MET Services for environmental optimisation

Climate-optimised aircraft trajectories

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***Abstract*— Aviation provides mobility and the aviation sector is increasing. Currently, the contribution of aviation operations is contributing to climate change by roughly 5%. This contribution stems from CO_2 emissions and non-CO_2 effects, such as contrail formation or ozone formation from NO_x emissions. Here, we address the potential to significantly reduce this climate impact, by climate optimal routing, i.e. avoiding climate sensitive regions in the atmosphere. We present, advanced MET-Services, which enable the forecasting of, e.g. NO_x climate impacts, on a daily basis. These so-called algorithmic climate change functions provide the information on the expected climate impact for a local emission and can directly be used in air trajectory optimization tools. We show that these regions can be avoided with only small changes in flight time and at low costs. Moreover, if, e.g., market-based measures were in place, which include these non-CO_2 effects, climate optimal routing would even be beneficial for airline operators. We address further steps, required to bring such a concept into operation.**

Keywords:-Climate, Contrails, Nitrogen oxides, Mitigation, Advanced MET-Service

I. INTRODUCTION

Aviation is a growing sector providing long-range mobility. The emissions of air traffic effects the atmospheric composition and hence climate. It currently contributes to the anthropogenic climate change by roughly 5% [1, 2]. This warming arises from emissions of CO_2 and of non-CO2 effects, which cause even a larger warming than CO_2. These non-CO_2 effects are the formation of contrails and the emission of NO_x, H_2O and particles.

In the light of the Paris international agreement to limit global warming by 2°C, aviation faces a challenge, since it not only contributes to climate change, but has also large annual growth rates in the order of 3-5%. As a consequence there are activities to limit the climate relevant emissions, such as CO_2, by various means, such as fuel efficient technologies and operations, as well as biofuels [3].

However, there are also means to reduce the aviation climate impact by reducing non-CO_2 effects, e.g. by avoiding warming contrails [4-7] or more effectively by avoiding climate sensitive regions [8, 9].

Here, we present results of the SESAR2020 Exploratory Research project ATM4E (Air Traffic Management for Environment, [10]), focusing on two aspects: (1) How to make information on climate sensitive regions available on a routinely basis (advanced MET-Services, Section II) and (2) what potential consequences the application of these Services on the air traffic has (Section III).

II. ADVANCED MET-SERVICE: ALGORITHMIC CLIMATE CHANGE FUNCTIONS AS PREICTORS FOR CLIMATE SENSITIVE REGIONS

Climate-Change-Functions (CCFs, [11, 12]) are 5D data sets (longitude, latitude, altitude, time, type of emission), which describe the specific climate impacts, i.e. the anticipated climate change for a local emission, or in other words, the climate change per flown kilometer and per emitted masses of the relevant species. Within the EU-project REACT4C (www.react4c.eu) high fidelity CCFs were computed for 8 representative weather situations for the North Atlantic [9, 13]. These were used in ATM4E to derive algorithms, which estimate the basic response and which can easily be implemented in any numerical weather prediction model (NWP) and thereby advancing the MET-Services.

A. High fidelity CCFs

In order to establish relations between localized emissions and their impact on climate we applied the EMAC model and released emissions at roughly 500 points in the atmosphere in the North-Atlantic region. The transport of these emitted species is calculated by 50 air parcel trajectories and microphysical processes are included to simulate contrail formation, ice particle sedimentation, and sublimation.

