levels, 12 members, 00,06,12 & 18UTC



Provision Ensemble Action de Recherche Petite Échelle Grande Échelle (PEARP)

Global, Hor. Res. 15.5 km (over France), 65 Vert. Levels, 35 members, 06 & 18UTC



European Centre for Medium-Range Weather Forecast (ECMWF)

Global, Hor. Res. ~32 km, Vert. 91 levels, 51 members, 00 & 12UTC

# Ensemble Prediction System (EPS)



**All world-wide weather centres run EPS systems daily**



Met Office Global and Regional Ensemble Prediction System (MOGREPS)  
Global, Hor. Res. ~33 km, 70 Vert. Levels, 12 members, 00,06,12 & 18UTC



Provision Ensemble Action de Recherche Petite Échelle Grande Échelle (PEARP)  
Global, Hor. Res. 15.5 km (over France), 65 Vert. Levels, 35 members, 06 & 18UTC



European Centre for Medium-Range Weather Forecast (ECMWF)  
Global, Hor. Res. ~32 km, Vert. 91 levels, 51 members, 00 & 12UTC

**SUPER**



Multi-model ensemble (mix of all ensembles)  
98 members, 18UTC initialisation time

# Overview



→ Introduction

→ **Ensemble Prediction System (EPS)**

→ **Comparison of EPSs**

→ Methodology (EPS + TP)

→ Example Case

→ Conclusions and Future Work

# Comparison of EPSs



## Relative Operating Characteristic (ROC) curve

ROC measures the **ability** of the **forecast** to discriminate between two alternative outcomes (yes/no) at different probability thresholds

ROC is conditioned on the observations (i.e., given that an event **occurred**, what was the **corresponding forecast**?)

The **Area Under the ROC** curve (**AUC**) is the value which is often used

Want **AUC** close to **1** as possible (translates to high Probability of Detection (**POD**) and low Probability of False Detection (**POFD**))

The **ROC** can be considered as a measure of potential **usefulness**

# Comparison of EPSs



## Relative Operating Characteristic (ROC) curve

ROC measures the **ability** of the **forecast** to discriminate between two alternative outcomes (yes/no) at different probability thresholds

ROC is conditioned on the observations (i.e., given that an event **occurred**, what was the **corresponding forecast**?)

The **Area Under the ROC** curve (**AUC**) is the value which is often used

Want **AUC** close to **1** as possible (translates to high Probability of Detection (**POD**) and low Probability of False Detection (**POFD**))

The **ROC** can be considered as a measure of potential **usefulness**

| Event<br>Forecast | Event Observed |          |
|-------------------|----------------|----------|
|                   | Yes            | No       |
| Yes               | <b>a</b>       | <b>b</b> |
| No                | <b>c</b>       | <b>d</b> |

$$HIT = \frac{a}{(a + c)} \quad POFD = \frac{b}{(b + d)}$$

# Comparison of EPSs



## Relative Operating Characteristic (ROC) curve

ROC measures the **ability** of the **forecast** to discriminate between two alternative outcomes (yes/no) at different probability thresholds

ROC is conditioned on the observations (i.e., given that an event **occurred**, what was the **corresponding forecast**?)

The **Area Under the ROC** curve (**AUC**) is the value which is often used

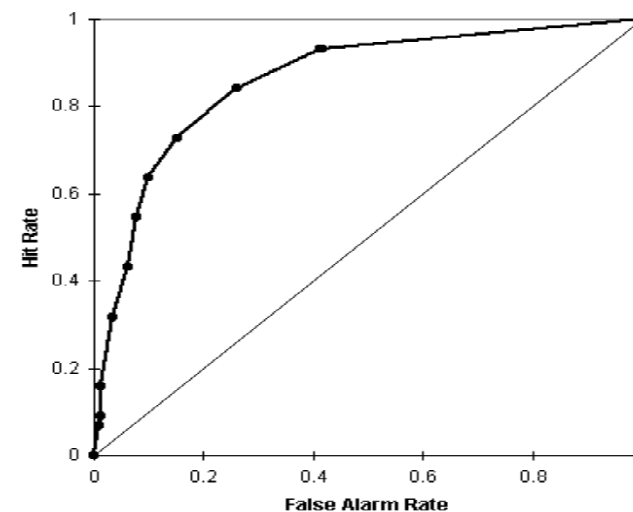
Want **AUC** close to **1** as possible (translates to high Probability of Detection (**POD**) and low Probability of False Detection (**POFD**))

