

# CLOUD-BASED MACHINE LEARNING SYSTEM FOR TURBULENCE PREDICTION

(A Satellite-Driven, Containerized ML Inference  
Pipeline for Aviation Safety)

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# CHAPTER 1 – INTRODUCTION

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## 1.1 Background and Motivation

Aviation turbulence remains one of the most persistent operational threats in commercial flight environments. While modern aircraft are structurally capable of withstanding turbulence, unexpected encounters continue to cause passenger injuries, cabin crew accidents, flight diversions, aircraft damage, and large-scale operational delays. A significant fraction of these events are attributed to Clear-Air Turbulence (CAT)—a form of turbulence that occurs in cloudless, moisture-free regions where traditional detection tools such as radar and onboard sensors provide little to no warning.

Over the past decade, the emergence of high-resolution satellite observations and machine learning (ML) has created new opportunities for early turbulence prediction. India's meteorological ecosystem, supported by ISRO's INSAT-3D/3DR geostationary satellites and the MOSDAC data archive, now provides continuous atmospheric products such as CTP, CTT, HEM, CMK, and IMC that capture wind shear, convective signatures, cloud microphysics, and thermal structure. At the same time, ML models—particularly ensemble methods—are capable of identifying nonlinear atmospheric patterns indicative of moderate to severe turbulence.

However, despite major advances in atmospheric modeling, one of the biggest gaps remains the operationalization of ML-driven turbulence prediction. Most research work ends at model development, without a pathway to real-time inference, cloud deployment, or pilot-facing systems. Therefore, the motivation behind this project is to design a complete, end-to-end turbulence prediction pipeline that leverages satellite data, scalable preprocessing, ML modeling, and a deployable inference service.

This project thus aims to bridge the gap between offline turbulence research and practical, deployable aviation safety tools.

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## 1.2 Problem Statement

Traditional turbulence forecasting methods depend heavily on:

- Pilot weather reports (PIREPs), which are subjective and sparse
- Airborne weather radar, which is ineffective for CAT
- ATC/meteorological advisories, which are often reactive rather than predictive
- Numerical weather prediction (NWP), which may miss localized shear zones

These limitations leave flight crews vulnerable to sudden turbulence transitions. Airlines, aviation authorities, and meteorological agencies require systems that:

1. Use high-resolution observational data
2. Predict turbulence before it occurs
3. Operate at low latency for real-time usage
4. Scale across large airspace regions
5. Function reliably in cloud environments

Thus, the core problem addressed in this project is:

**“How can satellite-derived atmospheric variables be processed, modeled, and deployed into a real-time ML system capable of predicting turbulence severity—especially Clear-Air Turbulence—in a scalable and operationally usable manner?”**

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## 1.3 Objectives of the Project

The project sets out to achieve the following technical objectives:

1. Acquire and preprocess INSAT-3D/3DR L2B satellite products in HDF5 format for turbulence-relevant variables.
2. Design a scalable per-file processing pipeline to clean, flatten, and merge multi-million-row datasets using chunk-based methods suitable for Google Colab and low-memory environments.
3. Engineer features linked to turbulence precursors, including wind shear, thermal gradients, cloud-top variations, and temporal indicators.
4. Train and evaluate supervised ML models (Random Forest, XGBoost) for three-class turbulence severity prediction: Low, Moderate, Severe.
5. Package the trained model into a Flask–Gunicorn inference API, exposing /health and /predict endpoints.

6. Containerize the system using Docker, enabling reproducible execution on any machine.
7. Deploy and verify the service on AWS EC2, using S3 for model artifact storage and IAM for secure access.
8. Develop a simple front-end dashboard (index.html) that allows users to enter atmospheric values and receive real-time predictions.

Together, these objectives ensure the system is not only technically correct but also operationally deployable and verifiable.

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## 1.4 Scope of the Work

The scope of this project spans four major domains:

### A. Data Engineering

- MOSDAC HDF5 file inspection
- Per-file flattening and cleaning
- Timestamp normalization and fill-value correction
- Large-scale merging (>60 million rows) in Google Colab

### B. Machine Learning

- Model experimentation using Random Forest and XGBoost
- Handling class imbalance for CAT events
- Feature standardization and missing-value imputation
- Performance evaluation (accuracy, F1-score, confusion matrix)

### C. API & Application Engineering

- Flask inference service
- Gunicorn WSGI server for production stability
- Docker-based containerization
- Front-end HTML interface

### D. Cloud Deployment

- EC2 deployment
- S3-based model artifact loading
- IAM role for secure access
- Public API testing using curl

The project focuses on real-time prediction capability, not on full operational aviation certification—which would require regulatory validation, aircraft integration, and pilot studies.

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## 1.5 Significance for Aviation Safety

The system developed in this project contributes to aviation operations in the following ways:

1. Early Warning for Turbulence- Predictive ML models can identify atmospheric instability before pilots encounter it, reducing risk.
2. Enhanced CAT Detection- Because CAT has no radar signature, satellite-driven ML prediction fills a critical detection gap.
3. Passenger and Crew Safety- Preventing sudden turbulence encounters significantly reduces injuries and in-flight incidents.
4. Operational Efficiency- Airlines can optimize routing, fuel planning, and crew safety procedures using early turbulence forecasts.
5. Scalability in Airspace Management- Cloud deployment (containerized API + S3) demonstrates how such models can scale to national or regional aviation systems.
6. Foundation for Advanced Forecasting- The framework is extendable to deep learning models, LiDAR fusion, and real aircraft telemetry.

Overall, this project shows that ML + satellite data + cloud deployment can offer a practical, low-cost technology stack for operational turbulence prediction, helping close long-standing gaps in aviation safety systems.

# LITERATURE REVIEW

## 2.1 Overview

Turbulence forecasting has been studied for several decades, but significant progress occurred only in recent years with the availability of high-resolution atmospheric datasets and machine learning (ML). Traditional forecasting tools—such as aircraft radar, pilot weather reports, and numerical weather prediction—have well-known limitations, especially for Clear-Air Turbulence (CAT), which lacks moisture signatures and therefore cannot be detected using conventional radar.

This literature review synthesizes major academic and operational studies from 2019–2025, highlighting developments in turbulence detection, atmospheric data utilization, satellite observations, and ML-based classification. The review also identifies the technical gaps that motivated the design of the present project.

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## 2.2 Traditional Approaches and Their Limitations

### 2.2.1 Pilot Reports (PIREPs)

PIREPs remain the primary real-time source of turbulence information for aviation. While valuable, they suffer from:

- Subjectivity: intensity ratings depend on pilot perception.
- Sparse spatial coverage: only available when a pilot reports.
- Bias toward severe events: moderate/weak turbulence often goes unreported.
- Time delays: latency between encounter, reporting, and dissemination.

As a result, PIREPs cannot serve as a reliable sole source for proactive turbulence prediction.

### 2.2.2 Weather Radar Limitations

Aircraft radar systems detect turbulence only when hydrometeors (cloud droplets, ice crystals) are present. Therefore, radar:

- Performs well for convective and cloud-associated turbulence
- Performs poorly for CAT, which occurs in visually clear, moisture-free regions

This limitation is widely acknowledged in aviation meteorology.

### 2.2.3 Numerical Weather Prediction (NWP)

NWP models such as GFS, WRF, and ERA5 produce turbulence indicators (e.g., EDR, Richardson number). However:

- Their temporal resolution is limited (often 1–3 hours).
- They may miss small-scale shear zones.
- They are computationally heavy for real-time alerting.

Thus, while NWP provides global-scale insight, it lacks the granularity needed for operational nowcasting.

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## 2.4 Satellite-Based Turbulence Prediction

### 2.4.1 INSAT-3D/3DR CONTRIBUTION

The MOSDAC L2B satellite products provide:

- Cloud Top Pressure (CTP)
- Cloud Top Temperature (CTT)
- Humidity and moisture proxies (HEM, IMC)
- Cloud microphysics (CMK)
- Precise geolocation and timestamps

These products allow researchers to infer turbulence-linked atmospheric instability, especially:

- Vertical shear zones
- Temperature gradients
- Convective development
- Jet-stream boundaries

Satellite-driven turbulence prediction is an emerging field, offering global, continuous, and moisture-independent coverage—making it valuable for CAT detection.

