



Better Contrails Mitigation - BeCoM

D2.1

Tests of the assimilation of cloud measurements
within the ICON global forecasting system based
on the MFASIS operator of RTTOV

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Executive summary

Persistent cirrus clouds and contrails have a strong warming effect on the energy budget of the earth atmosphere and therefore constitutes the major non-CO₂ effect of world-wide air traffic systems. In order to enhance the predictability of cirrus and contrail formation in the higher atmosphere the NWP model should be able to reliably predict super saturated areas in time and scale and sufficient, high quality humidity observations should be available.

Besides relative humidity observations from conventional systems (radiosondes, aircrafts) the improved usage of satellite-borne measurements and direct camera images (all-sky data assimilation) should be focused on.

Three different approaches are developed – a first approach where the model cloud microphysics is linearized and the derivation is formed, an AI approach and an ensemble approach – to map cloud variables with control variables used within the data assimilation scheme of the NWP model.

The pros and cons of all three approaches will be discussed and a first real data assimilation cycle using reflectance observations of the 0.6 μm channel on board of Meteosat 11 was carried out.

First results showed, that both the AI approach and the ensemble approach have still some shortcomings and best results were obtained by using the classical approach using the linearized cloud microphysics of the ICON parametrization including their derivations.

List of abbreviations

NWP	Numerical Weather Prediction
ICON	Icosahedral Nonhydrostatic Modell
ECMWF	European Centre for Medium-range Weather Forecasts
MFASIS	Method for FAsT Satellite Image Simulation
RTTOV	Radiation Transfer for TOVS
ML	Machine Learning
AI	Artificial Intelligence

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1. Introduction

In order to enhance the predictability of strongly warming contrails in NWP models and flight weather forecasts two major conditions have to be fulfilled. The model should be able to reliably predict the contrail-cirrus formation regions in time and scale and sufficient, high quality humidity observations should be available to estimate the initial state of the atmosphere in flight level as accurate as possible.

Therefore, it is planned in this project to use, on the one side new aircraft-based humidity observation from the IAGOS infrastructure and to improve the assimilation of satellite-borne measurements and direct camera images in order to enhance the representation of ice clouds within their ambient humidity field, and within their dynamical background in NWP models.

Additionally, a first AI based algorithm was developed for the identification of contrails in satellite pictures as well as in direct camera images. In order to assimilate contrail information from satellite or camera images a mapping between cloud variables (cloud amount, cloud liquid water content and cloud ice water content) and control variables (temperature, wind, humidity) has to be computed.

There are three different approaches to achieve that. First you can use cloud and radiation parametrization of the NWP model and compute the tangent-linear and the adjoint of the parametrization in order to use the transformation in a variational DA system. Or AI methods can be used to derive the transformation relationships between control variables and cloud and radiation variables and thirdly, you can use the ensemble system of the data assimilation system to derive the necessary relationships between cloud and control variables.

Within this project all three approaches will be developed and tested in an operational data assimilation environment.

2. Detection and assimilation of high cirrus clouds and contrails

2.1 Contrail detection

In order to explore the use of high cloud and contrail measurements within the operationally used Ensemble-Variational Data Assimilation System of DWD to improve the representation of supersaturated humidity and the prediction of contrails, the high contrail-cirrus clouds have to be properly identified and appropriate detection and characterisation algorithms have to be developed. This is also important for a proper verification of the quality of model forecast results. In Work Package 3 such detection algorithms will be developed and documented and here only two preliminary results will be presented

Figure 1 and Figure 2 show examples of contrail detections in camera images (Figure 1) and satellite pictures (Figure 2) where the algorithms developed in Work Package 3 can successfully detect contrails in the presence of other cloud types and different cloud image scenes. In the camera image the contrails can be separated from other high level clouds and from the horizon. In the satellite picture, the detection algorithm is able to separate the high level contrails from lower level stratus clouds.

A comprehensive description of the detection algorithms and corresponding contrail detection examples can be found in the documentation papers of Work Package 3.