The **ROC** can be considered as a measure of potential **usefulness**

| Event<br>Forecast | Event Observed |          |
|-------------------|----------------|----------|
|                   | Yes            | No       |
| Yes               | <b>a</b>       | <b>b</b> |
| No                | <b>c</b>       | <b>d</b> |

$$HIT = \frac{a}{(a + c)} \quad POFD = \frac{b}{(b + d)}$$

Sample ROC Curve



# Comparison of EPSs



|                  |                                                                                |
|------------------|--------------------------------------------------------------------------------|
| <b>AUC = 0.5</b> | <b>No discrimination/prediction skill (equal to climatology)</b>               |
| <b>0.6-0.7</b>   | <b>Poor discrimination/prediction skill (slightly better than climatology)</b> |
| <b>0.7-0.8</b>   | <b>Acceptable</b>                                                              |
| <b>0.8-0.9</b>   | <b>Excellent</b>                                                               |
| <b>&gt;0.9</b>   | <b>Outstanding</b>                                                             |

# Comparison of EPSs



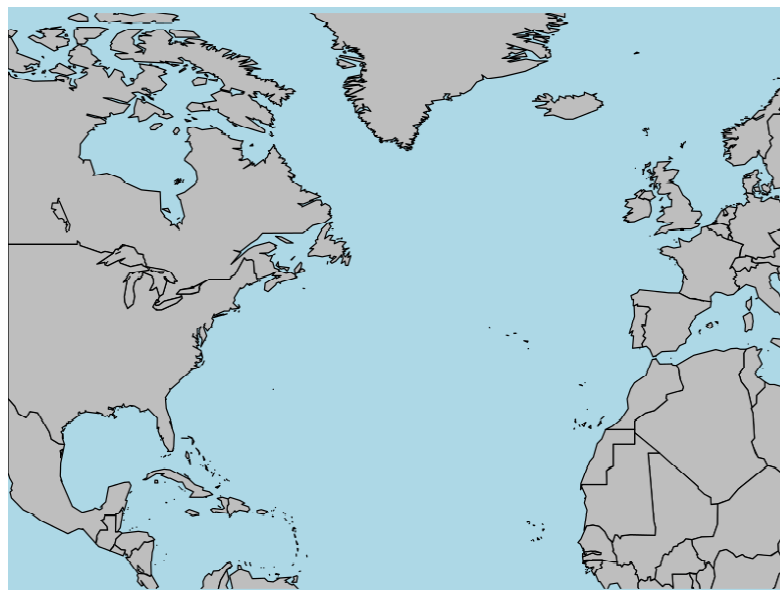
|                  |                                                                                |
|------------------|--------------------------------------------------------------------------------|
| <b>AUC = 0.5</b> | <b>No discrimination/prediction skill (equal to climatology)</b>               |
| <b>0.6-0.7</b>   | <b>Poor discrimination/prediction skill (slightly better than climatology)</b> |
| <b>0.7-0.8</b>   | <b>Acceptable</b>                                                              |
| <b>0.8-0.9</b>   | <b>Excellent</b>                                                               |
| <b>&gt;0.9</b>   | <b>Outstanding</b>                                                             |