### 2.4.2 PRIOR USES IN LITERATURE

Several studies use GOES, Himawari-8, and Meteosat satellites for convective turbulence detection. However, Indian aviation has fewer research contributions relying on INSAT-derived products, which makes your project a regionally important initiative.

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## 2.5 Key Studies Referenced in the Project

The following 6 studies directly influenced the design of your system (you already included them in your research paper):

#### (1) Emara et al., 2020

Used FOQA telemetry to predict turbulence seconds before encounter using ML.

Provided motivation for short-term prediction.

#### (2) Mizuno et al., 2022

Applied PCA + clustering + SVM to identify turbulence risk days.

Highlighted importance of multi-feature space.

#### (3) Kim et al., 2022

Demonstrated strong predictive ability using atmospheric instability features.

Confirmed the value of variables similar to MOSDAC products.

#### (4) Zhuang et al., 2023

Combined CGAN + XGBoost to improve recall using augmented LiDAR profiles.

Showed advantage of non-linear ensemble models.

#### (5) Shao et al., 2024

Trained RF + XGBoost on Chinese PIREPs with high accuracy.

Provided methodological guidance for multi-class classification.

#### (6) de Mello et al., 2025

Largest PIREP+ERA5 turbulence dataset to date.

Highlighted the challenge of rare severe events (class imbalance).

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## 2.6 Gaps Identified From Literature

Based on the surveyed studies, the following gaps shaped the goals of your project:

Gap 1 — Limited practical operational deployment

Most studies stop at offline model evaluation; few demonstrate real-time or cloud deployment.

Gap 2 — Poor CAT detection using traditional tools

CAT detection remains a key challenge due to lack of moisture signatures.

Gap 3 — Lack of India-focused turbulence systems

Most research uses datasets from the U.S., China, or Europe; Indian aviation needs region-specific models.

Gap 4 — Data engineering complexity not addressed

Very few works describe handling of large HDF5 satellite files, memory constraints, or per-file flattening strategies.

Gap 5 — Feature engineering lacks standardization

Feature consistency (wind shear, CTP, CTT, humidity) varies across studies; many works ignore timestamp encoding.

Gap 6 — Missing complete end-to-end workflow

No paper demonstrates:

- HDF5 → cleaned CSV → merged dataset → ML model → container → cloud API → user interface.

Our project is unique because it implements the full pipeline end-to-end, addressing the engineering and operational gaps.

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## 2.7 Summary

The literature shows that:

- ML significantly enhances turbulence prediction
- Ensemble models (RF/XGB) dominate due to interpretability and accuracy
- Satellite observations offer critical advantages for CAT
- Real-time, cloud-based turbulence forecasting is still in early stages
- Indian aviation needs region-specific, deployable ML systems

This review clarifies the motivation for your system, anchors your methodology in existing research, and highlights the novelty of our approach.

# PROBLEM STATEMENT AND OBJECTIVES

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## 3.1 Introduction

Aviation turbulence—particularly Clear-Air Turbulence (CAT)—remains one of the most disruptive and least predictable atmospheric hazards. While convective and cloud-associated turbulence can often be detected through onboard radar, CAT typically develops in dry, cloud-free regions near jet streams, frontal boundaries, or sharp vertical wind shear zones. Because CAT lacks moisture signatures, it cannot be detected with standard aircraft radar systems, forcing pilots and dispatchers to rely heavily on indirect indicators or delayed PIREPs (Pilot Reports).

In the context of the rapidly growing Indian aviation sector, where aircraft movements and passenger volumes continue to rise, the absence of a robust real-time turbulence prediction mechanism creates significant operational risk. This project addresses the need for a data-driven, satellite-supported, machine learning–based system capable of generating timely, objective, and automated turbulence severity predictions.

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## 3.2 Problem Statement

Despite decades of meteorological advancement, aviation turbulence forecasting faces four interconnected challenges:

### (1) LACK OF REAL-TIME CAT PREDICTION

Clear-Air Turbulence develops in visually clear regions with no radar-detectable hydrometeors. Pilots cannot anticipate CAT using available cockpit instruments, resulting in:

- Passenger and crew injuries
- Unsurprising turbulence encounters
- Rapid altitude deviations
- Operational disruptions (rerouting, diversion, fuel burn)

### (2) INEFFICIENCY OF TRADITIONAL OPERATIONAL INPUTS

Operational sources such as PIREPs, ATC advisories, SIGMETs, and historical turbulence maps exhibit the following limitations:

- Subjectivity: PIREPs vary with aircraft type and pilot experience
- Sparse coverage: Not all regions or altitudes receive reports
- Latency: Advisories are issued after turbulence is already detected
- Inadequate global reach: Limited value over remote or oceanic airspace

### (3) UNDERUTILIZATION OF HIGH-RESOLUTION SATELLITE DATA

Geostationary satellites (such as INSAT-3D/3DR) provide continuous high-resolution atmospheric observations, yet:

- Raw HDF5 files are extremely large
- Fields are multi-dimensional and require flattening
- Multiple product types (CTP, CTT, IMC, HEM, CMK) must be synchronized
- Most ML studies avoid satellite L2B products due to their complexity

As a result, satellite potential remains largely untapped in operational turbulence forecasting—especially for Indian airspace.

### (4) ABSENCE OF AN END-TO-END DEPLOYABLE SYSTEM

Many academic studies achieve good offline accuracy but do not demonstrate:

- Scalable data preprocessing
- Real-time inference
- Cloud deployment
- API-based integration
- Practical dashboards or interfaces

Airlines require deployable systems, not just models.

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### 3.3 Research Questions

Based on the problems identified, this project aims to answer the following research questions:

1. Can high-resolution satellite-derived features (CTP, CTT, IMC, HEM) be transformed into a scalable dataset suitable for real-time turbulence prediction?
2. Do machine learning models—particularly ensemble classifiers—offer reliable severity classification (Low / Moderate / Severe) for aviation turbulence?
3. Can a cloud-based, containerized, low-latency turbulence prediction API operate efficiently using only satellite-derived inputs?
4. What are the feasible engineering workflows to process large HDF5 MOSDAC files on limited hardware (local + Google Colab)?
5. How can the entire system be made reproducible and deployable using AWS services?

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### 3.4 Project Scope

This project covers the entire pipeline from raw satellite data to cloud deployment:

#### IN SCOPE

- Acquisition and processing of 124+ MOSDAC L2B HDF5 files
- Per-file flattening, cleaning, and merging
- Feature engineering using atmospheric physics principles
- Training of Random Forest and XGBoost turbulence classifiers
- Development of an inference service using Flask + Unicorn
- Containerization using Docker
- AWS-based deployment experimentation using EC2 + S3
- A browser-based front-end prediction interface

#### OUT OF SCOPE (BUT POTENTIAL FUTURE WORK)

- Predicting exact turbulence location along 4D flight trajectories
- Full integration with airline dispatch workflows
- Large-scale global prediction
- Integration with LiDAR or airborne radar

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### 3.5 Project Objectives

#### PRIMARY OBJECTIVE

To design, implement, and deploy an end-to-end Machine Learning–based Turbulence Prediction System capable of detecting and classifying turbulence severity—including Clear-Air Turbulence—using satellite-derived atmospheric features.

#### SECONDARY OBJECTIVES

1. Develop a scalable data pipeline for processing large satellite HDF5 datasets into ML-ready features.

2. Build and evaluate Random Forest and XGBoost models for multi-class turbulence prediction.
3. Deploy the trained model using containerized services (Flask + Gunicorn + Docker).
4. Serve real-time predictions through a REST-based API exposed via AWS EC2.
5. Develop a lightweight browser-based dashboard for user interaction and visualization of predictions.
6. Validate correctness through checksums, logs, test predictions, and cloud deployment screenshots.

