

COURSEWORK: Academic Year 2025/2026

CMM705 Big Data Programming

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Table of Contents

[Task 1] Designing a Solution Architecture

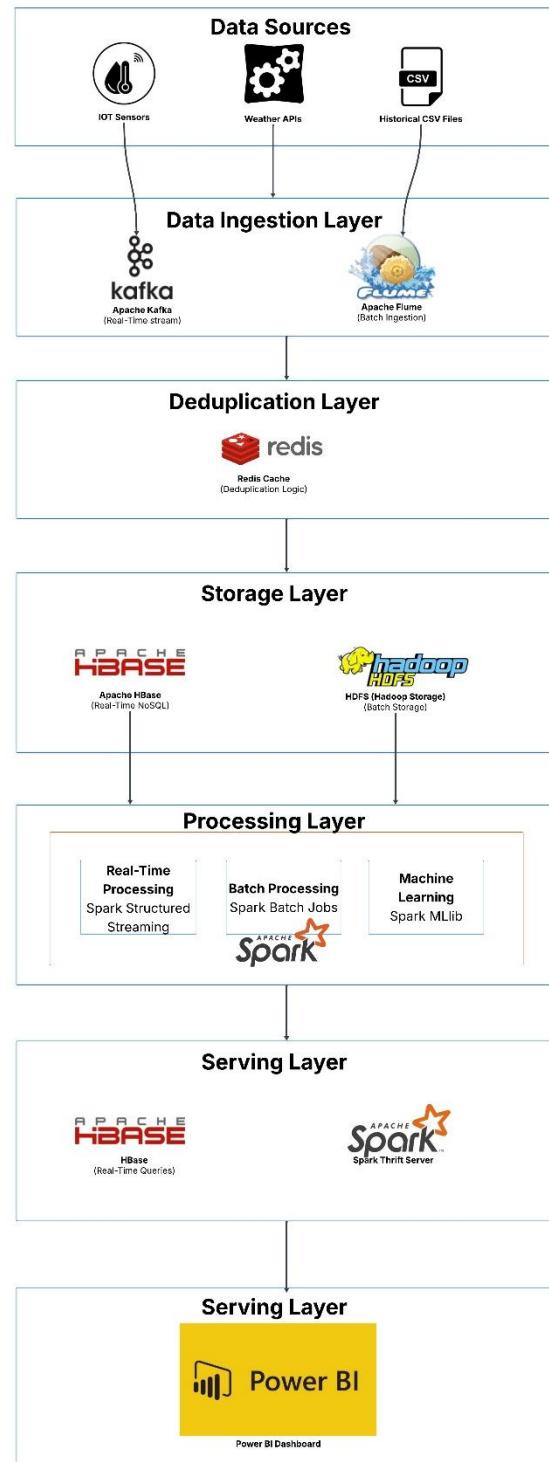
[Task 2] Data Analysis

[Task 3] Performing Machine Learning model using Spark MLlib

[Task 4] Presentation of the Analysis

[Task 1] - Designing a Solution Architecture

[Task 1] [1] Solution Architecture Design



[Task 1] [2] Roles of the components of the Designed Solution Architecture

1. Data Ingestion Layer

Apache Kafka → Collects live weather data

- Weather stations send data every 10-15 minutes
- Stores messages for 7 days (backup if processing fails)
- Partitions data by district (parallel processing)

Apache Flume → Loads historical CSV files

- Monitors folder for new CSV files
- Automatically uploads to HDFS
- Runs hourly batch ingestion

2. Deduplication Layer

Redis Cache → Prevents duplicate records

- Creates unique key: district:timestamp:temperature
- Check if data has already been seen in last 2 hours
- If duplicate → discard, if new → pass to storage
- Saves 30-40% storage by removing duplicates

3. Storage Layer

HBase → Fast access to recent data (last 30 days)

- Stores latest readings for real-time dashboard
- Query speed: <10ms (instant dashboard updates)
- Auto-deletes old data after 30 days (stays lean)

HDFS → Long-term historical storage (15+ years)

- Keeps all raw and processed data
- Scales to petabytes (add more nodes as needed)
- 3x replication (survives hardware failures)
- Uses Parquet format (10x smaller than CSV)

4. Processing Layer

Apache Spark → Does all the work (one tool for everything)

- Spark Streaming: Processes live Kafka data every 10 seconds
 - Reads messages → deduplicates → writes to HBase + HDFS
- Spark Batch: Scheduled jobs for aggregations
 - Daily: Calculate average temp, total rainfall per district
 - Hourly: Clean data, remove outliers
- Spark MLlib: Machine learning predictions
 - Trains model to predict evapotranspiration (ET_0)
 - Help farmers know how much to irrigate

5. Serving Layer

HBase REST API → Dashboard queries latest data

- When a user through Power BI asks "What's Colombo's current temperature?"
- HBase responds in <10ms with live data

Spark Thrift Server → Historical SQL queries

- When a user through Power BI asks "What was average rainfall in 2023?"
- Spark SQL queries HDFS and returns results
- Analysts run custom SQL queries

6. Visualization Layer

Power BI Dashboard → User interface

- Real-time panel: Shows live weather (refreshes every 30 sec)
- Historical trends: Charts showing patterns over years
- ML predictions: Evapotranspiration forecasts for irrigation planning