4 different model configurations compared using AUC score

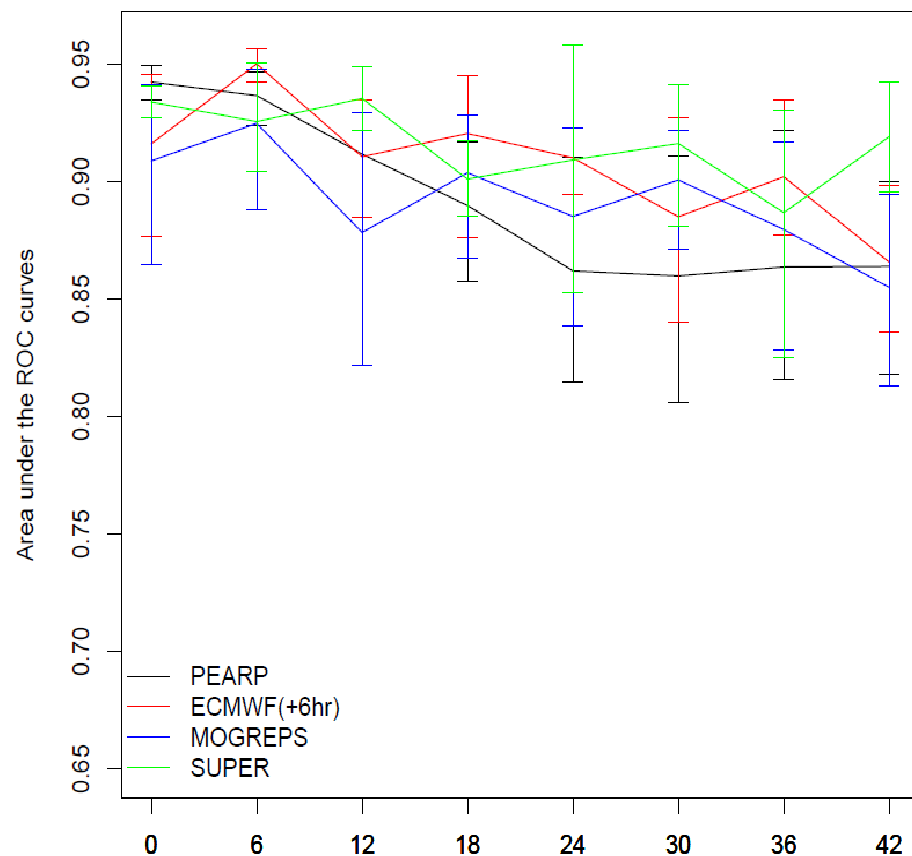
One month (**Jan 2015**) of observed **AMDAR** wind data at **FL340** compared to wind forecast by **model** at **250hPa**