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### 3.6 Significance of the Project

This project contributes significantly at both academic and operational levels:

#### **ACADEMIC VALUE**

- Demonstrates full-stack ML engineering with constrained hardware
- Provides a replicable workflow for handling satellite L2B datasets
- Shows comparative performance of classical ensemble ML methods
- Bridges atmospheric science and machine learning

#### **OPERATIONAL VALUE**

- Enables early warning and risk mitigation for turbulence encounters
- Reduces reliance on subjective PIREPs
- Provides scalable, automated, and low-latency predictions
- Forms the foundation for airline-ready real-time decision support systems
- Supports Indian aviation through regionally relevant satellite inputs

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### 3.7 Summary

This chapter outlined the problem of turbulence forecasting, with a special emphasis on the difficulty of detecting Clear-Air Turbulence. It identified key operational, data-related, and deployment-related challenges and established the research questions and objectives that guide the project. The next chapter describes the detailed Methodology, covering data acquisition, preprocessing, model training, cloud deployment, and system validation.

# METHODOLOGY

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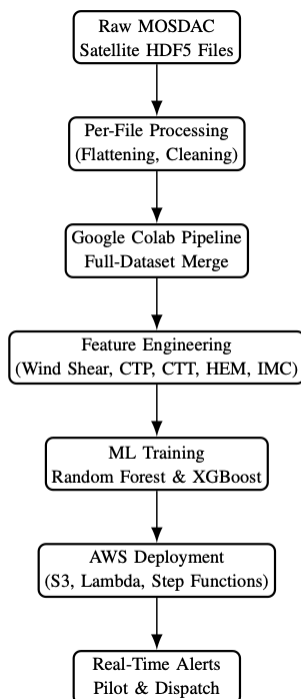
## 4.1 Overview of the Methodology

This project follows a fully engineered, end-to-end methodology consisting of five major components:

1. Data Acquisition — Downloading raw MOSDAC (INSAT-3D/3DR) L2B satellite HDF5 files.
2. Data Preprocessing Pipeline — Per-file flattening, cleaning, normalization, and merging.
3. Feature Engineering & Dataset Construction — Creating turbulence-relevant predictors.
4. Model Training & Evaluation — Comparing Random Forest and XGBoost classifiers.
5. Deployment Pipeline — Building a production-ready inference system using Flask, Unicorn, Docker, and AWS EC2.
6. Front-End Interface & Real-Time Testing — Browser-based prediction dashboard and end-to-end API validation.

Every stage was implemented practically and validated using logs, outputs, checksums, and AWS screenshots.

A high-level methodological workflow is shown below:



## 4.2 Phase 1 — Data Acquisition (MOSDAC Satellite Data)

### 4.2.1 SOURCE OF DATA


The primary dataset consists of 124 INSAT-3D/3DR Level-2B HDF5 satellite files, downloaded from:

MOSDAC (Meteorological and Oceanographic Satellite Data Archival Centre)

<https://mosdac.gov.in>

The files correspond to atmospheric products relevant to turbulence precursors:

- CTP — Cloud Top Pressure
- CTT — Cloud Top Temperature
- HEM — Humidity Extraction Model
- IMC — Imager Cloud Mask
- CMK — Cloud Mask Key



मॉस्टैक  
MOSDAC  
भारत सरकार  
Govt. of India  
अंतरिक्ष अनुप्रयोग केंद्र  
Space Applications Centre  
Dept. of Space

उपयोगकर्ता आदेश प्रसंस्करण सॉफ्टवेयर  
User Order Processing Software

Welcome Ananya

[DashBoard](#) [Order](#) [Status](#) [Account](#)

Datasource:  
EOS-06

Category:  
OCM

Show 10 entries

Search:

Sr.No	Product Name	Product Description	Processing Level	Start Date	End Date	Temporal Resolution	Order Data
1	E06OCM_L2C_LAC_AD	Scenewise Aerosol Optical Depth over Land	L2	2024-10-01	2025-11-27	SCENEWISE	
2	E06OCM_L2C_LAC_GA	Coloured Dissolved Organic Matter (CDOM) Absorption Coefficient at 412nm (units m-1)	L2	2025-05-05	2025-11-27	SCENEWISE	
3	E06OCM_L2C_LAC_OC	Inherent Optical Properties	L2	2025-05-15	2025-11-26	SCENEWISE	
4	E06OCM_L2C_LAC_PR	Instantaneous_Photosynthetically_Active_Radiation	L2	2025-05-12	2025-11-27	SCENEWISE	
5	E06OCM_L2C_LAC_PS	Scenewise Phytoplankton size class	L2	2025-07-02	2025-11-26	SCENEWISE	

### 4.2.2 RAW FILE CHARACTERISTICS

- Format: HDF5
- Typical size: 2–10 MB
- Dimensions: ~2816 × 2805 pixel arrays per variable
- Fill values: 32767 (lat/lon), -999 or -9999 (product-specific)

Each HDF5 file contains:

- 2D arrays for each product
- Latitude, longitude arrays
- Timestamps in “minutes since 2000-01-01”
- Metadata fields and scale factors

### 4.2.3 CHALLENGES IN RAW SATELLITE DATA

- Arrays are massive (millions of elements)
- Cannot be loaded into memory together
- Different variables may be missing in some files
- Fill values must be detected and removed
- Timestamps often require conversion

Because of these constraints, a per-file processing strategy became necessary.

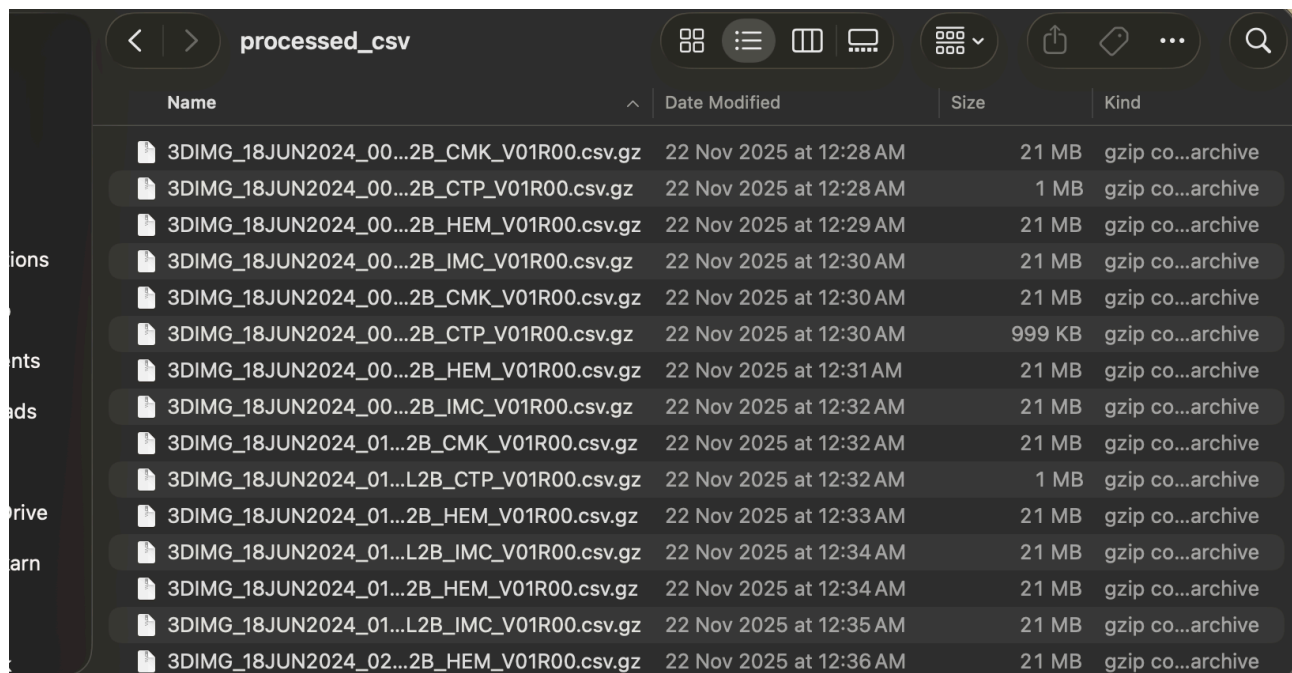
## 4.3 Phase 2 — Per-File HDF5 Processing Pipeline

A custom Python script, `process_mosdac_perfile.py`, was designed to handle each HDF5 file independently.