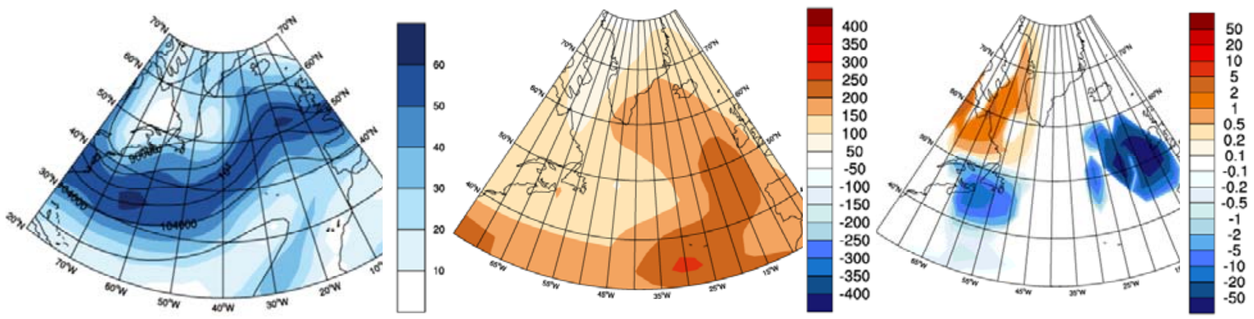

Figure 1: Climate-change-function for weather pattern 2: Left: geopotential (isolines, m2/s2) and wind speed (color, m/s); Mid: Ozone CCF (10^{-14} K/kg(NO_2); Right Contrail-CCF (10^{-14} K/km) [13]. Note that the left figure has a slightly larger cut-out.

A detailed chemical mechanism provides the evolution of contributions of the initial NO_x emission to the greenhouse gases ozone and methane. Washout processes (rain) and dry deposition is parameterized to account for the removal of the emitted species. Radiation calculation provides radiative forcing (RF; stratosphere adjusted) of the changes due to contrails and ozone, and radiation parameterizations provide estimates for the RF from water vapor, methane and carbon dioxide. These are then fed into climate metrics to provide estimates of the climate impact. Here we concentrate on one of the metrics, the average temperature response over 20 years (ATR20), since the results are almost independent of the chosen metric. The CCFs were calculated for 5 representative winter and 3 summer weather situations, following classification of Irvine [14]. Figure 1 shows exemplarily the winter weather pattern 2 (WP2) with a strong jet (dark blue) and a high pressure ridge, which reaches from Africa to the tip of Greenland. In this high pressure ridge, the Ozone –CCF shows a maximum. Contrail-CCFs (right) show positive (warming) and negative (cooling) climate impacts.

B. *Algorithmic CCFs*

The calculation of these climate-change-functions requires a large amount of computing time. It is not applicable to numerical weather forecasts. Therefore, within ATM4E; we have started to develop algorithmic climate change functions (aCCF), which represent a correlation of the weather system at the time of emission and the respective CCF. We have developed these functions for all regarded effects, i.e. the impact of water vapour emissions on climate, NO_x emissions on ozone and methane, separately [15] and the impact on contrails, separated for day and night contrails. Here we present exemplarily the H_2O-aCCF, where

$$aCCF^{H_2O}(PV,F) = (a + b \cdot PV) \cdot F \qquad (1)$$

with a=0.41 10^{-15} K/kg-fuel, b=1.5 10^{-16} K/PVU/kg-fuel, PV the potential vorticity in PV-Units, 1 PVU=10^{-6} K m^2/kg/s, and F the fuel consumption in kg-fuel.

Figure 2 (top) shows an example for H_2O-aCCFs. Above the tropopause the H_2O-CCF increases strongly (bottom). Obviously, the major trend between emission locations in the troposphere and stratosphere is captured by the PV approach, since large (small) PV values are typical for stratospheric (tropospheric) air masses. However, significant deviations are also visible.

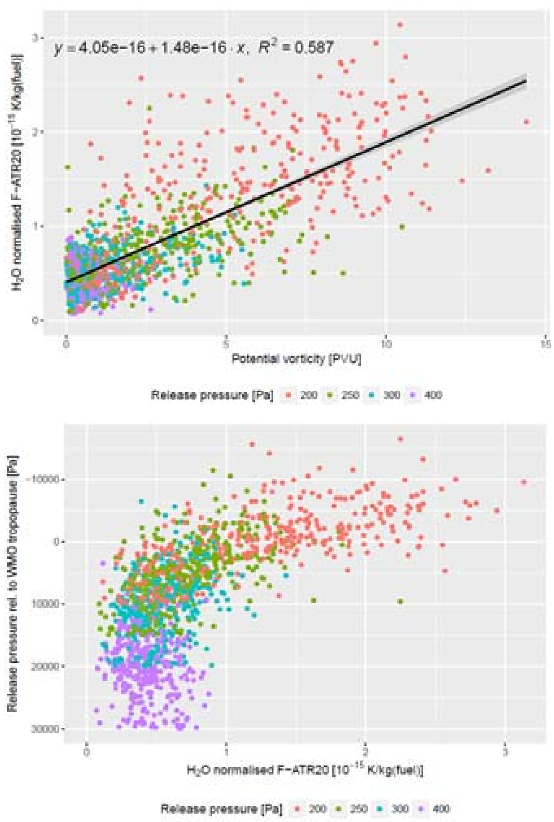

Figure 2: Top: Correlation of PV with H_2O-CCF. Bottom: Comparison of H_2O-CCF (circles) with air pressure relative to the tropopause.