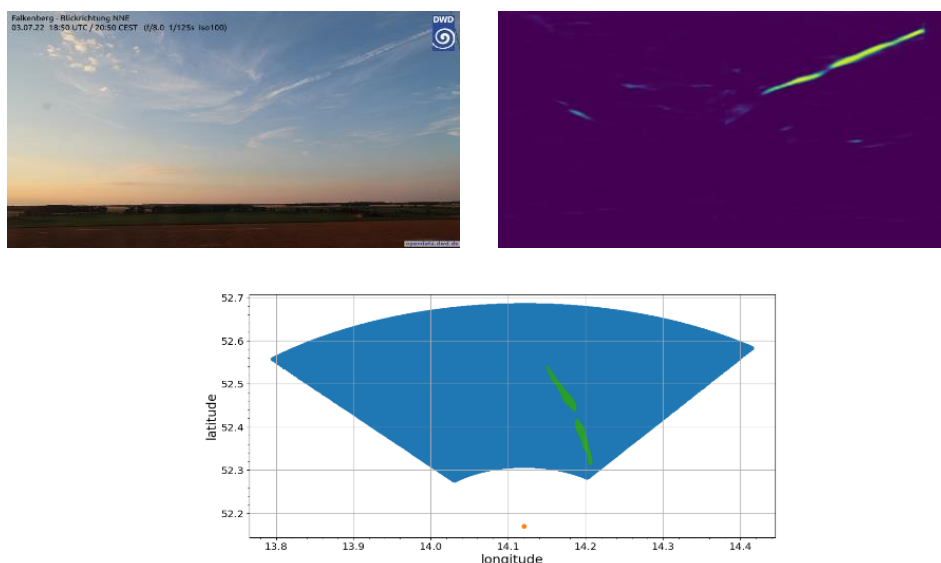


Figure 1: Contrail detection using a neuronal network. Left side: original camera image; right side: Contrail detection; below: projection in the plane

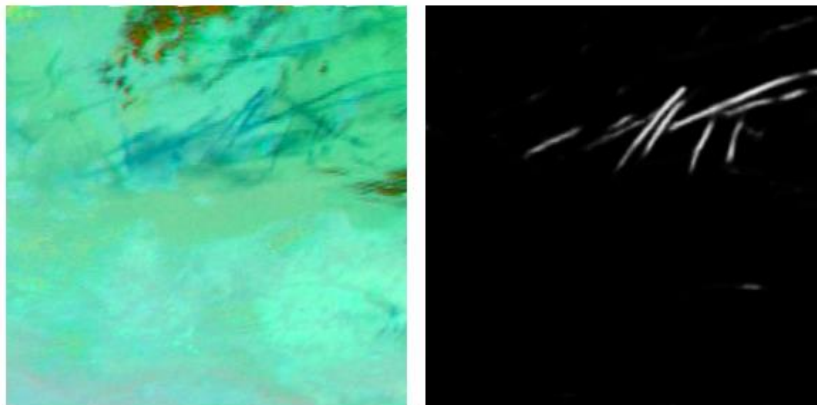


Figure 2: Contrail detection using the U-Net.

2.2 Observation Operator MFASIS

In order to assimilate visible satellite and camera images efficiently, an observation operator is necessary to map the observation variables onto the model variables. Therefore, the DWD in collaboration with the University of Munich in the framework of the German HerZ research program developed a fast and sophisticated observation operator called MFASIS to simulate satellite pictures and camera images in the visible spectral range. The MFASIS observation operator is used in the operational, local data assimilation system KENDA of DWD successfully and will be adapted for the use in the global data assimilation system ICON of the DWD within several national and European research projects including BeCoM.

Figure 3 compares a simulated $0.6\ \mu\text{m}$ SEVIRI channel of the global ICON Model with a real observed satellite image. In order to achieve consistency in resolution between the observed satellite image (3 km nadir) and the model resolution (here 40 km), the satellite observations are averaged onto the model resolution. Obviously, the observed cloud structures are well reproduced by the model cloud fields and larger differences are seen over tropical Africa and in the strong wind field zone in the Southern Hemisphere due to difficulties of the model to predict the clouds at the right place and time (see Fig 3 right difference image). A first evaluation period was started to identify systematic differences between simulated and observed satellite image in order to give hints to improve the cloud parametrization used in the model as well as to estimate an observation error and a possible bias correction in preparation for an future assimilation of camera and satellite images in the global NWP system of DWD.

