E-CONTRAIL

D3.1 Relevant data for deep-learning models

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Abstract

Contrails have significant impacts on radiative forcing, affecting Earth's climate. The present research proposes a deep-learning approach to predict radiative forcing induced by contrails using numerical weather prediction and air traffic data. The methodology involves temporal predictions with recurrent neural networks, short-term memory networks, and transformers, capturing temporal variability. Spatial predictions employ image-segmentation techniques based on convolutional neural networks to exploit spatial correlations in satellite images. Transfer learning enhances model performance using pre-trained models. The datasets include input parameters such as historical weather data, air traffic information, contrail and cloudiness data, and radiative forcing data as the output or target. These datasets provide essential information for the training, validation, and testing of the deep learning model. The combined temporal and spatial predictions offer comprehensive insights into contrail-induced radiative forcing, contributing to climate change research and sustainable aviation practices.

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E-CONTRAIL

ARTIFICIAL NEURAL NETWORKS FOR THE PREDICTION OF CONTRAILS AND AVIATION INDUCED CLOUDINESS

E-CONTRAIL

This document is part of a project that has received funding from the SESAR 3 Joint Undertaking under grant agreement No 101114795 under the European Union's Horizon Europe research and innovation programme.

We provide now a high-level summary of the project E-CONTRAIL:

Contrails and aviation-induced cloudiness effects on climate change show large uncertainties since they are subject to meteorological, regional, and seasonal variations. Indeed, under some specific circumstances, aircraft can generate anthropogenic cirrus with cooling. Thus, the need for research into contrails and aviation-induced cloudiness and its associated uncertainties to be considered in aviation climate mitigation actions becomes unquestionable.

We will blend cutting-edge AI techniques (deep learning) and climate science with application to the aviation domain, aiming at closing (at least partially) the existing gap in terms of understanding aviation-induced climate impact.

The overall purpose of E-CONTRAIL project is to develop artificial neural networks (leveraging remote sensing detection methods) for the prediction of the climate impact derived from contrails and aviation-induced cloudiness, contributing, thus, to a better understanding of the non-CO2 impact of aviation on global warming and reducing their associated uncertainties as essential steps towards green aviation.

Specifically, the objectives of E-CONTRAIL are:

- O-1 to develop remote sensing algorithms for the detection of contrails and aviation-induced cloudiness.
- O-2 to quantify the radiative forcing of ice clouds based on remote sensing and radiative transfer methods.
- O-3 to use of deep learning architectures to generate AI models capable of predicting the radiative forcing of contrails based on data- archive numerical weather forecasts and historical traffic.
- O-4 to assess the climate impact and develop a visualization tool in a dashboard.

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1 Introduction

Aviation contrails are cloud-like formations that occur when hot gases from aircraft engines mix with cold and humid air at higher altitudes. They consist primarily of ice crystals formed by the combination of water vapour in aircraft engine exhaust and low temperatures in the upper atmosphere. Impurities in the engine exhaust, such as sulphur compounds, act as nuclei for water droplets to freeze and create ice particles, forming the contrails. Depending on the atmospheric condition contrails can be visible for a short time or persist for hours, spreading and resembling natural cirrus clouds. It is essential to understand the effects of aviation-induced contrails on the atmosphere and its impacts on climate change. Numerous research being conducted around the world are continuously updating their knowledge about the effects of contrails on climate [1]–[5].

During the day, contrails reflect the radiation to space, leading to a cooling effect on the Earth's surface. However, at night, they can trap infrared radiation, resulting in a warming impact instead. This radiative forcing can affect stability and temperature patterns, ultimately influencing weather conditions. The overall impact of contrails on radiative forcing depends on factors such as their number, how long they persist in the sky, and at what altitude they form. Although aviation contrails do play a role in altering the Earth's radiation budget, their significance may be more pronounced in regions with heavy air traffic [6], [7]. In circumstances where there is intense air traffic or favourable atmospheric conditions in an area, contrails have the potential to transform into cirrus-like clouds known as "contrail cirrus." Contrails formed by aircraft have an impact on climate compared to naturally occurring cirrus clouds, and their influence on warming the climate might be more significant [8], [9].