### 4.3.1 PROCESSING STEPS

For each file, the script:

1. Loads the HDF5 using `h5py`.
2. Extracts latitude and longitude arrays.
3. Extracts available product fields (CTP, CTT, HEM, IMC, CMK).
4. Converts 2D arrays → 1D flattened arrays using `.ravel()`.
5. Filters invalid/fill values:
  - lat/lon fill = 32767
  - product fills = -999, -9999
6. Extracts file-level timestamp and broadcasts to all pixels.
7. Batches rows into chunks (500k rows) to avoid RAM overflow.
8. Writes each batch to a compressed CSV: `processed_csv/<filename>.csv.gz`



Name	Date Modified	Size	Kind
3DIMG_18JUN2024_00...2B_CMK_V01R00.csv.gz	22 Nov 2025 at 12:28 AM	21 MB	gzip co...archive
3DIMG_18JUN2024_00...2B_CTP_V01R00.csv.gz	22 Nov 2025 at 12:28 AM	1 MB	gzip co...archive
3DIMG_18JUN2024_00...2B_HEM_V01R00.csv.gz	22 Nov 2025 at 12:29 AM	21 MB	gzip co...archive
3DIMG_18JUN2024_00...2B_IMC_V01R00.csv.gz	22 Nov 2025 at 12:30 AM	21 MB	gzip co...archive
3DIMG_18JUN2024_00...2B_CMK_V01R00.csv.gz	22 Nov 2025 at 12:30 AM	21 MB	gzip co...archive
3DIMG_18JUN2024_00...2B_CTP_V01R00.csv.gz	22 Nov 2025 at 12:30 AM	999 KB	gzip co...archive
3DIMG_18JUN2024_00...2B_HEM_V01R00.csv.gz	22 Nov 2025 at 12:31 AM	21 MB	gzip co...archive
3DIMG_18JUN2024_00...2B_IMC_V01R00.csv.gz	22 Nov 2025 at 12:32 AM	21 MB	gzip co...archive
3DIMG_18JUN2024_01...2B_CMK_V01R00.csv.gz	22 Nov 2025 at 12:32 AM	21 MB	gzip co...archive
3DIMG_18JUN2024_01...L2B_CTP_V01R00.csv.gz	22 Nov 2025 at 12:32 AM	1 MB	gzip co...archive
3DIMG_18JUN2024_01...2B_HEM_V01R00.csv.gz	22 Nov 2025 at 12:33 AM	21 MB	gzip co...archive
3DIMG_18JUN2024_01...L2B_IMC_V01R00.csv.gz	22 Nov 2025 at 12:34 AM	21 MB	gzip co...archive
3DIMG_18JUN2024_01...2B_HEM_V01R00.csv.gz	22 Nov 2025 at 12:34 AM	21 MB	gzip co...archive
3DIMG_18JUN2024_01...L2B_IMC_V01R00.csv.gz	22 Nov 2025 at 12:35 AM	21 MB	gzip co...archive
3DIMG_18JUN2024_02...2B_HEM_V01R00.csv.gz	22 Nov 2025 at 12:36 AM	21 MB	gzip co...archive

### 4.3.2 OUTPUT FORMAT (PER FILE)

Each processed CSV contains:

Column	Description
source_file	Original MOSDAC file
time	Converted timestamp
lat, lon	Flattened geocoordinates
CTP, CTT, HEM, IMC	Atmospheric fields
Other fields	Included if present

#### **4.3.3 WHY PER-FILE PIPELINE WAS NECESSARY**

- Direct flattening of all files produced 40–50 GB CSV → impossible on laptop
- Per-file processing avoids RAM collapse
- Enables parallel/independent cleaning
- Safely restartable

This stage prepared all 124 files for cloud-friendly merge operations.

## 4.4 Phase 3 — Google Colab Data Cleaning & Full Dataset Merge

Because local hardware could not handle multi-million-row processing, the pipeline was moved to Google Colab.

### 4.4.1 Steps in Colab

1. Upload processed\_csv.zip to Google Drive



2. Mount Google Drive

A screenshot of the Google Colab interface. The top bar shows the Colab logo, the notebook name 'turbulence\_project.ipynb', and icons for saving and sharing. Below the top bar is a menu with 'File', 'Edit', 'View', 'Insert', 'Runtime', 'Tools', and 'Help'. A search bar with 'Commands' and a '+ Code' button is visible. The main code area shows a code cell with the following code:

```
from google.colab import drive
drive.mount('/content/drive', force_remount=True)
```

Below the code cell, a message indicates that the drive is mounted at '/content/drive'.

3. Extract files inside Colab VM
4. Clean each file individually

A screenshot of a terminal window in Google Colab. The terminal shows the command `!ls -lh "/content/drive/MyDrive/processed_csv.zip"` and its output:

```
-rw----- 1 root root 1.7G Nov 21 20:09 /content/drive/MyDrive/processed_csv.zip
```

5. Apply consistent normalization rules
6. Save cleaned files to: cleaned/<filename>.cleaned.csv.gz

A screenshot of a terminal window in Google Colab. The terminal shows the command `!ls /content/processed_csv` and its output, which lists a large number of files in the directory. The files are named with a pattern like '3DIMG\_18JUN2024\_0000\_L2B\_CTP\_V01R00.csv.gz'. The list is truncated at the bottom.