[Task 2] Data Analysis

Task 2 [1] 1 – Hadoop MapReduce Analysis - Final Output:

```
RGU_ID_2522702_IIT_ID_20250693 > Task_2 > task_2-1_mapreduce > outputs > task2-1-1_output.txt > data
1 Ampara had a total precipitation of 2852 hours with a mean temperature of 25 for 1st month
2 Ampara had a total precipitation of 2476 hours with a mean temperature of 25 for 2nd month
3 Ampara had a total precipitation of 1871 hours with a mean temperature of 27 for 3rd month
4 Ampara had a total precipitation of 1689 hours with a mean temperature of 28 for 4th month
5 Ampara had a total precipitation of 1466 hours with a mean temperature of 28 for 5th month
6 Ampara had a total precipitation of 693 hours with a mean temperature of 29 for 6th month
7 Ampara had a total precipitation of 708 hours with a mean temperature of 30 for 7th month
8 Ampara had a total precipitation of 816 hours with a mean temperature of 29 for 8th month
9 Ampara had a total precipitation of 1169 hours with a mean temperature of 28 for 9th month
10 Ampara had a total precipitation of 2523 hours with a mean temperature of 27 for 10th month
11 Ampara had a total precipitation of 3570 hours with a mean temperature of 26 for 11th month
12 Ampara had a total precipitation of 3652 hours with a mean temperature of 25 for 12th month
13 Anuradhapura had a total precipitation of 1461 hours with a mean temperature of 25 for 1st month
14 Anuradhapura had a total precipitation of 941 hours with a mean temperature of 26 for 2nd month
15 Anuradhapura had a total precipitation of 793 hours with a mean temperature of 27 for 3rd month
16 Anuradhapura had a total precipitation of 1360 hours with a mean temperature of 28 for 4th month
17 Anuradhapura had a total precipitation of 1925 hours with a mean temperature of 28 for 5th month
18 Anuradhapura had a total precipitation of 1182 hours with a mean temperature of 28 for 6th month
19 Anuradhapura had a total precipitation of 912 hours with a mean temperature of 28 for 7th month
20 Anuradhapura had a total precipitation of 1162 hours with a mean temperature of 28 for 8th month
21 Anuradhapura had a total precipitation of 1615 hours with a mean temperature of 27 for 9th month
22 Anuradhapura had a total precipitation of 2641 hours with a mean temperature of 26 for 10th month
23 Anuradhapura had a total precipitation of 3065 hours with a mean temperature of 25 for 11th month
24 Anuradhapura had a total precipitation of 2449 hours with a mean temperature of 25 for 12th month
25 Badulla had a total precipitation of 3259 hours with a mean temperature of 21 for 1st month
26 Badulla had a total precipitation of 2740 hours with a mean temperature of 21 for 2nd month
27 Badulla had a total precipitation of 1822 hours with a mean temperature of 23 for 3rd month
28 Badulla had a total precipitation of 1918 hours with a mean temperature of 24 for 4th month
29 Badulla had a total precipitation of 2063 hours with a mean temperature of 25 for 5th month
30 Badulla had a total precipitation of 1061 hours with a mean temperature of 25 for 6th month
31 Badulla had a total precipitation of 1063 hours with a mean temperature of 25 for 7th month
32 Badulla had a total precipitation of 1247 hours with a mean temperature of 25 for 8th month
33 Badulla had a total precipitation of 1549 hours with a mean temperature of 24 for 9th month
34 Badulla had a total precipitation of 2619 hours with a mean temperature of 23 for 10th month
35 Badulla had a total precipitation of 3335 hours with a mean temperature of 22 for 11th month
36 Badulla had a total precipitation of 3508 hours with a mean temperature of 22 for 12th month
37 Batticaloa had a total precipitation of 3301 hours with a mean temperature of 26 for 1st month
38 Batticaloa had a total precipitation of 2678 hours with a mean temperature of 26 for 2nd month
39 Batticaloa had a total precipitation of 1880 hours with a mean temperature of 27 for 3rd month
40 Batticaloa had a total precipitation of 1529 hours with a mean temperature of 28 for 4th month
41 Batticaloa had a total precipitation of 1529 hours with a mean temperature of 29 for 5th month
42 Batticaloa had a total precipitation of 738 hours with a mean temperature of 30 for 6th month
43 Batticaloa had a total precipitation of 728 hours with a mean temperature of 30 for 7th month
44 Batticaloa had a total precipitation of 806 hours with a mean temperature of 29 for 8th month
```

Task 2 [1] 1 - Implementation:

I have implemented the following Java classes.