1.1 Deep-learning Models Data Sources

Conceptual block #3 concerns the development of deep learning architectures for the prediction of the climate impact of contrails and aviation-induced cloudiness. See Figure 1. Deep-learning methods based on sequential processing and image-segmentation techniques will be developed and tested during this project. The methodology will follow two steps: temporal predictions and spatial predictions. **The input data used for training and testing will entail data-archive numerical weather forecasts and historical aircraft traffic (as planned) from WP1 and 2**. **The output of this block will be radiative forcing of contrails images as an input for WP4.** A complete description of the raw data and how it conforms to the FAIR principles will be included in the data management plan (DMP).

1.2 Temporal Predictions

The goal of this step is to model the temporal variability of parameters that are relevant to predicting the forcing of the contrails. The significance of this approach lies in mapping future states from previous states of the parameters, thereby exploiting the sequential (temporal) nature of the data. Relevant methods that will be employed in this project are recurrent neural networks (RNNs), such as long-short-term memory (LSTM) networks, and transformers, such as BERT (Bidirectional Encoder Representations from Transformers); introducing attention mechanisms to allow the model to query multiple hidden states relevant to predict the current state. RNNs take one input sequence element at a time and are widely applicable for short-term dependencies. For instance, RNNs have enjoyed application in determining temporal dynamics of low-order models of turbulence.

In contrast to RNNs and LSTMs, transformers are fed the entire sequential data (e.g., an entire sentence or time series), and exploit self-attention mechanisms in the encoder and decoder stages, which enable high parallelization with GPUs and reduced computational complexity. In the field of natural language processing, transformers are known to produce state-of-the-art results given their outstanding performance in classification tasks (e.g., machine translation), and recent studies demonstrate promising performance for regression tasks as well, such as time-series forecasting6, highly relevant for the methodology in this project.

1.3 Spatial Predictions

Image-segmentation techniques will be employed in this step of the methodology. The significance of this approach is to exploit spatial and channel cross-correlations in the satellite image data. This allows the spatial predictions to fully take advantage of the high-dimensional nature of the training set to learn relevant features with a low computational budget. Methods based on convolutional neural networks (CNN) will be used to extract shift-invariant features from the data. In previous studies, CNN-based methods have been shown to increase the lead time of thunderstorm prediction by using satellite image data and numerical weather forecasts. In particular, the features learned by these CNN models can potentially be reutilised for the task of predicting the contrails using transfer learning; thereby saving computational costs and dramatically accelerating the training process. Examples of these CNN-based models include ResNets (residual neural networks), U-Nets, and PSPNets (pyramid scene parsing networks), which pass and/or append features across layers to prevent vanishing gradients and improve the segmentation performance.

We will also explore the use of depth-wise separable convolutions, which separate the convolutional operation into channel and spatial convolutions, independently. The identification of contrails in this project will then be posed as an image segmentation problem, where pixels in the image with high (low) values correspond to a high (low) probability of contrails generated by the aircraft. We will also make use of deep generative models, such as generative adversarial networks (GANs) and variational autoencoders (VAEs), to produce super-resolution results from coarse data.

The main idea is to exploit the principle of dimensionality reduction to up-sample the data, and the key strength of using generative models is thus to learn a compact representation of the image data instead of the data itself. GANs are composed of a generator network, which creates fake data from a random vector, and a discriminator network, which