Large dataset and thus **statistically robust** verification of model ability

**Domain: 75N-  
10N, 105W-15E**

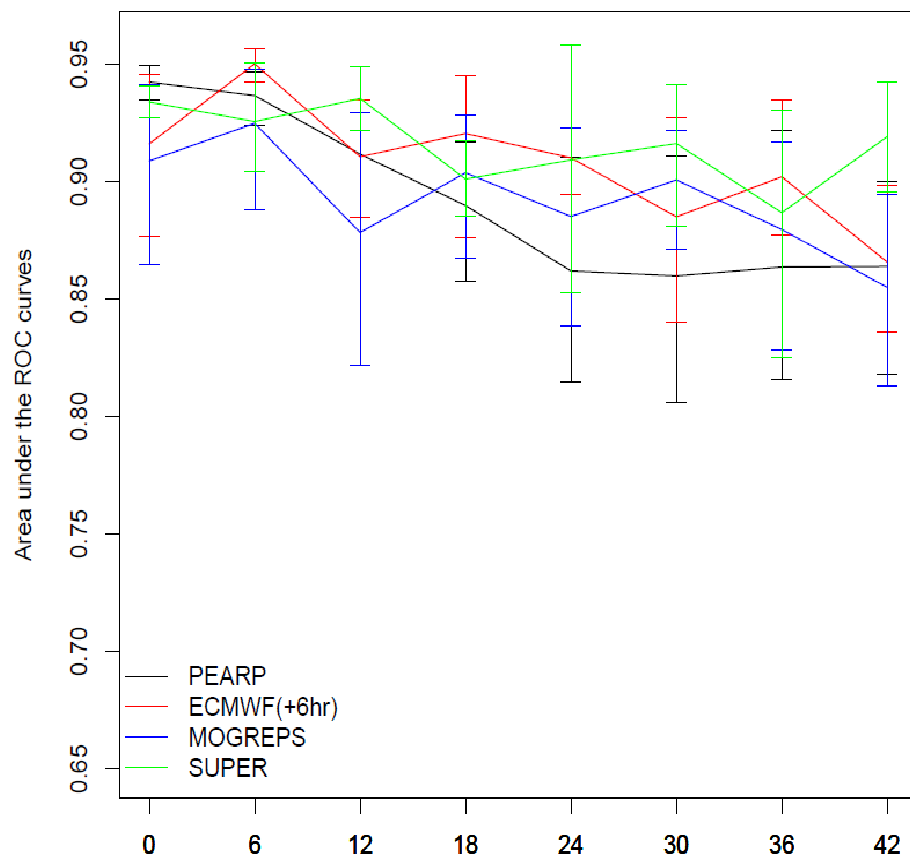


# Comparison of EPSs

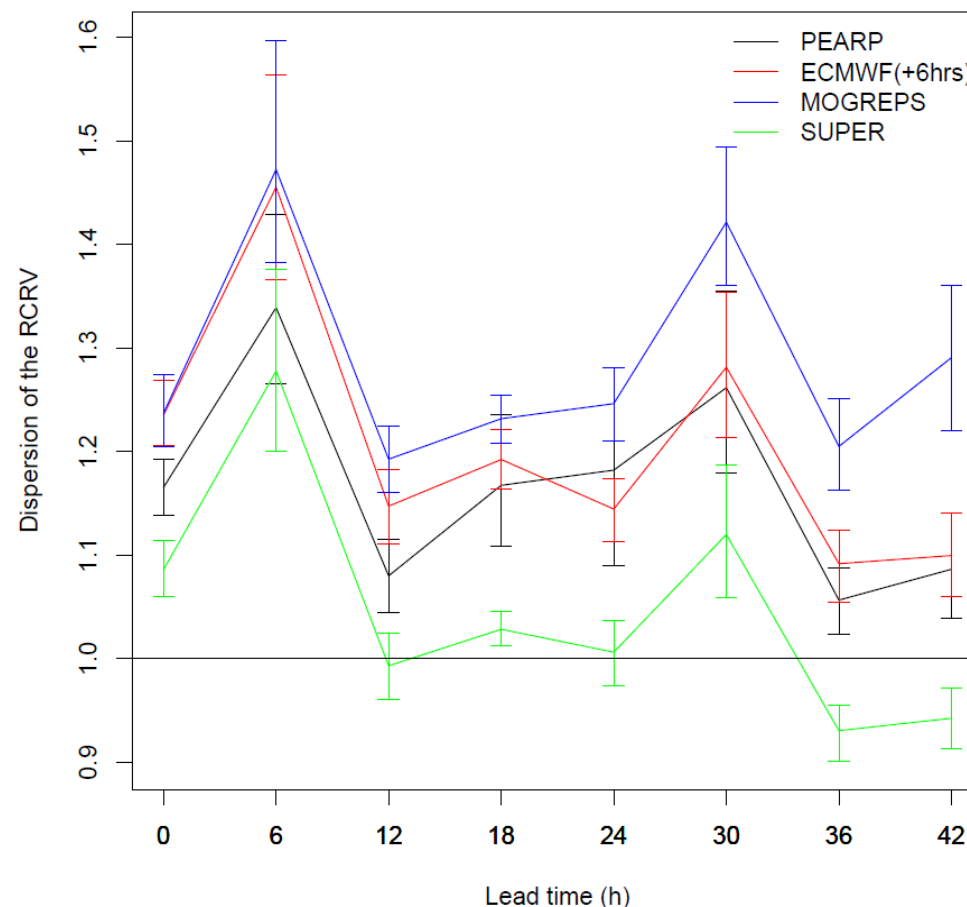


**AUC** score between **0.85** and **0.96** demonstrates **excellent** model resolution

# Comparison of EPSs



**AUC** score between **0.85** and **0.96** demonstrates **excellent** model resolution



Dispersion of **RCRV** score illustrates **models' spread**

**SUPER** (multi-model ensemble) has greatest spread at +36hr lead time

# Overview



- Introduction
- Ensemble Prediction System (EPS)
  - Comparison of EPSs
- **Methodology (EPS + TP)**
- Example Case
- Conclusions and Future Work