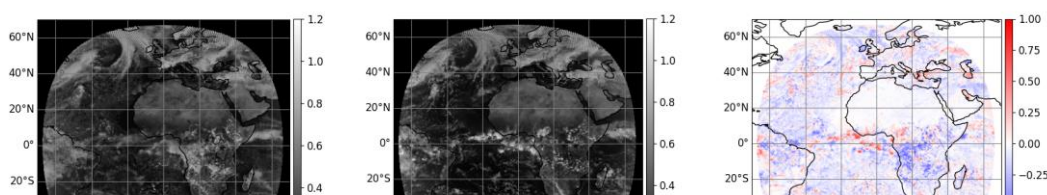


Figure 3: Comparison of a simulated Sevir satellite image using MFASIS and global ICON model fields (left) with an original Sevir satellite picture (middle) and the difference (left) for the $0.6\ \mu\text{m}$ channel of Sevir onboard Meteosat-11 for the 15 of March 2021, 12 UTC.

For example, a critical parameter for the correct simulation of observed satellite images in the visible spectral range is the effective radius separated for water and ice particles. Tests with different estimates of particle radii shows (Fig. 4) that the differences between the observed and simulated reflectance can't be explained by specifying only a correct effective radii but there must be additional effects not considered in the actual parametrization schemes which has to be taken into account.

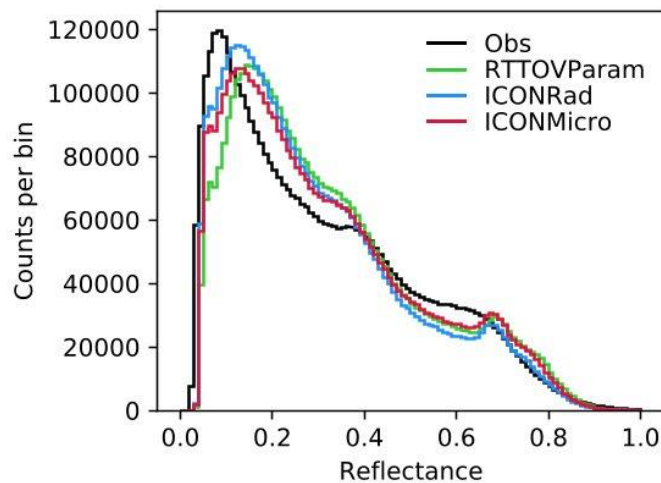


Figure 4: Frequency distribution of the observed reflectance compared to simulated reflectance with different choices of effective radii for water and ice clouds for the $0.6\ \mu\text{m}$ channel of Sevir on board of Meteosat-11 between 15 -21 Nov. 2020 and between 15 and 21 March 2021. For the simulation effective radii of RTTOV (RTTOVParam), effective radii from the radiation scheme of ICON and the one-moment microphysics were used.

2.3 Use cloud observations in the global DA system of DWD

In order to assimilate the identified contrail-cirrus clouds from satellite or camera images, the MFA-SIS observation operator will be used also in the global ensemble data assimilation system of DWD. To do so, several adaptations within the global data assimilation scheme have to be implemented. At the moment, only clear sky radiances are used in the global DA system. In order to assimilate also cloudy information from satellites or camera images, a mapping between cloud variables (cloud liquid/ice water content, cloud amount) and control (state) variables (temperature, humidity, wind) has to be computed in order to produce changes in the control variables in case a contrail or a cirrus cloud is detected in the satellite or camera image. In principal, three different approaches can be used (Fig:5).

- The classical approach is to compute the linearized derivations of the ICON cloud parametrization.
- To implement a novel AI approach, where the neuronal network learns the relationship between changes in the cloudiness resulting in changes in the humidity and temperature field.
- To use the Background Error Correlation Matrix used in our global data assimilation ensemble system to derive the correlations between control variables and cloud variables.