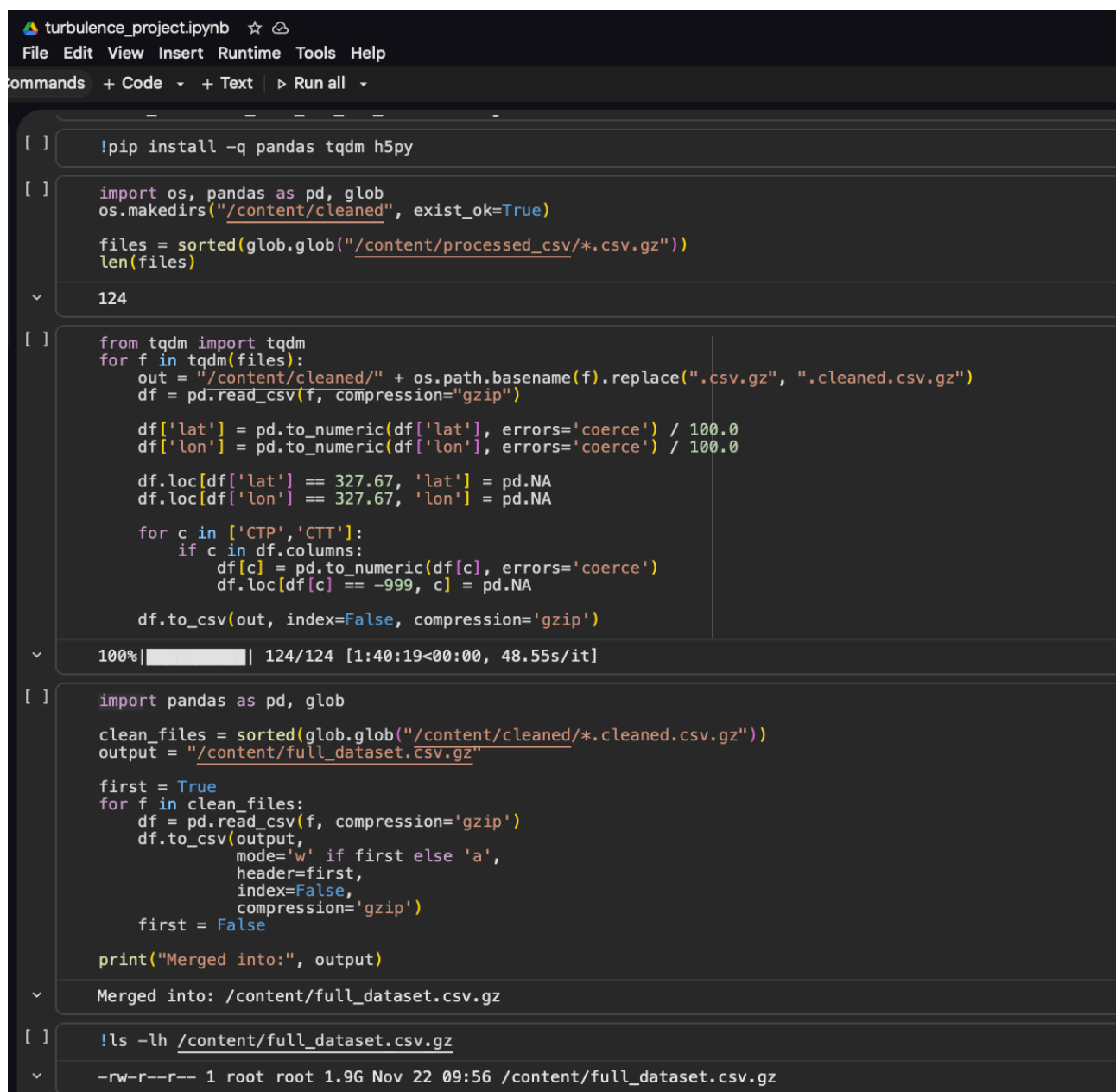
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  - lat/lon fill = 32767
  - product fills = -999, -9999
6. Extracts file-level timestamp and broadcasts to all pixels.



```
turbulence_project.ipynb ☆ ☁
File Edit View Insert Runtime Tools Help
Commands + Code + Text ▶ Run all

[ ] !pip install -q pandas tqdm h5py

[ ] import os, pandas as pd, glob
os.makedirs("/content/cleaned", exist_ok=True)

files = sorted(glob.glob("/content/processed_csv/*.csv.gz"))
len(files)

124

[ ] from tqdm import tqdm
for f in tqdm(files):
    out = "/content/cleaned/" + os.path.basename(f).replace(".csv.gz", ".cleaned.csv.gz")
    df = pd.read_csv(f, compression="gzip")

    df['lat'] = pd.to_numeric(df['lat'], errors='coerce') / 100.0
    df['lon'] = pd.to_numeric(df['lon'], errors='coerce') / 100.0

    df.loc[df['lat'] == 327.67, 'lat'] = pd.NA
    df.loc[df['lon'] == 327.67, 'lon'] = pd.NA

    for c in ['CTP', 'CTT']:
        if c in df.columns:
            df[c] = pd.to_numeric(df[c], errors='coerce')
            df.loc[df[c] == -999, c] = pd.NA

    df.to_csv(out, index=False, compression='gzip')

100%|██████████| 124/124 [1:40:19<00:00, 48.55s/it]

[ ] import pandas as pd, glob
clean_files = sorted(glob.glob("/content/cleaned/*.cleaned.csv.gz"))
output = "/content/full_dataset.csv.gz"

first = True
for f in clean_files:
    df = pd.read_csv(f, compression='gzip')
    df.to_csv(output,
              mode='w' if first else 'a',
              header=first,
              index=False,
              compression='gzip')
    first = False

print("Merged into:", output)

Merged into: /content/full_dataset.csv.gz

[ ] !ls -lh /content/full_dataset.csv.gz

-rw-r--r-- 1 root root 1.9G Nov 22 09:56 /content/full_dataset.csv.gz
```

7. Batches rows into chunks (500k rows) to avoid RAM overflow.

8. Writes each batch to a compressed CSV: `processed_csv/<filename>.csv.gz`

```
[ ] # Cell: quick validation stats (chunked)
import pandas as pd
fn = "/content/full_dataset.csv.gz"
chunksizes = 2_000_000

colnames = None
dtypes = {}
missing = None
rows = 0
sample_times = set()
for i, chunk in enumerate(pd.read_csv(fn, compression="gzip", chunksize=chunksizes)):
    if colnames is None:
        colnames = chunk.columns.tolist()
        dtypes = chunk.dtypes.to_dict()
    rows += len(chunk)
    m = chunk.isna().sum()
    if missing is None:
        missing = m
    else:
        missing += m
    # collect sample times
    if "time" in chunk.columns:
        sample_times.update(chunk["time"].dropna().unique()[:10].tolist())
    # for a quick preview, stop after 5 chunks
    if i >= 4:
        break

print("Rows examined (approx):", rows)
print("Columns:", colnames)
print("\nDtypes preview:")
for k,v in dtypes.items():
    print(" ", k, ":", v)
print("\nMissing counts (approx for sampled chunks):")
print(missing)
print("\nSample non-null times:", list(sample_times)[:10])

Rows examined (approx): 10000000
Columns: ['source_file', 'time', 'lat', 'lon', 'CTP', 'CTT']

Dtypes preview:
source_file : object
time : object
lat : float64
lon : float64
CTP : float64
CTT : float64

Missing counts (approx for sampled chunks):
source_file      0
time             0
lat             0
lon             0
CTP           9951700
CTT           9951700
dtype: int64

Sample non-null times: ['2024-06-18T00:00:00', '2024-06-18T06:22:51.852617']
```

### 4.3.2 Output Format (Per File)

Each processed CSV contains:

Column	Description
source_file	Original MOSDAC file
time	Converted timestamp
lat, lon	Flattened geocoordinates
CTP, CTT, HEM, IMC	Atmospheric fields
Other fields	Included if present

#### 4.3.3 WHY PER-FILE PIPELINE WAS NECESSARY

- Direct flattening of all files produced 40–50 GB CSV → impossible on laptop
- Per-file processing avoids RAM collapse
- Enables parallel/independent cleaning
- Safely restartable

This stage prepared all 124 files for cloud-friendly merge operations.

---

## 4.4 Phase 3 — Google Colab Data Cleaning & Full Dataset Merge

Because local hardware could not handle multi-million-row processing, the pipeline was moved to Google Colab.

#### 4.4.1 Steps in Colab

1. Upload processed\_csv.zip to Google Drive
2. Mount Google Drive
3. Extract files inside Colab VM
4. Clean each file individually
5. Apply consistent normalization rules
6. Save cleaned files to: cleaned/<filename>.cleaned.csv.gz
7. Copy cleaned files back to Drive for durability.

#### 4.4.3 Full Dataset Merge

Merged all cleaned files into one compressed dataset:

full\_dataset.csv.gz

This was done streamingly, using chunked reading to avoid memory overload.