# Methodology

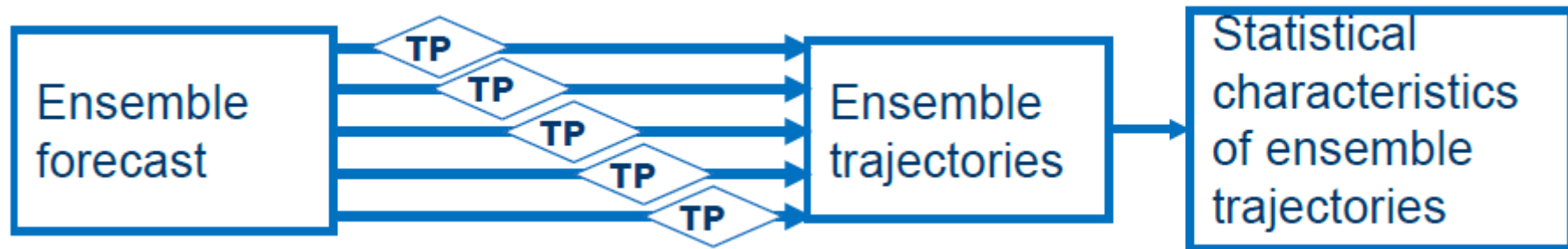


## Probabilistic Trajectory Prediction (PTP)

# Methodology



## Probabilistic Trajectory Prediction (PTP)



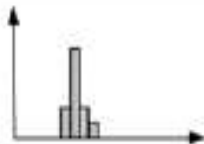
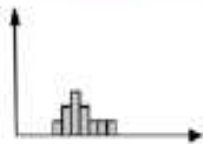
### Ensemble of trajectories

Represents **uncertainty** related to uncertainty in **MET forecasts**

Gives a degree of **uncertainty** on important **flight parameters**

# Methodology



|              |                  | Predicted Trajectory →                                                            |                                                                                     |     |                                                                                     |
|--------------|------------------|-----------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|-----|-------------------------------------------------------------------------------------|
|              |                  | $T^1$                                                                             | $T^2$                                                                               | ... | $T^m$                                                                               |
| ← EWF member | EWF member 1     | $t_{11}$                                                                          | $t_{12}$                                                                            | ... | $t_{1m}$                                                                            |
|              | EWF member 2     | $t_{21}$                                                                          | $t_{22}$                                                                            | ... | $t_{2m}$                                                                            |
|              | ...              | ...                                                                               | ...                                                                                 | ... | ...                                                                                 |
|              | EWF member $n$   | $t_{n1}$                                                                          | $t_{n2}$                                                                            | ... | $t_{nm}$                                                                            |
|              | PDF of $t_{.,m}$ |  |  | ... |  |

← predicted trajectory  
integrated parameter

# Methodology



|              |                  | Predicted Trajectory → |          |     |          |
|--------------|------------------|------------------------|----------|-----|----------|
|              |                  | $T^1$                  | $T^2$    | ... | $T^m$    |
| ← EWF member | EWF member 1     | $t_{11}$               | $t_{12}$ | ... | $t_{1m}$ |
|              | EWF member 2     | $t_{21}$               | $t_{22}$ | ... | $t_{2m}$ |
|              | ...              | ...                    | ...      | ... | ...      |
|              | EWF member $n$   | $t_{n1}$               | $t_{n2}$ | ... | $t_{nm}$ |
|              | PDF of $t_{.,m}$ |                        |          | ... |          |

← predicted trajectory  
integrated parameter

**High** projected cost (flight time/fuel)

But **low** uncertainty



← predicted trajectory  
integrated parameter

**High** projected cost (flight time/fuel)  
But **low** uncertainty

**Lower** projected cost  
(flight time/fuel)  
But **higher** uncertainty

# Overview



- Introduction
- Ensemble Prediction System (EPS)
  - Comparison of EPSs
- Methodology (EPS + TP)
- **Example Case**
- Conclusions and Future Work

# Example Case



A **12 member MOGREPS** ensemble was used as input to a simple TP system for a case study flight from **London (EGLL) to New York (KJFK) on the 25th of January 2015**