MonthlyWeatherDriver.java - Configures and launches the job

```
package com.rgu.bigdata;

import org.apache.hadoop.conf.Configuration;
import org.apache.hadoop.conf.Configured;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Job;
import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;
import org.apache.hadoop.util.Tool;
import org.apache.hadoop.util.ToolRunner;

/**
 * Driver for Task 2.1.1: Monthly precipitation and temperature analysis
 */
public class MonthlyWeatherDriver extends Configured implements Tool {

    @Override
    public int run(String[] args) throws Exception {
        if (args.length != 2) {
            System.err.println("Usage: MonthlyWeatherDriver <input path> <output path>");
            System.err.println(
                "Example: hadoop jar yourjar.jar com.rgu.bigdata.MonthlyWeatherDriver /input/weather.csv /output/monthly");
            return -1;
        }

        Configuration conf = getConf();
        Job job = Job.getInstance(conf, "Monthly Weather Analysis - Sri Lanka");

        job.setJarByClass(MonthlyWeatherDriver.class);

        // Set Mapper and Reducer
        job.setMapperClass(MonthlyWeatherMapper.class);
        job.setReducerClass(MonthlyWeatherReducer.class);

        // Set output types
        job.setOutputKeyClass(Text.class);
        job.setOutputValueClass(Text.class);

        // Set input and output paths
        FileInputFormat.addInputPath(job, new Path(args[0]));
        FileOutputFormat.setOutputPath(job, new Path(args[1]));

        boolean success = job.waitForCompletion(true);
        return success ? 0 : 1;
    }

    public static void main(String[] args) throws Exception {
        int exitCode = ToolRunner.run(new Configuration(), new MonthlyWeatherDriver(), args);
        System.exit(exitCode);
    }
}
```

MonthlyWeatherMapper.java - Extracts location, month, year, precipitation, temperature

```
package com.rgu.bigdata;

import org.apache.hadoop.io.LongWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Mapper;

import java.io.IOException;
import java.util.HashMap;
import java.util.Map;

/**
 * Task 2.1.1: Calculate total precipitation and mean temperature per district
 * per month over the past decade (2014-2024)
 */
public class MonthlyWeatherMapper extends Mapper<LongWritable, Text, Text, Text> {

    private Text outputKey = new Text();
    private Text outputValue = new Text();
    private Map<String, Integer> columnIndexMap = new HashMap<>();
    private boolean headerProcessed = false;

    @Override
    protected void map(LongWritable key, Text value, Context context)
        throws IOException, InterruptedException {

        String line = value.toString();
        String[] fields = line.split(",");

        // Process header to build column index map
        if (key.get() == 0) {
            for (int i = 0; i < fields.length; i++) {
                columnIndexMap.put(fields[i].trim(), i);
            }
            headerProcessed = true;
            return;
        }

        if (!headerProcessed) {
            return; // Safety check
        }
    }
}
```

MonthlyWeatherReducer.java - Aggregates data per district, per month

```

package com.rgu.bigdata;

import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Reducer;
import org.apache.hadoop.conf.Configuration;
import org.apache.hadoop.fs.FileSystem;
import org.apache.hadoop.fs.Path;

import java.io.BufferedReader;
import java.io.InputStreamReader;
import java.io.IOException;
import java.util.*;

/**
 * Task 2.1.1: Reducer for calculating total precipitation and mean temperature
 * per district per month over the past decade (2014-2024)
 *
 */
public class MonthlyWeatherReducer extends Reducer<Text, Text, Text, Text> {

    private Text outputKey = new Text();
    private Text result = new Text();

    // Store all results for sorting
    private List<OutputRecord> outputRecords = new ArrayList<>();

    // Inner class to hold output data
    private static class OutputRecord {
        String locationId;
        int month;
        String cityName;
        double totalPrecipitation;
        double meanTemperature;

        OutputRecord(String locationId, int month, String cityName,
                    double totalPrecipitation, double meanTemperature) {
            this.locationId = locationId;
            this.month = month;
            this.cityName = cityName;
            this.totalPrecipitation = totalPrecipitation;
            this.meanTemperature = meanTemperature;
        }
    }

    // Map location_id to city name (loaded dynamically from locationData.csv)
    private Map<String, String> locationMap = new HashMap<>();

    @Override
    protected void setup(Context context) throws IOException, InterruptedException {
        super.setup(context);
        loadLocationData(context);
    }

    /**
     * Load location names from locationData.csv in HDFS
     */
    private void loadLocationData(Context context) throws IOException {
        Configuration conf = context.getConfiguration();
        Path locationPath = new Path("/input/locationData.csv");
        FileSystem fs = FileSystem.get(conf);

        try (BufferedReader br = new BufferedReader(new InputStreamReader(fs.open(locationPath)))) {
            String line;
            boolean isHeader = true;

            while ((line = br.readLine()) != null) {
                if (isHeader) {
                    isHeader = false;
                    continue; // Skip header line
                }

                String[] fields = line.split(regex: ",");
                if (fields.length >= 8) {
                    String locationId = fields[0].trim();
                    String cityName = fields[7].trim();
                    locationMap.put(locationId, cityName);
                }
            }
            System.out.println("Loaded " + locationMap.size() + " locations from locationData.csv");
        }
    }
}