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III. Impact on Air Traffic

Climate sensitive regions represent a further objective function in the optimization [9, 10]. Hence this will have an impact on air traffic. For example, in areas with high traffic density a further objective function or constraint might have a severe impact on the controller's work load. The first step to evaluate this effect is to understand the air traffic flow changes, which are arising from climate optimal trajectories. Section III.A shows air traffic changes when avoiding regions where contrails form, Section III.B then gives an example for climate-optimized air traffic and Section C gives an outlook how costs changes and climate changes are related, based on the REACT4C project.

A. Contrail avoidance

The variability of trajectories for contrail avoidance has been thoroughly studied for a sample of transatlantic flights based on an annual simulation. The detailed discussions are presented in [7]. An example from the analysis is presented in the current section.

A multi-objective optimization strategy is employed to mitigate the contrail distance while minimizing the flight time. The objective function is constructed as in Eqn. (2).

$$f = (1-\alpha)\cdot t + \alpha \cdot K \cdot Dist_{CPC} \quad (2)$$

where t is the total flight time; $Dist_{CPC}$ is contrail distance as a product of contrail potential coverage and flight distance; K is a coefficient calculated by Eqn. (3) with a unit of time/distance, which indicates the time variation per unit reduction in the contrail distance; and α is a weigh control factor between [0, 1] to adjust the proportion of each objective.

$$K = \frac{t_{dist\_opt} - t_{t\_opt}}{Dist_{dist\_opt} - Dist_{t\_opt}} \quad (3)$$

where the subscript *dist_opt* represents the contrail distance fully optimal scenario; and the *t_opt* represents the flight time fully optimal scenario.

Depending on α value, six optimization scenarios are formed as provided in Table 1. When α equal zero, the optimizer minimizes flight time, and α equals one represents a minimal contrail distance condition. Any situations in between correspond to a partial mitigation strategy in contrail distance with different levels of reduction rates.

Table 1: The optimization scenario for given α value.

α value	Scenarios
0	Time_opt
0.2	Dist_CPC_0.2
0.4	Dist_CPC_0.4
0.6	Dist_CPC_0.6
0.8	Dist_CPC_0.8
1.0	CPC_opt

The simulation is performed with the Earth-System Model ECHAM/MESSy Atmospheric Chemistry (EMAC). The EMAC model is a numerical chemistry and climate simulation system that includes sub-models describing tropospheric and middle atmosphere processes and their interaction with oceans, land and human influences [16]. The model setup concerning the current study comprises of the sub models: AIRTRAF version1.0 [17] and CONTRAIL (supplementary of [11]). The detailed information on simulation setup is provided in Table 2.

Table 2: Trajectory optimization setup

Descriptions	**Specifications**
Flight plan	103 transatlantic flights (51eastbound/52westbound)
EMAC resolution	T42L31ECMWF (2.8° × 2.8° in latitude and longitude, 31 vertical pressure levels up to 10 hPa)
Simulation period	Annual simulation (201101-201112)
Aircraft/Engine	Current state of art long range aircraft/engine configuration
Altitude constrains	[FL290, FL410]/[8850m,12500m]
Mach number	0.82

The daily mean variation of flight time and contrail distance with respect to the time optimal scenario over the simulated year is presented in Figure 3. The results of the trajectory variability are grouped with respect to the four seasons. Each of the coded color area represents the variability in one season. The figure shows clear differences in the daily variability of the Pareto Front. It can be observed that for the same increase in flight time, the reduction in contrail distance varies in a wide range. The largest discrepancy exhibits between winter (December, January, and February (DJF)) and summer (June, July and August (JJA)).