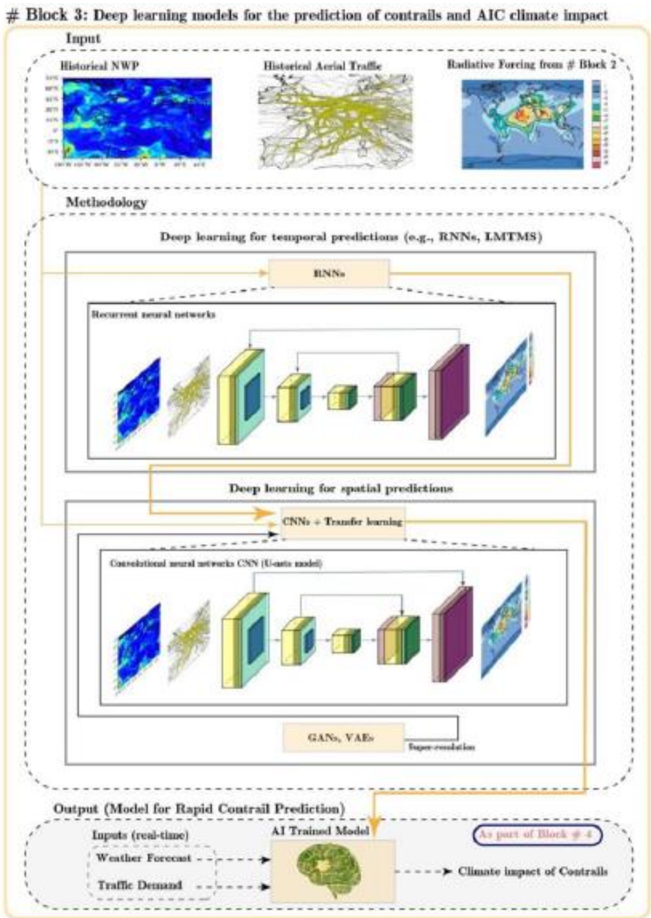

Figure 1: Methodological diagram Block #3

determines whether the data created by the generator is real or not. The model is trained until the discriminator no longer can distinguish whether the data generated is real or not. Similarly, VAEs are based on variational inference and regularization, and encode the input as a probability distribution over the latent space (often referred to as bottleneck), which is then sampled and decoded to yield the super-resolution output. Results from previous works on turbulent flow predictions will be of great relevance to this project.

2 Deep Learning Models

Using deep learning models to predict the radiative forcing of contrails based on data-archive numerical weather forecasts, contrails and historical air traffic data is a promising approach. The combination of the following models can act as an effective method in addressing this kind of problem: a) Convolutional Neural Networks (CNNs), b) Long Short-Term Memory (LSTM) networks, c) Transfer Learning, d) Generative Adversarial Networks (GANs), and e) variational autoencoders (VAEs).

- CNNs are well-suited for image-based data, and in this context, they can be used to process satellite images, which often provide valuable visual information about the presence and characteristics of contrails. The CNNs can extract features and patterns from these images, helping to analyse the spatial distribution and properties of contrails [10].
- LSTM networks are a type of recurrent neural network (RNN) designed to handle sequential data. They are particularly useful when the temporal aspect is important, such as when analysing the persistence and evolution of contrails over time. LSTM networks can capture dependencies in historical traffic data and numerical weather forecasts to predict the radiative forcing of contrails at different time intervals [11], [12].
- Transfer learning involves using pre-trained models that have been trained on a large dataset for a different but related task. In the context of predicting contrail radiative forcing, you can leverage existing deep learning models that have been trained on similar climate or atmospheric data. Fine-tuning or retraining these models on your specific dataset can help boost performance and reduce the need for extensive training from scratch [10].
- GANs can be employed for data augmentation and generation of synthetic contrail images. By training a GAN on the available contrail images, you can generate more diverse and realistic examples, which can help improve the robustness and generalization of your model [13].
- VAEs are another type of generative model that can be used for data synthesis. Similar to GANs, VAEs can create realistic contrail images, and they can also be applied to generate latent representations for the contrail data, which may help in feature extraction and representation learning [14].

The overall workflow involves preprocessing various datasets, integrating them into a unified dataset, and then using a combination of CNNs, LSTM networks, and transfer learning to build a predictive model. GANs and VAEs can be used for data augmentation and synthesis to increase the diversity of the dataset.

3 Dataset

The datasets are the foundation of successful deep-learning models for predicting the targets. They enable the models to learn from historical examples, generalize to new scenarios, and provide valuable insights into the complex interactions between datasets. Ensuring the quality and representativeness of the data is vital for building reliable and effective deep-learning models. The list of datasets proposed to be incorporated into this research are listed below:

a) Numerical Weather Prediction
b) Air Traffic Information
c) Radiative Forcing (Target)

The selection of the dataset plays a significant role in deep learning models. It serves as the foundation for training the model and has a direct impact on the model's performance, generalization capabilities, and applicability to real-world scenarios. The key significances of selected datasets are discussed as follows:

3.1 Numerical Weather Prediction

Numerical Weather Prediction (NWP) data plays a crucial role in training deep-learning models for predicting radiative forcing induced by aviation contrails. Historical NWP data provides detailed information about past atmospheric conditions, which is essential for understanding the relationship between contrail formation and radiative forcing. NWP data provides a comprehensive view of atmospheric conditions, including maximum and minimum temperature, precipitation, wind properties, and atmospheric pressure, at various altitudes with different space and time intervals. This information is critical for identifying the conditions conducive to contrail formation and persistence [15]. By correlating historical NWP data with observed contrail occurrences, the deep learning model can learn to identify patterns and relationships between atmospheric conditions and the likelihood of contrail formation. The NWP data serves as the primary source for extracting relevant features that influence contrail formation and radiative forcing [16]. Historical NWP data can be used for model validation, where the deep learning model's predictions are compared to historical contrail observations. This helps assess the model's accuracy and reliability in capturing the relationship between atmospheric conditions and contrail-induced radiative forcing.

NWP data spans a range of time intervals, allowing the model to capture the temporal variability of atmospheric conditions and contrail occurrences. This temporal aspect is crucial for understanding how radiative forcing changes with time and identifying long-term trends. By combining historical NWP data with corresponding radiative forcing data, a comprehensive training dataset can be constructed. This dataset consists of input features and target values (radiative forcing), which the deep learning model uses to learn the mapping between atmospheric conditions and radiative forcing. NWP data can also be utilized for transfer learning, where pre-trained models on atmospheric data (e.g., climate models) are fine-tuned for contrail-induced radiative forcing prediction. This approach leverages knowledge learned from related tasks to improve the deep learning model's performance on the specific prediction task [10]. Historical NWP data allows for sensitivity analysis, where the deep learning model can be used to explore how variations in specific atmospheric conditions impact contrail formation and radiative forcing.

Incorporating historical NWP data into the deep learning model training process enhances the model's ability to understand the complex interactions between atmospheric conditions and aviation contrail radiative forcing. It helps researchers gain insights into the environmental impact of contrails and contributes to the development of more accurate and comprehensive climate models for aviation emissions assessment. It is essential to consider the quality and spatial/temporal resolution of the NWP data, as well as the availability of corresponding contrail and radiative forcing observations for effective model training and validation [17].

3.2 Air Traffic Information

The recent rise in air traffic and its related emissions and contrails has raised concern worldwide [19]. Air traffic information provides details about the flight paths, altitudes, and other characteristics of aircraft, which are essential for understanding contrail formation and their radiative impact. It also data provides insights into the density and distribution of flights in different regions and at various altitudes. Air traffic data includes altitude information for individual flights. The climate impact of air traffic emissions is usually calculated by combining this information with NWP data [20]. This allows the model to identify the altitude range where contrails are most likely to form and persist. Different aircraft types can produce varying contrail characteristics due to differences in engine type, fuel consumption, and emissions. Air traffic information provides data about the types of aircraft operating in the airspace, allowing the model to account for these variations.

Contrail formation and persistence are influenced by factors such as atmospheric conditions and air traffic patterns. Air traffic data helps the model understand how long contrails are likely to persist based on the flight density and patterns. Air traffic information provides spatial and temporal distribution of flight activities. By combining this data with NWP data, the deep learning model can capture the spatiotemporal variations in contrail formation and radiative forcing. By integrating air traffic information data with numerical weather prediction data, deep learning models gain a more comprehensive understanding of the relationship between aviation activities, contrail formation, and radiative forcing. This will help in understanding the impacts of the contrails on the environment by providing accurate predictions.