```

```

// Calculate mean temperature
double meanTemperature = count > 0 ? totalTemperature / count : 0.0;

// Parse key to get location_id and month (NO year - aggregated across all
// years)
String[] keyParts = key.toString().split("-");
if (keyParts.length == 2) {
    String locationId = keyParts[0];
    int month = Integer.parseInt(keyParts[1]);

    // Get city name from map (loaded from locationData.csv)
    String cityName = locationMap.getOrDefault(locationId, "Location_" + locationId);

    // Store the record for later sorting
    outputRecords.add(new OutputRecord(locationId, month, cityName,
        totalPrecipitation, meanTemperature));
}
}

@Override
protected void cleanup(Context context) throws IOException, InterruptedException {
    // Sort by city name, then by month
    Collections.sort(outputRecords, new Comparator<OutputRecord>() {
        @Override
        public int compare(OutputRecord o1, OutputRecord o2) {
            // First compare by city name
            int cityCompare = o1.cityName.compareTo(o2.cityName);
            if (cityCompare != 0)
                return cityCompare;

            // Then by month
            return Integer.compare(o1.month, o2.month);
        }
    });
}

// Output all sorted records
for (OutputRecord record : outputRecords) {
    String output = String.format(
        format: "%s had a total precipitation of %.0f hours with a mean temperature of %.0f for %s month",
        record.cityName, record.totalPrecipitation, record.meanTemperature,
        getOrdinal(record.month));

    outputKey.set("");
    result.set(output);
    context.write(outputKey, result);
}
}

```

```

/**
 * Helper method to convert month number to ordinal (1st, 2nd, 3rd, etc.)
 */
private String getOrdinal(int month) {
    if (month >= 11 && month <= 13) {
        return month + "th";
    }
    switch (month % 10) {
        case 1:
            return month + "st";
        case 2:
            return month + "nd";
        case 3:
            return month + "rd";
        default:
            return month + "th";
    }
}

```

Task 2 [1] 1 – Execution Steps:

1. Copied datasets to namenode container.

```

iitgcpuser@instance-20251011-010203:~/cw/RGU_ID_2522702_IIT_ID_20250693/Task_2/task_2-1_mapreduce$ docker cp /home/iitgcpuser/CMM705---Big-Data-Programming---Coursework/Datasets/weatherData.csv namenode:/tmp/
Successfully copied 15.7MB to namenode:/tmp/
iitgcpuser@instance-20251011-010203:~/cw/RGU_ID_2522702_IIT_ID_20250693/Task_2/task_2-1_mapreduce$ docker cp /home/iitgcpuser/CMM705---Big-Data-Programming---Coursework/Datasets/locationData.csv namenode:/tmp/
Successfully copied 3.58kB to namenode:/tmp/

```

2. Uploaded copied data into HDFS

```

iitgcpuser@instance-20251011-010203:~/cw/RGU_ID_2522702_IIT_ID_20250693/Task_2/task_2-1_mapreduce$ docker exec namenode hdfs
  dfs -mkdir -p /input
iitgcpuser@instance-20251011-010203:~/cw/RGU_ID_2522702_IIT_ID_20250693/Task_2/task_2-1_mapreduce$ docker exec namenode hdfs -put -f /tmp/weatherData.csv /input/
2025-12-17 15:31:55,314 INFO sasl.SaslDataTransferClient: SASL encryption trust check: localHostTrusted = false, remoteHostTrusted = false
iitgcpuser@instance-20251011-010203:~/cw/RGU_ID_2522702_IIT_ID_20250693/Task_2/task_2-1_mapreduce$ docker exec namenode hdfs
  -put -f /tmp/locationData.csv /input/
2025-12-17 15:32:18,509 INFO sasl.SaslDataTransferClient: SASL encryption trust check: localHostTrusted = false, remoteHostTrusted = false
iitgcpuser@instance-20251011-010203:~/cw/RGU_ID_2522702_IIT_ID_20250693/Task_2/task_2-1_mapreduce$ docker exec namenode hdfs
  -du -h /input/
1.6 K   4.8 K   /input/locationData.csv
14.9 M  44.8 M  /input/weatherData.csv

```

3. Built the MapReduce JAR

```
[INFO] Replacing original artifact with shaded artifact.  
[INFO] Replacing /home/iitgcpuser/cw/RGU_ID_2522702_IIT_ID_20250693/Task_2/task_2-1_mapreduce/target/cmm7  
T_ID_20250693/Task_2/task_2-1_mapreduce/target/cmm705-coursework-1.0-SNAPSHOT-shaded.jar  
[INFO] -----  
[INFO] BUILD SUCCESS  
[INFO] -----  
[INFO] Total time: 5.858 s  
[INFO] Finished at: 2025-12-17T15:25:30Z  
[INFO] -----
```

4. Copied the generated JAR into namenode.

```
iitgcpuser@instance-20251011-010203:~/cw/RGU_ID_2522702_IIT_ID_20250693/Task_2/task_2-1_mapreduce$ docker cp target/cmm705-coursework-1  
0-SNAPSHOT.jar & hadoop com.rgu.bigmdata.MonthlyWeatherDriver /input/weatherData.csv /output/task2-1-1 output"  
Successfully copied 2.25MB to namenode:/tmp/
```