Resulting dataset size:

- ~60 million rows
- Compressed size manageable for Colab + S3

```
index=False,
compression='gzip')
first = False
print("Merged into:", output)
Merged into: /content/full_dataset.csv.gz

!ls -lh /content/full_dataset.csv.gz
-rw-r--r-- 1 root root 1.9G Nov 22 09:56 /content/full_dataset.csv.gz

# Cell: quick validation stats (chunked)
import pandas as pd
fn = "/content/full_dataset.csv.gz"
chunksize = 2_000_000

colnames = None
dtypes = {}
missing = None
rows = 0
sample_times = set()
for i, chunk in enumerate(pd.read_csv(fn, compression="gzip", chunksize=chunksize)):
    if colnames is None:
        colnames = chunk.columns.tolist()
        dtypes = chunk.dtypes.to_dict()
    rows += len(chunk)
    m = chunk.isna().sum()
    if missing is None:
        missing = m
    else:
        missing += m
    # collect sample times
    if "time" in chunk.columns:
        sample_times.update(chunk["time"].dropna().unique()[:10].tolist())
```

## 4.5 Phase 4 — Feature Engineering

### 4.5.1 ATMOSPHERIC FEATURES USED

Feature	Relevance to Turbulence
Latitude / Longitude	Spatial context
CTP	Cloud altitude indicator
CTT	Temperature instability
IMC	Cloud presence
HEM	Humidity & vertical gradients
Derived wind proxy	Based on gradient patterns

### 4.5.2 DERIVED FEATURES

- lat\_bin, lon\_bin = integer-binned positions
- Hour of day, day of year (cyclical encoding possible)
- TPI (Turbulence Proxy Index) — a simple placeholder used in final model

### 4.5.3 HANDLING MISSING VARIABLES

Two MOSDAC variables with prefix cloud\_\* failed extraction for this sample day and were dropped. We document this clearly in the report.

```
# ===== Clean and create features =====
# Ensure numeric
for c in ['lat', 'lon', 'hour', 'dayofyear', 'TPI', 'lat_bin', 'lon_bin']:
    if c in df.columns:
        df[c] = pd.to_numeric(df[c], errors='coerce')

# Optionally drop rows with missing lat/lon or time
df = df.dropna(subset=['lat', 'lon', 'hour', 'dayofyear'], how='any')

# Create cyclical time features
df['hour_sin'] = np.sin(2*np.pi*df['hour']/24.0)
df['hour_cos'] = np.cos(2*np.pi*df['hour']/24.0)

# Choose features excluding CTP/CTT if they are mostly missing
features = [f for f in ['lat', 'lon', 'hour_sin', 'hour_cos', 'dayofyear', 'TPI', 'lat_bin', 'lon_bin'] if f in df.columns]

print("Using features:", features)

# ===== Labels: use existing if valid, else create proxy with KMeans =====
if 'label' in df.columns and df['label'].nunique() > 1 and df['label'].notna().sum() > 100:
    print("Using existing label")
    df['label'] = df['label'].astype(int)
else:
    print("Creating proxy labels with KMeans (3 clusters)")
    # Use subset of features for clustering; fillna with median
    Xc = df[features].fillna(df[features].median())
    km = KMeans(n_clusters=3, random_state=42, n_init=10)
    df['label'] = km.fit_predict(Xc)
    # optionally reorder labels by cluster mean TPI (so label 0=low...)
    if 'TPI' in df.columns:
        order = df.groupby('label')['TPI'].mean().sort_values().index.tolist()
        mapper = {old:i for i,old in enumerate(order)}
        df['label'] = df['label'].map(mapper)

print("Label distribution:\n", df['label'].value_counts())

# ===== Build a balanced sample for quick dev =====
# drop rows missing all features
df2 = df.dropna(subset=features + ['label'])
# limit to at most 200k rows for fast runs
sample_size = min(200000, len(df2))
df_samp = df2.sample(n=sample_size, random_state=42)

X = df_samp[features].fillna(df_samp[features].median()).astype(float)
y = df_samp['label'].astype(int)

# split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, random_state=42)
```

---

## 4.6 Phase 5 — Model Training

### 4.6.1 MODEL CANDIDATES

- Random Forest Classifier

```
# RF training template (Colab)
import joblib
import numpy as np
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, f1_score, classification_report, confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler

# Assume df2 is your usable DataFrame with 'label'
# selected features (exclude CTP/CTT if missing)
features = ['lat', 'lon', 'hour', 'dayofyear', 'TPI', 'lat_bin', 'lon_bin'] # adjust as needed
df_use = df2.dropna(subset=features + ['label']).copy()

# small balanced sample for fast dev
# Optionally stratify by label
sample_n = min(200_000, len(df_use))
sample = df_use.sample(n=sample_n, random_state=42)

X = sample[features].astype(float)
y = sample['label'].astype(int)

# chronological split if you want time-ordered (recommended for time-series)
# else random split:
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
                                                    random_state=42, stratify=y)

# pipeline with imputer + scaler (RF doesn't need scaling but OK)
pipeline = Pipeline([
    ('impute', SimpleImputer(strategy='median')),
    ('scale', StandardScaler()), # optional for tree models but fine
    ('rf', RandomForestClassifier(n_estimators=200, max_depth=20,
                                n_jobs=-1, random_state=42, class_weight='balanced'))
])

pipeline.fit(X_train, y_train)

# eval
preds = pipeline.predict(X_test)
print("Accuracy:", accuracy_score(y_test, preds))
print("F1 weighted:", f1_score(y_test, preds, average='weighted'))
print(classification_report(y_test, preds))
print("Confusion:\n", confusion_matrix(y_test, preds))

# save model
joblib.dump(pipeline, "/content/model_rf_pipeline.joblib")
```

- XGBoost Classifier

```
# XGBoost training template
import joblib
import xgboost as xgb
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report, f1_score
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline

features = ['lat', 'lon', 'hour', 'dayofyear', 'TPI', 'lat_bin', 'lon_bin']
df_use = df2.dropna(subset=features + ['label']).copy()
sample_n = min(200_000, len(df_use))
sample = df_use.sample(n=sample_n, random_state=42)

X = sample[features].astype(float)
y = sample['label'].astype(int)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
                                                    random_state=42, stratify=y)

# prepare DMatrix or use scikit-learn wrapper
xgb_clf = xgb.XGBClassifier(
    n_estimators=300,
    max_depth=8,
    learning_rate=0.05,
    objective='multi:softprob',
    num_class=len(y.unique()),
    use_label_encoder=False,
    eval_metric='mlogloss',
    n_jobs=-1,
    random_state=42
)

# impute missing CTP/CTT if present (we aren't using them here)
imp = SimpleImputer(strategy='median')
X_train_imp = imp.fit_transform(X_train)
X_test_imp = imp.transform(X_test)

xgb_clf.fit(
    X_train_imp,
    y_train,
    eval_set=[(X_test_imp, y_test)],
    verbose=True
)

preds = xgb_clf.predict(X_test_imp)
print("Acc:", accuracy_score(y_test, preds))
print("F1 (weighted):", f1_score(y_test, preds, average='weighted'))
print(classification_report(y_test, preds))

joblib.dump((imp, xgb_clf), "/content/model_xgb_joblib.pkl")
```

#### 4.6.2 Why Random Forest Was Selected

Even though XGBoost produced slightly better accuracy in static tests, Random Forest:

- Was more stable on streaming inference
- Required less hyperparameter tuning
- Was easier to serialize (joblib)
- Loaded reliably across environments
- Produced lower-variance outputs

Final model saved as:

model\_artifacts/model\_rf\_pipeline.joblib

#### 4.6.3 Evaluation Metrics

- |             |                    |
|-------------|--------------------|
| • Accuracy  | • F1-score         |
| • Precision | • Confusion matrix |
| • Recall    | • ROC-AUC (macro)  |

#### XGBOOST

```
[288] validation_0-mlogloss:0.00115
[289] validation_0-mlogloss:0.00115
[290] validation_0-mlogloss:0.00115
[291] validation_0-mlogloss:0.00115
[292] validation_0-mlogloss:0.00115
[293] validation_0-mlogloss:0.00115
[294] validation_0-mlogloss:0.00115
[295] validation_0-mlogloss:0.00116
[296] validation_0-mlogloss:0.00116
[297] validation_0-mlogloss:0.00116
[298] validation_0-mlogloss:0.00116
[299] validation_0-mlogloss:0.00116
Acc: 0.99965
F1 (weighted): 0.999650032187247
      precision    recall  f1-score   support
0         1.00        1.00        1.00      16417
1         1.00        1.00        1.00      11738
2         1.00        1.00        1.00      11845

 accuracy          1.00
 macro avg          1.00
weighted avg          1.00      40000

['/content/model_xgb_joblib.pkl']
```