FlightRadar24 is a renowned flight tracking service that provides a piece of real-time flight information for many aircraft worldwide. The platform gathers data from various flight tracking system sources, including Automatic Dependent Surveillance-Broadcast (ADS-B) receivers. FlightRadar24 provides real-time and historical datasets (Up to 3 years), which include the following information:

- Real-time Aircraft Positions
- Flight Identification
- Flight Status
- Aircraft Information
- Flight Path and Route
- Historical Data
- Weather Conditions
- Airport Information
- Airspace Information

3.3 Radiative Forcing (Target)

Radiative Forcing (RF) is a measure of Earth's energy balance caused by greenhouse gases. It represents the effect of incoming radiation at the top of the Earth's atmosphere. A positive RF indicates a warming effect, which signifies that energy being trapped in the Earth's atmosphere is more than the energy radiated back to space and vice versa for negative RF. The RF value is usually expressed in units of watts per square meter (W/m^2). The impact of aviation on climate change is often described with the help of RF in any climate modelling setup. The aviation contrails act as a sensitive parameter for predicting RF which quantifies the additional warming or cooling effect caused by the presence of contrails in the atmosphere [21],[22].

In the context of predicting climate change impacts induced by aviation contrails, RF data plays a crucial role as the target for building a deep learning model. The deep learning model is trained to learn the relationship between various input variables (numerical weather prediction data, air traffic data, and contrail information) and the corresponding RF values. The model aims to understand how different atmospheric conditions, air traffic patterns, and characteristics of contrails contribute to the radiative forcing effect. During the training process, the model is presented with a large dataset that includes the input variables and the corresponding RF values. By using RF data as the target, the model optimizes its internal parameters (weights and biases) to minimize the prediction errors between its output and the true RF values. This training process allows the model to effectively map the input variables to the target RF values and make accurate predictions for new and unseen data.

By utilizing RF data as the target, the deep learning model can capture the complex and non-linear relationships between the input variables and radiative forcing, which may not be easily discernible through traditional analytical methods. It enables the model to gain insights into the complex interactions between atmospheric variables, air traffic, and contrails, leading to more accurate predictions of radiative forcing induced by aviation contrails. Overall, radiative forcing data as the target in deep learning model training is essential for developing accurate and reliable predictions of the environmental impact of aviation contrails. It provides valuable information for understanding the climate implications of contrails and contributes to the development of sustainable aviation practices and climate change mitigation strategies.

4 Training and Testing

Training and testing are crucial steps in building, evaluating, and fine-tuning any deep-learning model.

4.1 Training

In the training phase, the deep learning model is exposed to a large dataset that includes NWP data, air traffic data, contrail data and corresponding radiative forcing values. The model learns to capture spatial and temporal patterns, correlations, and dependencies between NWP variables, contrails, and radiative forcing effects. The training process involves adjusting the model's internal parameters (weights and biases) through an optimization algorithm, such as stochastic gradient descent, to minimize the prediction errors between its predictions and the actual radiative forcing values in the training dataset. The dataset is typically divided into batches, and the model iteratively updates its parameters using backpropagation and gradient descent to improve its predictions.

4.2 Validation

During training, a portion of the training dataset is set aside as the validation dataset, which is not used for training the model. The model's performance is evaluated on the validation dataset at regular intervals during the training process. Evaluation metrics, such as mean squared error or mean absolute error, are used to assess the model's performance on the validation dataset. Validation helps in detecting overfitting and allows for early stopping when the model's performance on the validation set starts to degrade.

4.3 Testing

Once the model is trained and validated, it is evaluated on a separate dataset called the testing dataset. The testing dataset contains new, unseen data that the model has not encountered during training or validation. The model's predictions for radiative forcing induced by contrails and aviation-induced cloudiness are compared against the actual radiative forcing values in the testing dataset to assess its performance on unseen data. Testing provides an estimate of the model's ability to generalize to real-world scenarios and unseen atmospheric conditions and air traffic patterns.

5 Prediction

In the context of predicting the forcing of aviation contrails, temporal predictions aim to model the temporal variability of relevant parameters over time. This approach is significant because it allows the deep learning model to capture the dynamic nature of atmospheric conditions, air traffic patterns, and contrail formation, which vary over time.

5.1 Temporal Predictions

The use of RNNs and LSTM networks in this step is valuable due to their ability to handle sequential data and capture the dependencies over time. RNNs and LSTMs can process time-series data by maintaining a hidden state that carries information from one time step to the next, allowing the model to retain the memory of past states and use it to predict future states. This is especially useful when predicting the evolution of contrails and aviation-induced cloudiness, where the current state is influenced by previous atmospheric conditions and air traffic. Furthermore, the inclusion of transformers, such as Bidirectional Encoder Representations from Transformers (BERT), in this temporal prediction step demonstrates the use of state-of-the-art natural language processing techniques for time-series forecasting. Transformers utilize self-attention mechanisms, allowing the model to focus on relevant temporal dependencies and query multiple hidden states to predict the current state accurately. Their parallelization capability with GPUs and reduced computational complexity enable efficient processing of long sequences, making them suitable for handling large time-series datasets.