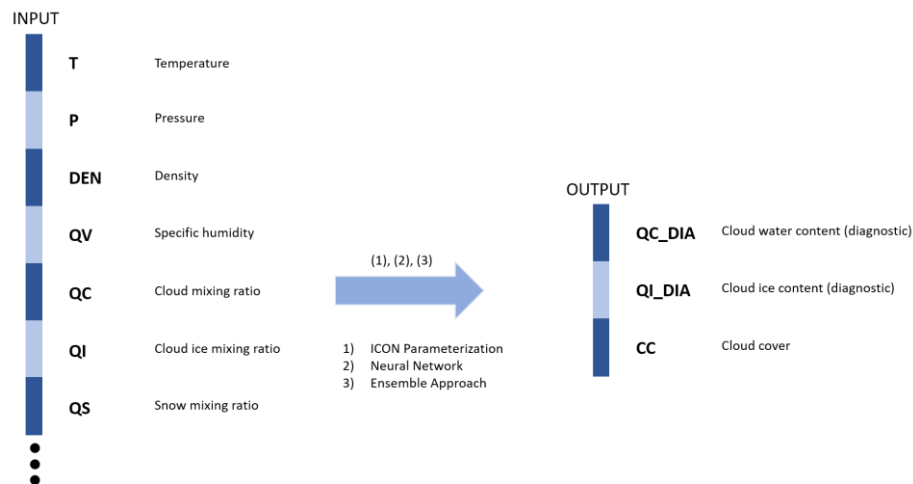


Figure 5 : Schematic illustration of the mapping between control variables of the data assimilation scheme (left side) and model cloud variables (right side)

Hereby, not only the functional dependency but also the derivations between the input and the output variables have to be taken into account, in order to use the cloud observations in a variational data assimilation method.

Within the BeCoM project the focus lies on the development of appropriate ML/AI methods to derive a mapping between cloud and control variables.

In the first approach, the ICON cloud parametrization has to be linearized and the corresponding derivations of the control variables depending on the cloud variables have to be computed. This requires the extension of the input/output variables of the DA system by the cloud variables and the differentiability of the cloud physics parametrization which was done first by hand and then by functions of specific Fortran libraries.

For the AI emulation of the dependencies between control and cloud variables several methods were tested. Figure 6 compares results of the classical method with results of the best AI method for the mapping of the control variables temperature and humidity with the corresponding cloud variables cloud cover, cloud water and cloud ice.

Obviously, the classical method is very sharp, detecting the low level water cloud and the high level cirrus cloud clearly, whereas the AI method tends to show multiple maxima and a broader distribution in general, especially for cloud ice.

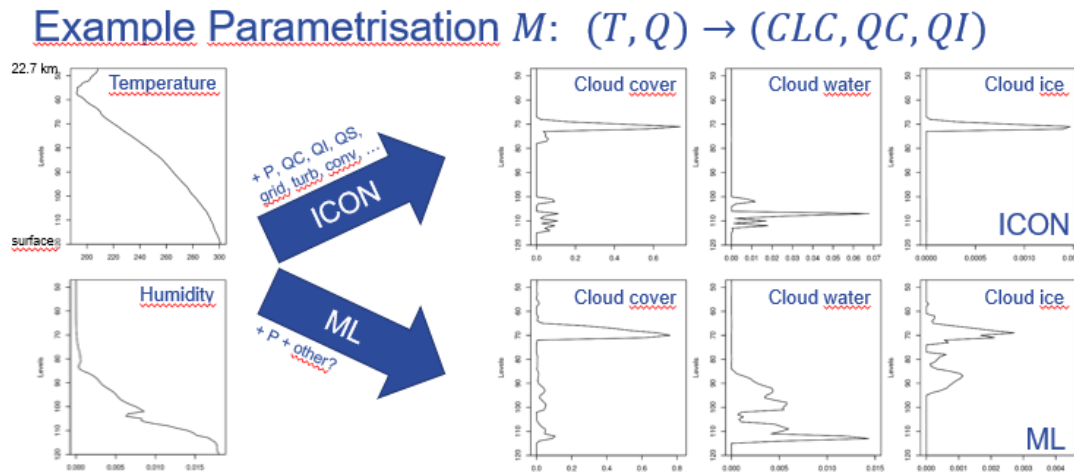


Figure 6 : Comparison of the classical and AI method to map the data assimilation control variables temperature and humidity onto the cloud variables cloud cover, cloud water and cloud ice for an arbitrary example.

For the emulation of the dependencies between control and cloud variables using ML techniques, different methods were tested.