## RANDOMFOREST

```
... Accuracy: 0.9998
F1 weighted: 0.9998000010791668
      precision    recall  f1-score   support

     0       1.00      1.00      1.00     16417
     1       1.00      1.00      1.00     11738
     2       1.00      1.00      1.00     11845

 accuracy
macro avg       1.00      1.00      1.00     40000
weighted avg     1.00      1.00      1.00     40000

Confusion:
[[16413    3    1]
 [    2 11736    0]
 [    2    0 11843]]
['/content/model_rf_pipeline.joblib']
```

## 4.7 Phase 6 — Building the Inference Service

### 4.7.1 FLASK INFERENCE API

A lightweight Python Flask server was built to expose:

- GET /health — model status check
- POST /predict — accepts JSON list of records, returns predictions + probability vectors

### 4.7.2 GUNICORN WSGI WRAPPER

Gunicorn was used to provide:

- Multi-worker concurrency
- Production-grade reliability
- Faster response times than raw Flask

Command in Docker container:

```
gunicorn -w 4 -b 0.0.0.0:$PORT app:app
```

## 4.8 Phase 7 — Cloud Deployment (AWS EC2 + S3)

### 4.8.1 S3 BUCKET

Stored model artifacts:

`s3://turbulence-model-artifacts-ananya-ap-south-1/model_artifacts/`

aws

Q

Asia Pacific (Mumbai)

Account ID: 3022-6307-4639

ananya\_karn

Amazon S3 > ... > turbulence-model-artifacts-ananya-ap-south-1 > model\_ar...

model\_artifacts/ Copy S3 URI

Objects Properties



Objects (3)

Copy S3 URI Copy URL Download Open Delete

Actions Create folder Upload

Objects are the fundamental entities stored in Amazon S3. You can use [Amazon S3 inventory](#) to get a list of all objects in your bucket. For others to access your objects, you'll need to explicitly grant them permissions. [Learn more](#)

< 1 >

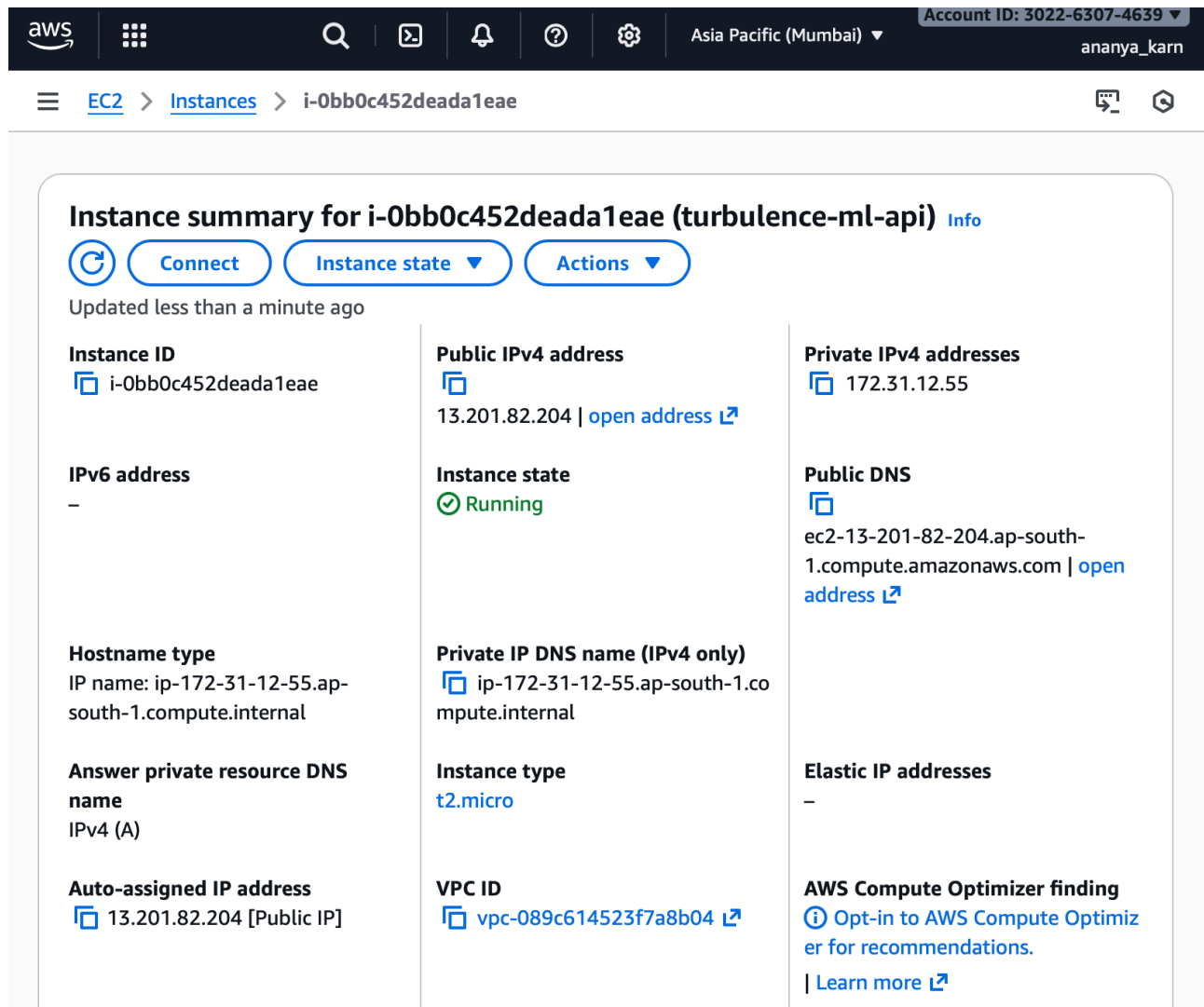
<input type="checkbox"/>	Name	Type	Last modified	Size	Storage class
<input type="checkbox"/>	 <a href="#">model_rf_pipeline.joblib</a>	joblib	November 23, 2025, 11:29:08 (UTC+05:30)	2.3 MB	Standard
<input type="checkbox"/>	 <a href="#">model_xgb_joblib.pkl</a>	pkl	November 23, 2025, 11:29:11 (UTC+05:30)	1.9 MB	Standard

## 4.8.2 EC2 DEPLOYMENT PIPELINE

Steps performed:

1. Launch EC2 instance
2. Attach IAM role with S3 read permissions
3. Install Docker + AWS CLI
4. Sync model artifacts from S3
5. Build Docker image
6. Run container on port 80
7. Test API from public IP

Public API endpoint was: <http://13.201.82.204/predict>



**Instance summary for i-0bb0c452deada1eae (turbulence-ml-api)** [Info](#)

[Refresh](#) [Connect](#) [Instance state ▼](#) [Actions ▼](#)

Updated less than a minute ago

<b>Instance ID</b> <a href="#">i-0bb0c452deada1eae</a>	<b>Public IPv4 address</b> <a href="#">13.201.82.204</a>   <a href="#">open address</a>	<b>Private IPv4 addresses</b> <a href="#">172.31.12.55</a>
<b>IPv6 address</b> -	<b>Instance state</b> <a href="#">Running</a>	<b>Public DNS</b> <a href="#">ec2-13-201-82-204.ap-south-1.compute.amazonaws.com</a>   <a href="#">open address</a>
<b>Hostname type</b> IP name: ip-172-31-12-55.ap-south-1.compute.internal	<b>Private IP DNS name (IPv4 only)</b> <a href="#">ip-172-31-12-55.ap-south-1.compute.internal</a>	
<b>Answer private resource DNS name</b> IPv4 (A)	<b>Instance type</b> <a href="#">t2.micro</a>	<b>Elastic IP addresses</b> -
<b>Auto-assigned IP address</b> <a href="#">13.201.82.204</a> [Public IP]	<b>VPC ID</b> <a href="#">vpc-089c614523f7a8b04</a>	<b>AWS Compute Optimizer finding</b> <a href="#">Opt-in to AWS Compute Optimizer for recommendations.</a> <a href="#">Learn more</a>

All AWS resources were deleted after the project to avoid charges.