By employing RNNs, LSTMs, and transformers, the deep learning model can effectively learn and exploit the temporal patterns and dependencies in the data, enhancing the accuracy of temporal predictions. This approach allows the model to map future states from past states, making it capable of making predictions for multiple time steps ahead. Overall, temporal predictions using deep learning methods contribute to a comprehensive understanding of the temporal dynamics of contrail formation, cloudiness, and radiative forcing induced by aviation activities. The results obtained from this step can provide valuable insights into how contrails and aviation impact the Earth's atmosphere over time, supporting climate change research, aviation emissions assessment, and the development of sustainable aviation practices.

5.2 Spatial Predictions

The use of image-segmentation techniques, mainly based on convolutional neural networks (CNNs), in the methodology has several significant advantages for predicting contrails and aviation-induced cloudiness.

- Exploiting Spatial Correlations: Image-segmentation techniques leverage spatial and channel cross-correlations in the satellite image data. This enables the model to capture spatial patterns and dependencies between pixels, which are crucial for identifying and delineating contrails and aviation-induced cloudiness accurately.
- High-Dimensional Data Processing: Satellite images are high-dimensional data with a large number of pixels and channels. CNN-based methods are well-suited for processing such data due to their ability to learn hierarchical and shift-invariant features from images efficiently.
- Transfer Learning: CNN-based models trained on related tasks, such as predicting thunderstorms from satellite images, can be repurposed for predicting contrails using transfer learning. By leveraging pre-trained CNN models, the approach saves computational costs and

speeds up the training process, as the model can use the knowledge learned from previous tasks.

- Improved Segmentation Performance: CNN-based models like ResNets, U-Nets, and PSPNets are designed to handle vanishing gradients and improve segmentation performance. These architectures allow the model to pass and append features across layers, enabling better feature representation and more accurate segmentation of contrails in satellite images.
- Depth-wise Separable Convolutions: Exploring the use of depth-wise separable convolutions further enhances the efficiency of the model by reducing the number of computations. This separation of convolution operations into channel and spatial convolutions helps optimize the model's performance and resource utilization.
- Image Segmentation for Contrail Identification: By treating contrail identification as an image segmentation problem, the model can output probability maps, where pixels with high values correspond to a high probability of contrails generated by aircraft. This probabilistic approach allows for better uncertainty estimation and quantification of contrail presence.
- Super-Resolution with Generative Models: The use of deep generative models like GANs and VAEs for super-resolution results in producing high-resolution images from coarse data. This capability is valuable for enhancing the resolution of satellite images, enabling better identification and characterization of contrails and aviation-induced cloudiness.
- Transfer from Turbulent Flow Predictions: Insights and methodologies from previous works on turbulent flow predictions are relevant and can be adapted to enhance the predictive capabilities of the model for contrail-induced radiative forcing.

6 Summary and Open Questions

The research aims to predict radiative forcing induced by contrails and aviation-induced cloudiness using deep learning models. The approach involves temporal predictions, utilizing RNNs, LSTM networks, and BERT to capture the temporal variability of relevant parameters over time. This allows the model to understand how atmospheric conditions, air traffic patterns, and contrail formation evolve and influence radiative forcing. In the spatial prediction aspect, image-segmentation techniques based on CNNs are employed to exploit spatial correlations in satellite image data. The CNNs can efficiently process high-dimensional data and extract shift-invariant features, enabling accurate identification of contrails and aviation-induced cloudiness. Transfer learning from pre-trained models further enhances segmentation performance, saves computational costs, and speeds up training.