**Trajectories** shown in each **panel** with the **Probability Density Function (PDF)** of the flight times for each trajectory shown in the **bottom right**

The **grey bars** represent the **standard deviation of the flight times**

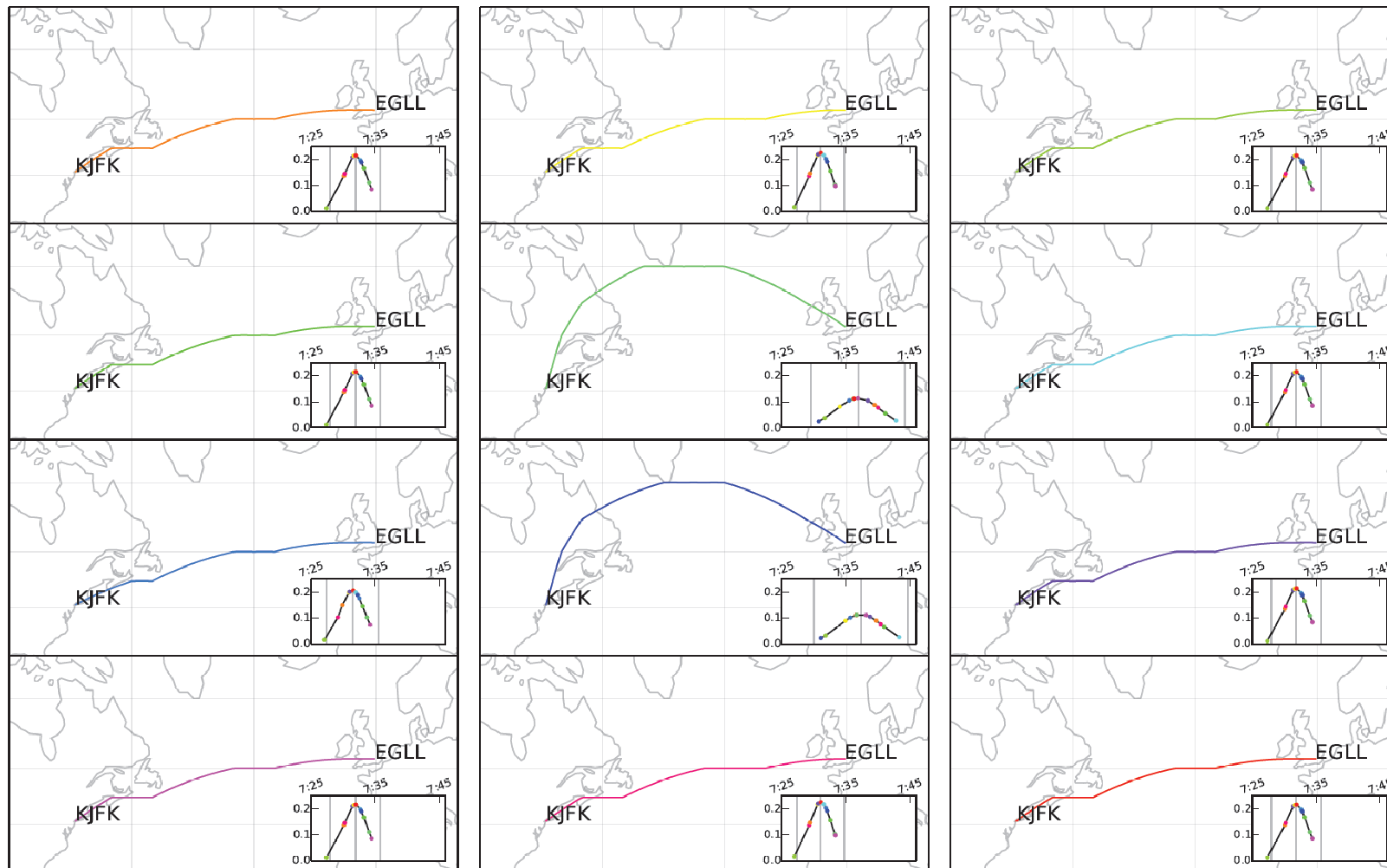
# Example Case



A **12 member MOGREPS** ensemble was used as input to a simple TP system for a case study flight from **London (EGLL) to New York (KJFK) on the 25th of January 2015**