- Multi- layer perceptron
- Column wise versus cell wise
- One model per output versus all at once
- Min-max normalization

ML - Technical implementation

→ Tensorflow/Keras library (python):

- train network
- save architecture, weights, biases, ...

→ Data Assimilation Coding Environment (fortran):

- rebuild network, load weights
- calculate allsky variables
- calculate derivatives
w.r.t. weights (iterative learning),
w.r.t. inputs



Figure 7: Schematic illustration of the technical implementation of the AI methods used for the training of the mapping between DA control variables and cloud variables

Based on the best possible method and the knowledge of the physical based processes a AI training module was written in python including a FORTRAN interface to our operational data assimilation code (Fig. 7). As output variables, the AI method uses all three cloud variables in order to enhance the forecast performance. This allows the training of the model in such way that all cloud variables can be adjusted in the training process simultaneously. First diagnostics of the quality of the training method

are estimated (Fig. 8). Using the first training set-up, the simulated reflectance are closer to the observed reflectance but the simulated cloud parameters show some changes which are not meteorological meaningful and have to be investigated further.

ML - RMSE – cloud cover

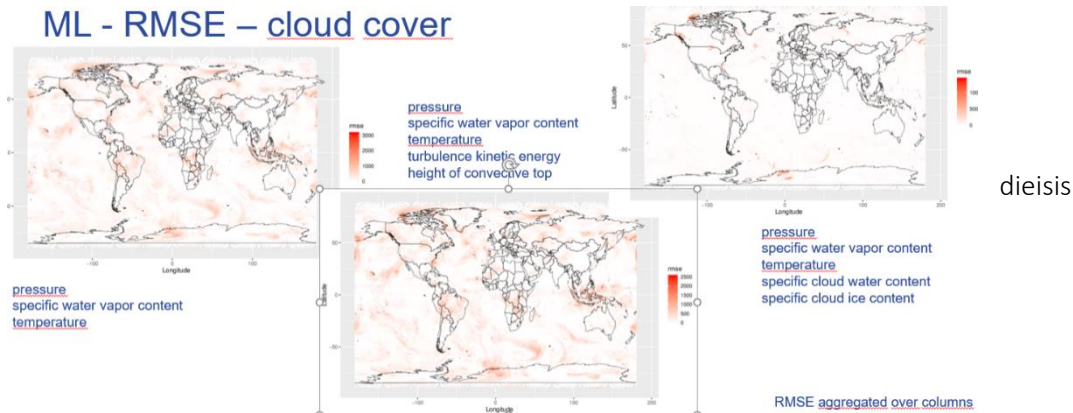


Figure 8: RMSE of observed minus ML trained cloud cover for three different AI training methods using different control variables as input for the ML training model.

The ensemble method uses the forty operational analysis ensembles to estimate the dependencies between control and cloud variables. In order to do that, the Moor-Penrose-Inverse of the ensemble matrix has to be solved.

Figure 9 illustrates comparisons of cloud profiles, between the physical based parametrization within the data assimilation scheme, the AI technique, the ensemble approach and the original ICON model implementation. Obviously, the errors between original ICON model and the physical based parametrization in the DA code are smallest (green curve). The other two methods show larger errors but in the same range. The minimization of these errors will be one major part of the remaining project duration.