The datasets used in the deep learning model are critical for training and testing. NWP data provide information about atmospheric conditions and contrail persistence, while air traffic data gives insights into flight paths and altitudes affecting contrail formation. Contrails and aviation-induced cloudiness data offer characteristics and spatial distribution of contrails, aiding in understanding their radiative effects. The target data, radiative forcing, quantify changes in the Earth's energy balance due to various factors, including contrails. By integrating these datasets, the deep learning model learns the relationships between atmospheric conditions, air traffic, and radiative forcing. Training and testing phases ensure the model's accuracy and generalization to unseen data. The combination of temporal and spatial predictions using deep learning facilitates a comprehensive understanding of contrail-induced radiative forcing, supporting climate research and sustainable aviation practices.

6.1 Open Questions

Nevertheless, there are still some open questions that we need to solve as we deep into the implementation activities of the project. These open questions, which we will be addressing in the upcoming months, are:

- What is the boundary selected for the study?
- Which numerical weather prediction model is to be considered?
- What are the weather parameters considered from the NWP model?
- What are the criteria for the selection of weather parameters?
- How to address the variation in spatiotemporal aspects of datasets from different sources?
- Which are the relevant air traffic information parameters?
- Is upscaling/downscaling required to unify the datasets to a common grid?
- Is sensitivity analysis required for the selection of optimum input parameters?
- Is the timescale considered sufficient to address seasonal/climatic changes?

7 References

[1] V. Ballal, O. Cavalett, F. Cherubini, and M. D. B. Watanabe, “Climate change impacts of e-fuels for aviation in Europe under present-day conditions and future policy scenarios,” *Fuel*, vol. 338, p. 127316, Apr. 2023, doi: 10.1016/j.fuel.2022.127316.

[2] M. Jarošová and M. Pajdlhauser, “Aviation and Climate Change,” *Transp. Res. Procedia*, vol. 65, pp. 216–221, Jan. 2022, doi: 10.1016/j.trpro.2022.11.025.

[3] R. Chevallier, M. Shapiro, Z. Engberg, M. Soler, and D. Delahaye, “Linear Contrails Detection, Tracking and Matching with Aircraft Using Geostationary Satellite and Air Traffic Data,” *Aerospace*, vol. 10, no. 7, Art. no. 7, Jul. 2023, doi: 10.3390/aerospace10070578.

[4] J. P. Hoffman, T. F. Rahmes, A. J. Wimmers, and W. F. Feltz, “The Application of a Convolutional Neural Network for the Detection of Contrails in Satellite Imagery,” *Remote Sens.*, vol. 15, no. 11, Art. no. 11, Jan. 2023, doi: 10.3390/rs15112854.

[5] L. Kulik, “Satellite-based detection of contrails using deep learning,” Thesis, Massachusetts Institute of Technology, 2019. Accessed: Aug. 02, 2023. [Online]. Available: https://dspace.mit.edu/handle/1721.1/124179

[6] Y. Y. Lai *et al.*, “Analysing the opportunities and challenges for mitigating the climate impact of aviation: A narrative review,” *Renew. Sustain. Energy Rev.*, vol. 156, p. 111972, Mar. 2022, doi: 10.1016/j.rser.2021.111972.

[7] S. Gössling and A. Humpe, “The global scale, distribution and growth of aviation: Implications for climate change,” *Glob. Environ. Change*, vol. 65, p. 102194, Nov. 2020, doi: 10.1016/j.gloenvcha.2020.102194.

[8] U. Burkhardt and B. Kärcher, “Global radiative forcing from contrail cirrus,” *Nat. Clim. Change*, vol. 1, no. 1, Art. no. 1, Apr. 2011, doi: 10.1038/nclimate1068.

[9] “Process-based simulation of contrail cirrus in a global climate model - Burkhardt - 2009 - Journal of Geophysical Research: Atmospheres - Wiley Online Library.” https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2008JD011491 (accessed Aug. 04, 2023).

[10] A. M. S. Kheir, A. Elnashar, A. Mosad, and A. Govind, “An improved deep learning procedure for statistical downscaling of climate data,” *Heliyon*, vol. 9, no. 7, p. e18200, Jul. 2023, doi: 10.1016/j.heliyon.2023.e18200.