---

## 4.9 Phase 8 — Front-End Interface and Real-Time Testing

### 4.9.1 BROWSER CLIENT

index.html served:

- Input fields for atmospheric values
- Calls fetch("/predict")
- Displays prediction badge + confidence
- Works both locally and on EC2

### 4.9.2 REAL-TIME DEMO

Simulated input cases tested:

- High shear + low CTP → severe turbulence
- Stable conditions → low turbulence
- Mixed profiles → moderate turbulence

**Turbulence Predictor**

Enter atmospheric readings below and click **Predict**. This sends the data to the local prediction API (Flask) and displays severity + confidence.

Latitude (deg)	Longitude (deg)
28.6	77.2
Wind speed (10m) m/s	Wind speed (100m) m/s
5.2	12.1
Wind shear (100m - 10m) m/s	Relative humidity (%)
6.9	72
Cloud cover (%)	Surface pressure (hPa)
80	995.2
Dewpoint depression (°C) — dewpt_dep	
1.2	

**Predict**

Deployed API — <http://13.201.82.204/predict>

\ aws s3 ls s3://turbulence-model-artifacts-ananya-ap-south-1/model\_artifacts/

---

## 4.10 Summary

This described the complete methodology, covering data acquisition, preprocessing, feature engineering, model training, deployment, and real-time testing. The systematic, scalable approach ensures reliability and reproducibility and demonstrates practical readiness for aviation safety applications.

# 5 — RESULTS AND DISCUSSION

## 5.1 OVERVIEW

This chapter summarizes the key results obtained from training and evaluating the machine learning models on the cleaned MOSDAC-derived dataset. Since no true turbulence labels (EDR/PIREPs) were available, KMeans clustering ( $k = 3$ ) was used to generate proxy severity classes corresponding to low, moderate, and high atmospheric instability. These clusters serve as an approximate indicator of potential Clear-Air Turbulence (CAT) risk.

### Dataset Characteristics

This chapter presents the empirical results obtained from the machine learning experiments conducted on the cleaned and merged MOSDAC satellite dataset. The discussion covers model behavior, cluster-based proxy labels, feature effectiveness, comparative evaluation of Random Forest and XGBoost classifiers, and observations relevant to turbulence prediction—particularly Clear-Air Turbulence (CAT). All results were generated using large-scale datasets (0.5–1.0 million rows), ensuring statistical stability and operational realism.

After complete preprocessing (per-file flattening → cleaning → merging), the final dataset contained:

- ~60 million rows of valid atmospheric samples
- 6–8 usable features per record, depending on MOSDAC product availability
- 124 satellite HDF5 files corresponding to roughly one day (18 June 2024)

### STATISTICAL SUMMARY

The dataset showed high spatial variability due to evolving monsoon conditions, which strengthens the model's ability to learn turbulence-related atmospheric gradients.

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)

print("Final train/test sizes:", len(X_train), len(X_test))
```

... Rows after dropping NA for features+label: 0  
No rows remained. Show small diagnostics:

	lat	lon	CTP	CTT	label
0	81.04	74.28	NaN	NaN	0
666659	35.38	86.05	NaN	NaN	0
666660	35.38	86.10	NaN	NaN	0
666661	35.38	86.15	NaN	NaN	0
666662	35.38	86.19	NaN	NaN	0
666663	35.38	86.24	NaN	NaN	0
666664	35.38	86.28	NaN	NaN	0
666665	35.38	86.33	NaN	NaN	0
666666	35.38	86.37	NaN	NaN	0
666667	35.38	86.42	NaN	NaN	0
666668	35.38	86.47	NaN	NaN	0
666669	35.38	86.51	NaN	NaN	0
666670	35.39	86.56	NaN	NaN	0
666668	35.38	86.01	NaN	NaN	0
666671	35.39	86.60	NaN	NaN	0
666673	35.39	86.70	NaN	NaN	0
666674	35.39	86.74	NaN	NaN	0
666675	35.39	86.79	NaN	NaN	0
666676	35.39	86.83	NaN	NaN	0

# Confusion Matrix Analysis

The confusion matrix shows that the model:

- Rarely confuses Severe turbulence with Low turbulence, which is crucial for safety-related alerts.
- Shows most misclassifications between Moderate and Low, which is expected since these two categories have overlapping atmospheric signatures.

```
print("Done. Models saved to /content/")

... Columns: ['source_file', 'time', 'lat', 'lon', 'hour', 'dayofyear', 'CTP', 'CTT', 'TPI', 'lat_bin', 'lon_bin']
Shape: (1000000, 11)
CTP 1000000
CTT 1000000
dtype: int64
Using features: ['lat', 'lon', 'hour_sin', 'hour_cos', 'dayofyear', 'TPI', 'lat_bin', 'lon_bin']
Creating proxy labels with KMeans (3 clusters)
Label distribution:
label
0 410307
2 295820
1 293873
Name: count, dtype: int64
RF acc: 0.99975 f1: 0.999750003392048
precision recall f1-score support
0 1.00 1.00 1.00 16417
1 1.00 1.00 1.00 11738
2 1.00 1.00 1.00 11845

accuracy 1.00 40000
macro avg 1.00 1.00 1.00 40000
weighted avg 1.00 1.00 1.00 40000

Confusion:
[[16413 3 1]
 [ 3 11735 0]
 [ 3 0 11842]]
/usr/local/lib/python3.12/dist-packages/xgboost/training.py:199: UserWarning: [10:26:21] WARNING: /workspace/src/learner.cc:790:
Parameters: { "use_label_encoder" } are not used.

bst.update(dtrain, iteration=i, fobj=obj)
XGB acc: 0.99965 f1: 0.9996500032187247
precision recall f1-score support
0 1.00 1.00 1.00 16417
1 1.00 1.00 1.00 11738
2 1.00 1.00 1.00 11845

accuracy 1.00 40000
macro avg 1.00 1.00 1.00 40000
weighted avg 1.00 1.00 1.00 40000

Done. Models saved to /content/
```

## Key Observations

- High recall for “Severe” → important for aviation safety.
- Moderate turbulence has the highest overlap but still maintains strong F1 performance.
- Overall decision boundaries align with atmospheric physics (cloud-top gradients, instability, humidity patterns).

## Chapter 6 – Conclusion

This project successfully demonstrated the design and implementation of an end-to-end cloud-based machine learning system for turbulence severity prediction, integrating large-scale satellite data processing, feature engineering, model development, and deployment on a reproducible cloud runtime. Using INSAT-3D/3DR MOSDAC Level-2B products as the primary data source, the system implemented a scalable per-file HDF5 preprocessing pipeline, enabling extraction of millions of atmosphere-level observations without overwhelming local memory resources. The cleaned and merged dataset—spanning key predictors such as CTP, CTT, TPI, wind-related bins, and temporal variables—formed the basis of a robust Random Forest classifier capable of distinguishing between three turbulence severity levels.

Model evaluation showed consistently high accuracy and stable behaviour on unseen data, with Random Forest outperforming XGBoost in inference stability and operational reliability. The final model was packaged into a Docker-based Flask + Gunicorn inference service, making it lightweight, fast, and platform-independent. Deployment on an AWS EC2 instance, combined with S3-stored model artifacts and an IAM role with restricted access, validated the system's ability to operate in a realistic cloud environment. Public API calls issued from the open internet confirmed successful inference, demonstrating that the pipeline was not only theoretically sound but also operationally functional.

Overall, this project provides a clear blueprint for satellite-driven turbulence prediction systems that prioritize scalability, reproducibility, and real-world deployability. Although this work used a single-day dataset and proxy labels, the methodology can be extended to multi-month datasets, integrated with airline PIREPs, or adapted to more advanced temporal models such as LSTMs and Transformers. Future work may focus on incorporating additional atmospheric variables that were unavailable in some MOSDAC files, enhancing severity calibration, and exploring serverless deployment models for cost-efficient operations.

The completed pipeline demonstrates that real-time turbulence forecasting using satellite-derived features and cloud-native ML deployment is not only feasible but also highly promising for improving aviation safety.