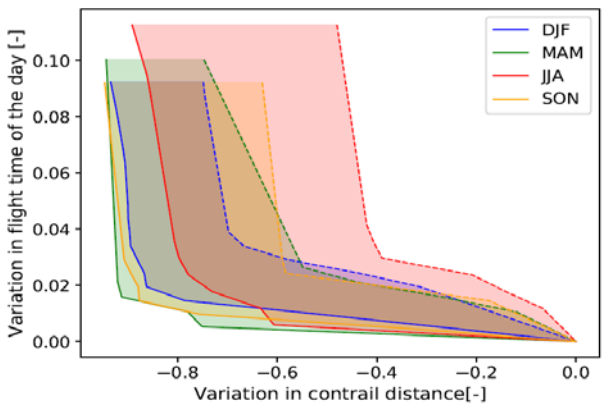

Figure 3: Variation in contrail distance and flight time among different seasons. The dashed curve indicates the minimal reduction in contrail distance. The solid line represents the maximal reduction in contrail distance. DJF is winter, MAM is spring, JJA is summer, and SON is autumn [7].

The lateral and vertical shifts of the trajectories, which are simulated to achieve the variability in Figure 3, are presented in Figure 4 and Figure 5, respectively. Both, latitude and altitude are averaged along the flight trajectory. In each season, there are five boxplots, which are corresponding to different degrees of reduction in the given season controlled by the weight factor (α).

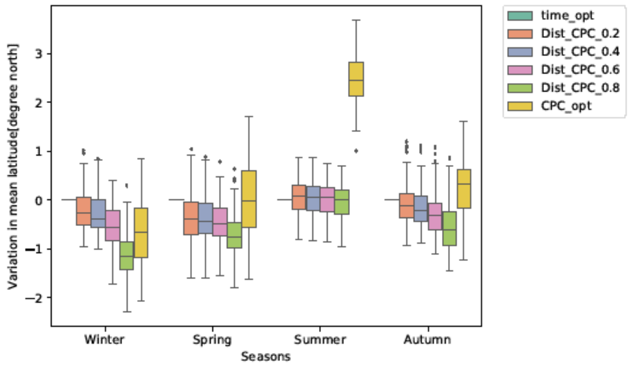

Figure 4: The lateral shifts in each season: winter (DJF), spring (MAM), summer (JJA), autumn (SON) [7].

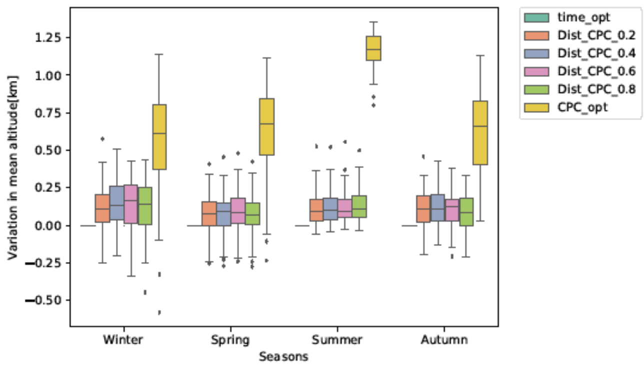

Figure 5: The vertical shift in each season: winter (DJF), spring (MAM), summer (JJA), autumn (SON) [7].

For partial mitigation in contrail distance, the flights tend to shift slightly to higher altitudes and southwards. As the reduction in contrail distance increases, the more southward the flights tend to be. The vertical change remains nearly identical for the partial mitigation of contrail distance. However, one could observe that only the lateral shift is not satisfactory to achieve the full mitigation in contrail. Therefore, the flight altitude increases significantly by 0.5 km to 0.7 km until it reaches the uppermost troposphere to lowermost stratosphere, where the air is dry hence minimal possibility to form contrails. It is also noticeable that the aforementioned tendency is valid in most of the seasons except for summer.

The average lateral shift in summer (JJA) shows slightly northward in the contrail partial mitigation situations, which is opposite to the behaviors in non-summer seasons. As for the minimal contrail distance trajectories, an increase in altitude by more than 1 km occurs in combination with a northwards shift by nearly 3 degree.

B. Climate optimized air traffic

Within ATM4E, climate-optimized flight trajectories are determined with the Trajectory Optimization Module (TOM). It is based on an Optimal Control approach and hence optimizes the control input (e.g. thrust, heading) such that a given cost functional is minimized while satisfying dynamic constraints [18]. These dynamic constraints constitute a set of simplified equations of motion in three degrees of freedom assuming a point-mass model with variable mass for the aircraft. The aircraft performance is modeled using EUROCONTROL's Base of Aircraft Data (family 4). Engine emissions are estimated by assuming a stoichiometric combustion for CO_2 and H_2O. In contrast, NO_x emissions are obtained by applying the Boeing Fuel Flow Method 2 [19].