[11] K. Venkatachalam, P. Trojovský, D. Pamucar, N. Bacanin, and V. Simic, “DWFH: An improved data-driven deep weather forecasting hybrid model using Transductive Long Short Term Memory (T-LSTM),” *Expert Syst. Appl.*, vol. 213, p. 119270, Mar. 2023, doi: 10.1016/j.eswa.2022.119270.

[12] X. Yuan, C. Chen, X. Lei, Y. Yuan, and R. Muhammad Adnan, “Monthly runoff forecasting based on LSTM–ALO model,” *Stoch. Environ. Res. Risk Assess.*, vol. 32, no. 8, pp. 2199–2212, 2018, doi: 10.1007/s00477-018-1560-y.

[13] A. Huang, R. Shen, W. Di, and H. Han, “A methodology to reconstruct LAI time series data based on generative adversarial network and improved Savitzky-Golay filter,” *Int. J. Appl. Earth Obs. Geoinformation*, vol. 105, p. 102633, Dec. 2021, doi: 10.1016/j.jag.2021.102633.

[14] Y.-F. Zhang and P. J. Thorburn, “A deep surrogate model with spatio-temporal awareness for water quality sensor measurement,” *Expert Syst. Appl.*, vol. 200, p. 116914, Aug. 2022, doi: 10.1016/j.eswa.2022.116914.

[15] U. Schumann, “Formation, properties and climatic effects of contrails,” *Comptes Rendus Phys.*, vol. 6, no. 4, pp. 549–565, May 2005, doi: 10.1016/j.crhy.2005.05.002.

[16] G. Love, A. Soares, and H. Püempel, “Climate Change, Climate Variability and Transportation,” *Procedia Environ. Sci.*, vol. 1, pp. 130–145, Jan. 2010, doi: 10.1016/j.proenv.2010.09.010.

[17] S. R. Dorling, R. J. Foxall, D. P. Mandic, and G. C. Cawley, “Maximum likelihood cost functions for neural network models of air quality data,” *Atmos. Environ.*, vol. 37, no. 24, pp. 3435–3443, 2003, doi: 10.1016/S1352-2310(03)00323-6.
[18] K. Gierens, S. Matthes, and S. Rohs, “How Well Can Persistent Contrails Be Predicted?,” *Aerospace*, vol. 7, no. 12, Art. no. 12, Dec. 2020, doi: 10.3390/aerospace7120169.
[19] D. P. Bajgai and K. L. Shrestha, “Evaluation of aircraft emission at Tribhuvan international airport and its contribution to air quality in Kathmandu, Nepal,” *Atmospheric Environ. X*, vol. 17, p. 100204, Jan. 2023, doi: 10.1016/j.aeaoa.2023.100204.
[20] K. Dahlmann, V. Grewe, C. Frömming, and U. Burkhardt, “Can we reliably assess climate mitigation options for air traffic scenarios despite large uncertainties in atmospheric processes?,” *Transp. Res. Part Transp. Environ.*, vol. 46, pp. 40–55, Jul. 2016, doi: 10.1016/j.trd.2016.03.006.
[21] C. Frömming, M. Ponater, U. Burkhardt, A. Stenke, S. Pechtl, and R. Sausen, “Sensitivity of contrail coverage and contrail radiative forcing to selected key parameters,” *Atmos. Environ.*, vol. 45, no. 7, pp. 1483–1490, Mar. 2011, doi: 10.1016/j.atmosenv.2010.11.033.
[22] J. D. Scheelhaase *et al.*, “How to best address aviation’s full climate impact from an economic policy point of view? – Main results from AviClim research project,” *Transp. Res. Part Transp. Environ.*, vol. 45, pp. 112–125, Jun. 2016, doi: 10.1016/j.trd.2015.09.002.

8 List of acronyms

Acronym	Description
ADS-B	Automatic Dependent Surveillance-Broadcast
BERT	Bidirectional Encoder Representations from Transformers
CNN	Convolutional neural networks
DMP	Data Management Plan
GANs	Generative adversarial networks
LSTM	Long-short-term memory
NWP	Numerical Weather Prediction
PSPNets	Pyramid scene parsing networks
ResNets	residual neural networks
RF	Radiative Forcing
RNNs	recurrent neural networks
VAEs	Variational autoencoders

Table 1: List of acronyms