**Trajectories** shown in each **panel** with the **Probability Density Function (PDF)** of the flight times for each trajectory shown in the **bottom right**

The **grey bars** represent the **standard deviation of the flight times**



# Overview



- Introduction
- Ensemble Prediction System (EPS)
  - Comparison of EPSs
- Methodology (EPS + TP)
- Example Case
- **Conclusions and Future Work**

# Conclusions



A universal methodology has been proposed which incorporates ensemble prediction systems (EPSs) into existing deterministic TP systems.

# Conclusions



- A universal methodology has been proposed which incorporates ensemble prediction systems (EPSs) into existing deterministic TP systems.
- Using specific metrics, we have shown that the EPSs are capable of capturing specific nominal weather 36 hours before take-off time. A combination of the EPSs further improves performance.

# Conclusions



- A universal methodology has been proposed which incorporates ensemble prediction systems (EPSs) into existing deterministic TP systems.
- Using specific metrics, we have shown that the EPSs are capable of capturing specific nominal weather 36 hours before take-off time. A combination of the EPSs further improves performance.
- A trajectory ensemble was generated using each member of an EPS. A representation of the uncertainty involved in each member of the trajectory ensemble was demonstrated to help in decision making by providing a range of trajectory cost (flight time, fuel) values.

# Conclusions



- A universal methodology has been proposed which incorporates ensemble prediction systems (EPSs) into existing deterministic TP systems.
- Using specific metrics, we have shown that the EPSs are capable of capturing specific nominal weather 36 hours before take-off time. A combination of the EPSs further improves performance.
- A trajectory ensemble was generated using each member of an EPS. A representation of the uncertainty involved in each member of the trajectory ensemble was demonstrated to help in decision making by providing a range of trajectory cost (flight time, fuel) values.
- This would allow TP users to select a suitable trajectory according to their optimum cost distributions.

# Future Work

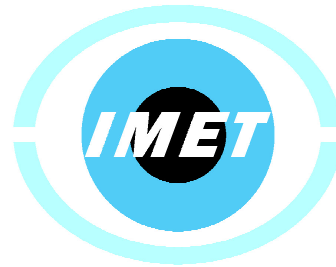


Our **approach** is currently being validated within **WP11.1**

Extend the approach to the **time interval** close to the **execution** phase using **nowcasting**

Further developments on **Ensemble Weather Forecast (EWF)** **optimisation**, e.g. ensemble weighting

# Thank you for your attention



Alan Hally, Jacob Cheung, Jaap Heijstek,  
Adri Marsman, Jean-Louis Brenguier

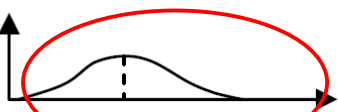
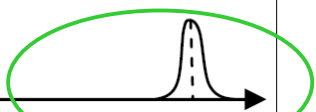
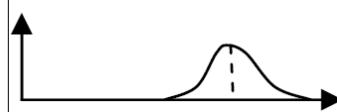


SESAR INNOVATION DAYS, 1st-3rd  
Dec. 2015, Bologna



# Methodology



| TP \ Cost | $T^1$                                                                               | $T^2$                                                                                | ... | $T^m$                                                                                 |
|-----------|-------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------|-----|---------------------------------------------------------------------------------------|
| Weather 1 | $t_{11}$                                                                            | $t_{21}$                                                                             | ... | $t_{m1}$                                                                              |
| Weather 2 | $t_{12}$                                                                            | $t_{22}$                                                                             | ... | $t_{m2}$                                                                              |
| ...       | ...                                                                                 | ...                                                                                  | ... | ...                                                                                   |
| Weather n | $t_{1n}$                                                                            | $t_{2n}$                                                                             | ... | $t_{mn}$                                                                              |
| PDF       |  |  |     |  |

**Low** projected cost (flight time/fuel)

But **high** uncertainty

**Higher** projected cost (flight time/fuel)

But **lower** uncertainty