The cost functional for each optimized trajectory is defined as the weighted sum of direct operating costs (DOC) and climate impact, measured as average temperature response (ATR). DOC and ATR values are normalized with respect to corresponding reference values according to Eqn. (4). Both, DOC and ATR values are multiplied with corresponding weighting factors (C_{DOC}, C_{ATR}). Pareto optimal trajectories are obtained by varying the weights of DOC and ATR.

$$J = C_{DOC} \cdot \frac{DOC}{DOC_{ref}} + C_{ATR} \cdot \frac{ATR}{ATR_{ref}} \tag{4}$$

$$C_{DOC} + C_{ATR} = 1$$

Additionally, it is intended to integrate local air quality as well as noise issues in the cost functional (see paper Matthes et al.).

Figure 6 shows example climate optimized trajectories on the trans-Atlantic route from point 2 to point C. Laterally and vertically (3D) optimized trajectories are shown in black, only laterally (2D) optimized trajectories are illustrated in blue. Wind data and climate change functions, which are obtained from winter weather pattern 1 (see section II.A), are shown at an altitude of 10,500 m. COC-optimal trajectories (C_{DOC}=1) are represented by the black (3D) and gray (2D) solid lines: both are shifted to the north of the great circle connection (blue) in order to avoid headwinds caused by the jet stream. If the climate weighting factor C_{ATR} is increased, trajectories are successively shifted to regions with lower climate sensitivities. As a result, flight time, fuel burn and hence DOC are increasing.

In ATM4E this approach is used to optimize one representative day of European air traffic and study the implications to the ATM network. Based on meteorological considerations and traffic characteristics we selected December 18, 2015 from a set of candidate days. As a reference we obtained actual flight data from EUROCONTROL's Demand Data Repository for that day and only focus on intra-European flight that both depart and land on that day and which are operated by aircraft contained in the BADA model database. A resulting dataset of nearly 13300 flights is compiled in this way, which contributes to approximately 2.4 billion of Available Seat Kilometers (ASKs). This reference traffic produces about 150 thousand metric tons of CO_2 emissions and more than 700 metric tons of NO_x emissions. Flights, which are filtered out, are not optimized with regard to environmental aspects, but will be considered as "background" flights within the hotspot analysis.