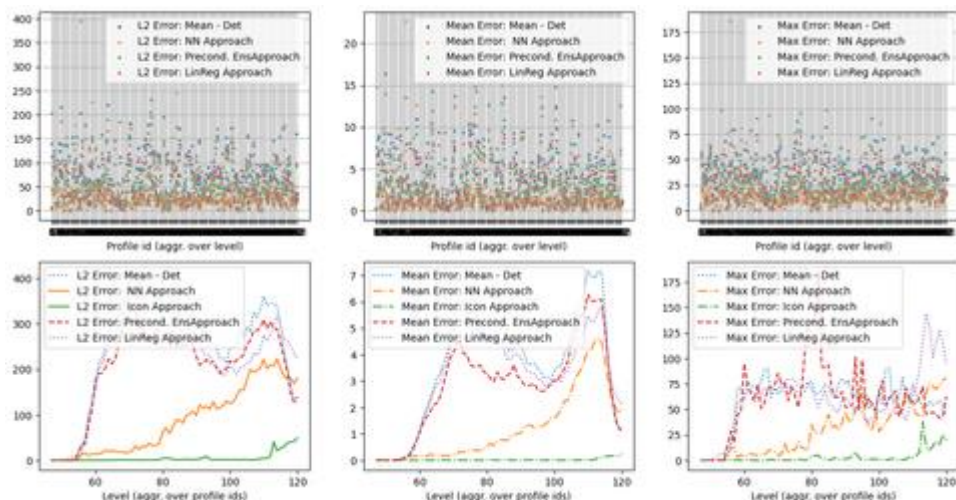


Figure 9: Differences of cloud profiles between the original ICON model, the physical based DA parametrization, the ML method and the ensemble based approach for three different cloud types.

2.4 First data assimilation tests

The operational data assimilation system of DWD consists of a three-dimensional, three-hourly variational ensemble data assimilation using a three hourly ICON model forecast as background and all available observations closest to the analysis time. The use of satellite and camera images of high cirrus clouds and contrails was tested successfully using all three techniques described in chapter 2.3 :

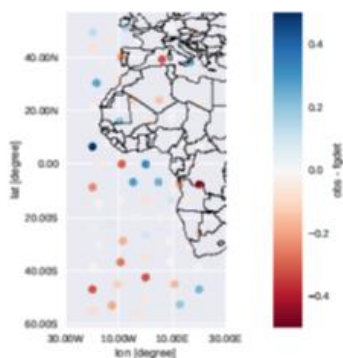
- Integration of the physical cloud parametrisation of the ICON model in the DA environment including its derivations.
- Use of a AI-based emulation of the parametrisation including its derivations.
- Use of an ensemble based correlation between cloud and state variables including its derivations.

As observation operator, the RTTOV-MFASIS operator was used. Figure 10 shows a first data assimilation test using the classical method to derive an analysis, starting from a three-hourly model forecast as first guess and assimilating the Sevir 0.6 mm channel reflectance onboard Meteosat 11. The left picture shows the observation minus first guess values for an area off the coast of west Africa. Moderate differences between -0.4 and 0.4 can be observed.

The right picture shows the result of an assimilation using the ML/AI method. A lot of dots show very small differences between the analysis and the observation indicating in principal that the method works and the model is drawn towards the observations in the analysis. The very small differences also indicate, that the analysis is too close to the observations which might be due to an too small observation error specified for the observations. For some points, the observation minus analysis difference increases, which needs to be further investigated.

Reflectance ICON Parametrisation:

obs - RTTOV(FG)



obs - RTTOV(current best state)

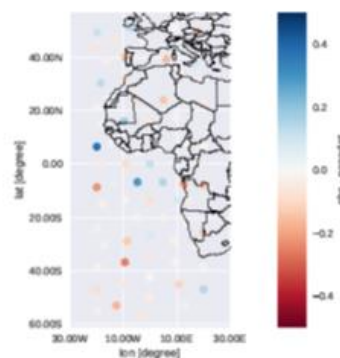


Figure 10: Observation minus First Guess and Observation minus Analyses for reflectance measurement points of the coast of West Africa using the ML/AL ICON parametrization and its derivations.

3. Conclusions

Long lasting cirrus clouds and contrails have a strong warming effect of the atmosphere and constitutes a major non-CO₂ effect of the world-wide air traffic fleet. In order to improve the predictability of cirrus clouds and contrails formation the NWP model should be able to predict super-saturated areas as precisely as possible.

Besides the improvement of model physics, the use of new satellite and camera images in the visible spectral range is necessary to improve the initial condition of ice supersaturation in the higher troposphere. Therefore, different techniques are tested to use reflectance measurements of satellite and camera images in different spectral ranges within the global data assimilation system ICON of DWD.

Hereby, three different techniques are developed and applied. First, the classical technique to compute the linearized cloud microphysics parametrization of the ICON and its derivations is tested, supplemented by an ML/AI approach, where the relationship between the model state variables and the model cloud variables are learned with the help of a neuronal network and by an ensemble method using the background error co-variances and correlations to derive the connection between model control variables and model cloud variables.

All three methods are technically implemented and all three methods were tested in a first assimilation step. Whereas the ML/AI and the ensemble methods still show some shortcomings the classical method offers good results and will be further tested in some longer assimilation runs.

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