5. Ran MapReduce Job MonthlyWeatherDriver.

```
iitgcpuser@instance-20251011-010203:~/cw/RGU_ID_2522702_IIT_ID_20250693/Task_2/task_2-1_mapreduce$ docker exec namenode bash -c "export HADOOP_CLASSPATH=/tmp/cmm705-coursework-1  
0-SNAPSHOT.jar & hadoop com.rgu.bigmdata.MonthlyWeatherDriver /input/weatherData.csv /output/task2-1-1 output"  
2025-12-17 15:39:28,651 INFO impl.MetricsSystemImpl: JobTracker metrics system started  
2025-12-17 15:39:28,556 INFO input.FileInputFormat: Total input files to process : 1  
2025-12-17 15:39:29,016 INFO mapreduce.JobSubmitter: number of splits:1  
2025-12-17 15:39:29,148 INFO mapreduce.JobSubmitter: Submitting tokens for job: job_local394916937_0001  
2025-12-17 15:39:29,148 INFO mapreduce.JobSubmitter: Executing with tokens: []  
2025-12-17 15:39:29,273 INFO mapreduce.Job: The url to track the job: http://localhost:8080/  
2025-12-17 15:39:29,274 INFO mapreduce.Job: Running job: job_local394916937_0001  
2025-12-17 15:39:29,275 INFO mapreduce.Job: OutputCommitter set in config null  
2025-12-17 15:39:29,284 INFO output.FileOutputCommitter: File Output Committer Algorithm version is 2  
2025-12-17 15:39:29,284 INFO output.FileOutputCommitter: File Output Committer skip cleanup _temporary folders under output directory:false, ignore cleanup failures: false  
2025-12-17 15:39:29,285 INFO mapred.LocalJobRunner: OutputCommitter is org.apache.hadoop.mapred.lib.output.FileOutputCommitter  
2025-12-17 15:39:29,334 INFO mapred.LocalJobRunner: Waiting for map tasks  
2025-12-17 15:39:29,334 INFO mapred.LocalJobRunner: Starting task: attempt_local394916937_0001_m_000000_0  
2025-12-17 15:39:29,359 INFO output.FileOutputCommitter: File Output Committer Algorithm version is 2  
2025-12-17 15:39:29,359 INFO output.FileOutputCommitter: File Output Committer skip cleanup _temporary folders under output directory:false, ignore cleanup failures: false  
2025-12-17 15:39:29,377 INFO mapred.Task: Using ResourceCalculatorProcessTree : [ ]  
2025-12-17 15:39:29,381 INFO mapred.MapTask: Processing split: hdfs://namenode:9000/input/weatherData.csv+0+15654150  
2025-12-17 15:39:29,446 INFO mapred.MapTask: (EQUATOR) 0 kv: 26214396(104857584)  
2025-12-17 15:39:29,446 INFO mapred.MapTask: mapreduce.task.io.sort.mb: 100  
2025-12-17 15:39:29,446 INFO mapred.MapTask: sort_start = 83886080  
2025-12-17 15:39:29,446 INFO mapred.MapTask: bufstart = 0; bufvoid = 104857600  
2025-12-17 15:39:29,446 INFO mapred.MapTask: kystart = 26214396; length = 6553600  
2025-12-17 15:39:29,451 INFO mapred.MapTask: Map output collector class = org.apache.hadoop.mapred.MapTask$MapOutputBuffer  
2025-12-17 15:39:29,477 INFO sasl.SaslDataTransferClient: SASL encryption trust check: localHostTrusted = false, remoteHostTrusted = false  
2025-12-17 15:39:30,240 INFO mapred.LocalJobRunner:  
2025-12-17 15:39:30,243 INFO mapred.MapTask: Starting flush of map output  
2025-12-17 15:39:30,243 INFO mapred.MapTask: Spilling map output  
2025-12-17 15:39:30,243 INFO mapred.MapTask: bufstart = 0; bufend = 1358653; bufvoid = 104857600  
2025-12-17 15:39:30,243 INFO mapred.MapTask: kystart = 26214396(104857584); kyend = 25833208(103332800); length = 381197/6553600  
2025-12-17 15:39:30,280 INFO mapred.MapTask: Job: Job_local394916937_0001 running in uber mode : false  
2025-12-17 15:39:30,281 INFO mapred.MapTask: map % reduce 0%  
2025-12-17 15:39:419 INFO mapred.MapTask: Finished spill 0  
2025-12-17 15:39:431 INFO mapred.Task: Task:attempt_local394916937_0001_m_000000_0 is done. And is in the process of committing  
2025-12-17 15:39:435 INFO mapred.LocalJobRunner: map  
2025-12-17 15:39:436 INFO mapred.Task: Task :attempt_local394916937_0001_m_000000_0 is done.  
2025-12-17 15:39:444 INFO mapred.Task: Final Counters for attempt_local394916937_0001_m_000000_0: Counters: 23  
File System Counters  
FILE: Number of bytes read=2246248  
FILE: Number of bytes written=4324880  
FILE: Number of read operations=0  
FILE: Number of large read operations=0  
FILE: Number of write operations=0  
HDFS: Number of bytes read=15654150  
HDFS: Number of bytes written=0  
HDFS: Number of read operations=5  
HDFS: Number of large read operations=0  
HDFS: Number of write operations=1  
HDFS: Number of bytes read erasure-coded=0  
Map-Reduce Framework  
Map input records=142372  
Map output records=95300  
Map output bytes=1350653  
Map output materialized bytes=1541259  
Input split bytes=107  
Combine input records=0  
Spilled Records=95300  
Failed Shuffles=0  
Merged Map outputs=0  
GC time elapsed (ms)=187  
Total committed heap usage (bytes)=1011875840  
File Input Format Counters  
Bytes Read=15654150
```

```

0:~> w 1000=202594
2025-12-17 15:39:30,971 INFO mapred.LocalJobRunner: Finishing task: attempt_local1394916937_0001_r_000000_0
2025-12-17 15:39:30,971 INFO mapred.LocalJobRunner: reduce task executor complete.
2025-12-17 15:39:31,253 INFO mapreduce.Job: map 100% reduce 100%
2025-12-17 15:39:31,253 INFO mapreduce.Job: Job job_local1394916937_0001 completed successfully
2025-12-17 15:39:31,294 INFO mapreduce.Job: Counters: 36
  File System Counters:
    FILE: Number of bytes read=757946
    FILE: Number of bytes written=10191010
    FILE: Number of read operations=0
    FILE: Number of large read operations=0
    FILE: Number of write operations=0
    HDFS: Number of bytes read=28354
    HDFS: Number of bytes written=28354
    HDFS: Number of read operations=16
    HDFS: Number of large read operations=0
    HDFS: Number of write operations=4
    HDFS: Number of bytes read erasure-coded=0
  Map-Reduce Framework
    Map input records=12372
    Map output records=2030
    Map output materialized bytes=1541259
    Input split bytes=107
    Combine input records=0
    Combine output records=0
    Reduce input groups=300
    Reduce shuffle bytes=1541259
    Reduce input records=300
    Redundant output bytes=0
    Spilled Records=190000
    Shuffled Maps =1
    Failed Shuffles=0
    Merged Map outputs=1
    GC time elapsed (ms)=187
    Total committed heap usage (bytes)=2023751688
  Shuffle Errors
    MAP=0
    CONNECTION=0
    IO_ERROR=0
    WRONG_LENGTH=0
    WRONG_MAP=0
    WRONG_REDUCE=0
  File Input Format Counters
    Bytes Read=15654150
  File Output Format Counters
    Bytes Written=28354