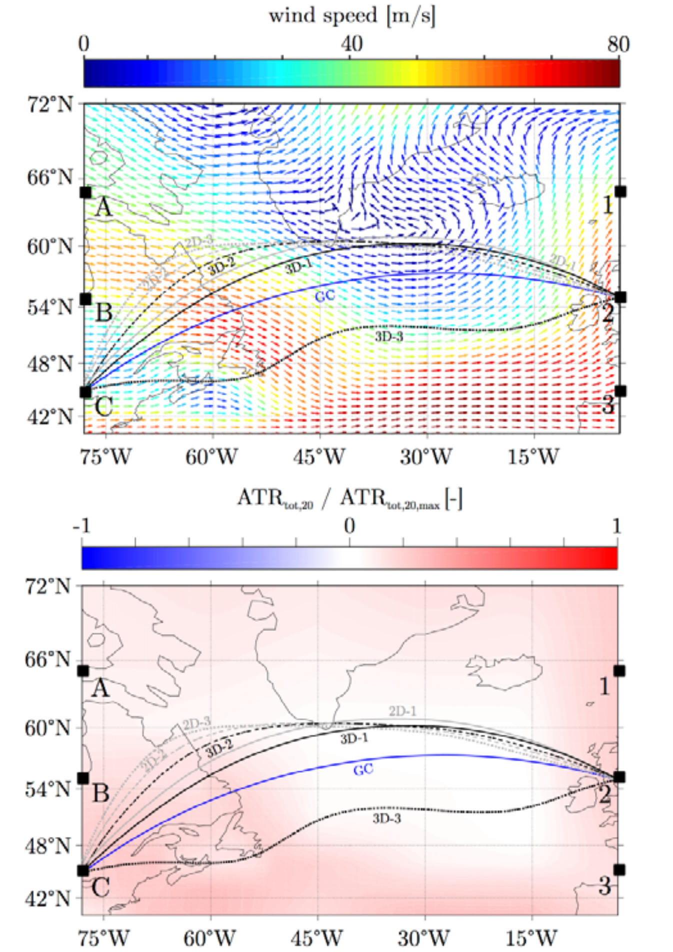

Figure 6: Lateral plots of climate optimized trajectories on the trans-Atlantic route from point 2 to point C with varying weighting factors. Wind speeds and directions (top) and total climate change functions (bottom) are shown for a flight altitude of 10,500 m. Lines represent optimized trajectories with regard to COC (solid) and ATR (dotted). Pareto-optimal solutions are depicted as dashed lines. 3D (vertically and laterally) optimized trajectories are colored in black. 2D (laterally) optimized trajectories are colored in gray. The great circle connection is shown in blue [18].

C. *Eco-efficiency of climate-optimized flying*

The CCFs for the 8 weather situations were included in the SAAM simulations, roughly 800 cross-Atlantic flights were considered and 84 arbitrary alternative trajectories for each route calculated. A Pareto-front showing the optimal change of costs (fuel and crew) and climate impact is derived relative to the situation, where all aircraft fly cost optimal (Figure 7, point of origin). The individual weather situations are weighted by their frequency of occurrence. The results clearly show a very flat Pareto-Front (Figure 7, top), indicating that there is a large potential to reduce the climate impact by small changes in the routing [9]. For some weather situations the difference between westbound and eastbound flights is prominent, e.g. for situation with a very strong zonal wind [8], in a climatological sense this effect is largely reduced, though still visible.

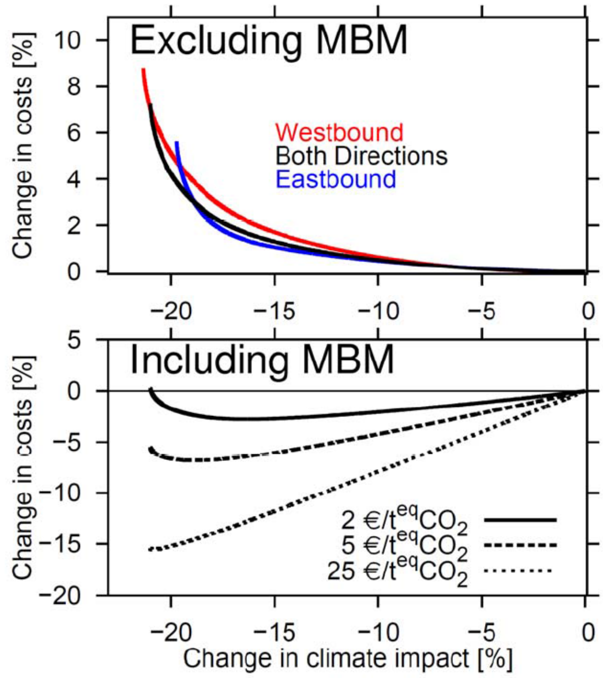

Figure 7: Optimal climate-cost relations for trans-Atlantic air traffic. The set of trans-Atlantic aircraft trajectories, which has minimum operational costs, is taken as the reference, i.e. the point of origin. Mean of 5 representative winter and 3 summer days averaged over the climatological frequency of all weather situations. West- and eastbound traffic is given relative to the climate impact of aviation flown west- and eastbound at minimum costs, respectively. Top: Fuel and crew costs are included; Bottom: Environmental costs are included in addition [9].

IV. Future Advanced MET-Services

Reducing the climate impact of aviation is a challenge not at least against the background of increasing transport demands. Here we propose climate-optimized aircraft trajectories and showed that using aCCFs (Section II), i.e. the required data describing these climate-sensitive regions, may well be generated routinely by a numerical weather prediction model and made available through services, such as SWIM, to any aviation stakeholder. These would then be available as forecasts with different forecasting horizons, as well as an analysis giving the best estimate for past situations.

V. Conclusion

Within ATM4E we were able to formulate simple algorithms describing the impact on global climate of a localized emission, for the first time. It is clear that a verification and uncertainty analysis of the aCCFs is required and first steps will be undertaken in ATM4E.

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