```

- MonthlyWeatherDriver job has executed successfully, and results had saved into a txt file in HDFS.

[Task 2] 1. 2 Hadoop MapReduce Analysis

Task 2 [1] 2 – Hadoop MapReduce Analysis - Final Output:

```

RGU_ID_2522702_IIT_ID_20250693 > Task_2 > task_2-1_mapreduce > outputs > task2-1-2_output.txt
1      10th month in 2018 had the highest total precipitation of 11007 hours
2

```

Task 2 [1] 2 – Implementation:

- MaxPrecipitationDriver.java - Configures and launches the job

```
package com.ngu.bigdata;

import org.apache.hadoop.conf.Configuration;
import org.apache.hadoop.conf.Configured;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Job;
import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;
import org.apache.hadoop.util.Tool;
import org.apache.hadoop.util.ToolRunner;

/**
 * Driver for Task 2.1.2: Find the month and year with the highest total
 * precipitation
 * This job aggregates precipitation data by month and identifies the month
 * with the maximum total precipitation across all districts in Sri Lanka.
 */
public class MaxPrecipitationDriver extends Configured implements Tool {

    @Override
    public int run(String[] args) throws Exception {
        if (args.length != 2) {
            System.err.println("Usage: MaxPrecipitationDriver <input_path> <output_path>");
            System.err.println("Example: hadoop jar bigdata-weather-1.0.jar " +
                "com.ngu.bigdata.MaxPrecipitationDriver " +
                "/data/weatherData.csv /output/task2_1_2");
            return -1;
        }

        Configuration conf = getConf();
        Job job = Job.getInstance(conf, "Task 2.1.2 - Maximum Precipitation Month");

        job.setJarByClass(MaxPrecipitationDriver.class);
        job.setMapperClass(MaxPrecipitationMapper.class);
        job.setReducerClass(MaxPrecipitationReducer.class);

        // Output key/value types
        job.setOutputKeyClass(Text.class);
        job.setOutputValueClass(Text.class);

        // Input/output paths
        FileInputFormat.addInputPath(job, new Path(args[0]));
        FileOutputFormat.setOutputPath(job, new Path(args[1]));
    }
}
```

```

System.out.println(x: "=====");
System.out.println(x: "Task 2.1.2: Maximum Precipitation Analysis");
System.out.println(x: "=====");
System.out.println("Input Path: " + args[0]);
System.out.println("Output Path: " + args[1]);
System.out.println(x: "Mapper: MaxPrecipitationMapper");
System.out.println(x: "Reducer: MaxPrecipitationReducer");
System.out.println(x: "=====");

boolean success = job.waitForCompletion(true);

if (success) {
    System.out.println(x: "\n✓ Job completed successfully!");
    System.out.println("Check output at: " + args[1]);
    System.out.println(x: "Look for '==== MAXIMUM PRECIPITATION MONTH ====' in the output file");
} else {
    System.err.println(x: "\n✗ Job failed!");
}

return success ? 0 : 1;
}

Run | Debug
public static void main(String[] args) throws Exception {
    int exitCode = ToolRunner.run(new Configuration(), new MaxPrecipitationDriver(), args);
    System.exit(exitCode);
}
}

```

- MaxPrecipitationMapper.java - Extracts month, year, precipitation

```

package com.ngu.bigdata;

import org.apache.hadoop.io.LongWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Mapper;

import java.io.IOException;
import java.util.HashMap;
import java.util.Map;

/**
 * Mapper for Task 2.1.2: Find the month and year with the highest total
 * precipitation
 *
 * Input CSV format:
 * location_id,date,weather_code,...,precipitation_hours(12),...
 * Output: Key = "Month-Year" (e.g., "2-2019"), Value = precipitation_hours
 *
 * This mapper extracts the month-year and precipitation from each record,
 * allowing the reducer to find the month with maximum total precipitation.
 */
public class MaxPrecipitationMapper extends Mapper<LongWritable, Text, Text, Text> {

    private Text outputKey = new Text();
    private Text outputValue = new Text();
    private Map<String, Integer> columnIndexMap = new HashMap<>();
    private boolean headerProcessed = false;

    @Override
    protected void map(LongWritable key, Text value, Context context)
        throws IOException, InterruptedException {

        String line = value.toString();
        String[] fields = line.split(regex: ",");

        // Process header to build column index map
        if (key.get() == 0) {
            for (int i = 0; i < fields.length; i++) {
                columnIndexMap.put(fields[i].trim(), i);
            }
            headerProcessed = true;
            return;
        }

        if (!headerProcessed) {
            return; // Safety check
        }
    }
}

```

```
try {
    // Extract fields by column name
    String locationId = fields[columnIndexMap.get(key: "location_id")].trim();
    String dateStr = fields[columnIndexMap.get(key: "date")].trim();
    String precipitationHours = fields[columnIndexMap.get(key: "precipitation_hours (h)")].trim();

    // Parse date to extract month and year
    String[] dateParts = dateStr.split(regex: "/");
    if (dateParts.length == 3) {
        String month = dateParts[0]; // Month
        String year = dateParts[2]; // Year

        // Create key: month-year
        String yearMonth = month + "-" + year;
        outputKey.set(yearMonth);

        // Emit precipitation value
        outputValue.set(precipitationHours);
        context.write(outputKey, outputValue);
    }
} catch (Exception e) {
    // Skip records with parsing errors
    System.err.println("Error parsing line: " + line);
}
}
```

- MaxPrecipitationReducer.java - Finds month with highest precipitation

```

package com.rgu.bigdata;

import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Reducer;

import java.io.IOException;

/**
 * Reducer for Task 2.1.2: Find the month and year with the highest total
 * precipitation
 * This reducer aggregates precipitation for each month and tracks the maximum.
 */
public class MaxPrecipitationReducer extends Reducer<Text, Text, Text, Text> {

    // Global variable to track maximum precipitation month
    private double globalMaxPrecipitation = Double.MIN_VALUE;
    private String maxMonth = "";

    @Override
    protected void reduce(Text key, Iterable<Text> values, Context context)
        throws IOException, InterruptedException {

        double totalPrecipitation = 0.0;
        int count = 0;

        // Aggregate precipitation for this month-year
        for (Text value : values) {
            try {
                double precipitation = Double.parseDouble(value.toString());
                totalPrecipitation += precipitation;
                count++;
            } catch (NumberFormatException e) {
                System.err.println("Error parsing precipitation value: " + value.toString());
            }
        }

        // Check if this is the global maximum
        if (totalPrecipitation > globalMaxPrecipitation) {
            globalMaxPrecipitation = totalPrecipitation;
            maxMonth = key.toString();
        }

        // Emit all months with their totals
        String output = String.format(format: "Total Precipitation: %.2f hours (from %d records)",
            totalPrecipitation, count);
        // context.write(key, new Text(output));
    }
}

```

```

@Override
protected void cleanup(Context context) throws IOException, InterruptedException {
    // Emit the maximum month summary at the end
    if (!maxMonth.isEmpty()) {
        String[] parts = maxMonth.split(regex: "-");
        String month = parts[0];
        String year = parts[1];

        // Format: "2nd month in 2019 had the highest total precipitation of 300 hr"
        String result = String.format(format: "%s month in %s had the highest total precipitation of %.0f hours",
            getOrdinal(Integer.parseInt(month)), year, globalMaxPrecipitation);

        context.write(new Text(""), new Text(result));
    }
}

/**
 * Helper method to convert month number to ordinal (1st, 2nd, 3rd, etc.)
 */
private String getOrdinal(int month) {
    if (month >= 11 && month <= 13) {
        return month + "th";
    }
    switch (month % 10) {
        case 1:
            return month + "st";
        case 2:
            return month + "nd";
        case 3:
            return month + "rd";
        default:
            return month + "th";
    }
}
}

```

Task 2 [1] 2 – Execution Steps:

- After copying the input datasets into HDFS as in previous step, executed the MapReduce MaxPrecipitationDriver job.

```

$ ./bigdata/maxPrecipitationDriver /input/weatherData.csv
0-SNAPSHOT.jar && hadoop com.rgu.bigdata.MaxPrecipitationDriver /input/weatherData.csv /output/task2-1_output"
/opt/hadoop-3.2.1/libexec/hadoop-functions.sh: line 2401: HADOOP_CONF_DIR: bad substitution
/opt/hadoop-3.2.1/libexec/hadoop-functions.sh: line 2366: HADOOP_CONF_DIR: bad substitution
/opt/hadoop-3.2.1/libexec/hadoop-functions.sh: line 2481: HADOOP_CONF_DIR: bad substitution

```

Task 2.1.2: Maximum Precipitation Analysis

```

=====
Input: /input/weatherData.csv
Output Path: /output/task2-1_output
Mapper: MaxPrecipitationMapper
Reducer: MaxPrecipitationReducer
=====

2025-12-17 15:58:37,966 INFO mapred.JobMetricsConfig: Loaded properties from mapred-metrics2.properties
2025-12-17 15:58:37,969 INFO mapred.JobMetricsConfig: Scheduled Metric snapshot period at 10 second(s).
2025-12-17 15:58:37,943 INFO mapred.MetricsSystemMap: JobTracker metrics system started
2025-12-17 15:58:37,764 INFO input.FileInputFormat: Total input files to process : 1
2025-12-17 15:58:37,829 INFO mapred.JobSubmitter: number of splits:1
2025-12-17 15:58:37,966 INFO mapreduce.JobSubmitter: Submitting tokens for job: job_local1195488467_0001
2025-12-17 15:58:38,067 INFO mapreduce.JobSubmitter: Executing with tokens: []
2025-12-17 15:58:38,069 INFO mapreduce.Job: Job tracking page available: http://localhost:8088/jobs/job_local1195488467_0001
2025-12-17 15:58:38,098 INFO mapreduce.Job: Running job: job_local1195488467_0001
2025-12-17 15:58:38,108 INFO mapred.LocalJobRunner: OutputCommitter set in config null
2025-12-17 15:58:38,109 INFO output.FileOutputCommitter: File Output Committer Algorithm version is 2
2025-12-17 15:58:38,112 INFO output.FileOutputCommitter: FileOutputCommitter skip cleanup temporary folders under output directory:false, ignore cleanup failures: false
2025-12-17 15:58:38,112 INFO output.FileOutputCommitter: org.apache.hadoop.mapreduce.lib.output.FileOutputCommitter
2025-12-17 15:58:38,159 INFO mapred.LocalJobRunner: Waiting for map tasks
2025-12-17 15:58:38,169 INFO mapred.LocalJobRunner: Starting task: attempt_local1195488467_0001_m_000000
2025-12-17 15:58:38,186 INFO output.FileOutputCommitter: File Output Committer Algorithm version is 2
2025-12-17 15:58:38,186 INFO output.FileOutputCommitter: FileOutputCommitter skip cleanup temporary folders under output directory:false, ignore cleanup failures: false
2025-12-17 15:58:38,186 INFO mapred.MapTask: Using RecordReader class: org.apache.hadoop.mapred.TextInputFormat : []
2025-12-17 15:58:38,213 INFO mapred.MapTask: Using Split: hdfs://localhost:9000/input/weatherData.csv:0+16564159
2025-12-17 15:58:38,277 INFO mapred.MapTask: (EQUATOR) 0 kv: 26214396(104857584)
2025-12-17 15:58:38,277 INFO mapred.MapTask: mapred.task.io.sort.mb: 100
2025-12-17 15:58:38,277 INFO mapred.MapTask: soft limit at 83886080
2025-12-17 15:58:38,300 INFO mapred.MapTask: bufstart = @ 0 bufvoid = 0@0557000
2025-12-17 15:58:38,377 INFO mapred.MapTask: bufstart = @ 0 bufvoid = 0@6533600
2025-12-17 15:58:38,281 INFO mapred.MapTask: Map output collector class: org.apache.hadoop.mapred.MapTask$MapOutputBuffer
2025-12-17 15:58:39,062 INFO mapred.LocalJobRunner:
2025-12-17 15:58:39,065 INFO mapred.MapTask: Starting flush of map output
2025-12-17 15:58:39,065 INFO mapred.MapTask: Spilling map output
2025-12-17 15:58:39,065 INFO mapred.MapTask: kvstart = 0@0 bufend = 1362341; bufvoid = 104857600
2025-12-17 15:58:39,065 INFO mapred.MapTask: kvstart = 26214396(104857584); kvend = 25644916(102579664); length = 569481/6553600
2025-12-17 15:58:39,106 INFO mapred.MapTask: job job_local1195488467_0001 running in uber mode : false
2025-12-17 15:58:39,107 INFO mapred.Job: map 0% reduce 0%

```

```

File System Counters
  FILE: Number of bytes read=7786506
  FILE: Number of bytes written=10513325
  FILE: Number of read operations=0
  FILE: Number of large read operations=0
  FILE: Number of write operations=0
  HDFS: Number of bytes read=31398300
  HDFS: Number of bytes written=71
  HDFS: Number of read operations=15
  HDFS: Number of large read operations=0
  HDFS: Number of write operations=4
  HDFS: Number of bytes read erasure-coded=0
Map-Reduce Framework
  Map input records=142372
  Map output records=142371
  Map output bytes=1362241
  Map output materialized bytes=1646989
  Input split bytes=107
  Combine input records=0
  Combine output records=0
  Reduce input groups=174
  Reduce shuffle bytes=1646989
  Reduce input records=142371
  Reduce output records=1
  Spilled Records=284742
  Shuffled Maps =1
  Failed Shuffles=0
  Merged Map outputs=1
  GC time elapsed (ms)=166
  Total committed heap usage (bytes)=2048917504
Shuffle Errors
  BAD_ID=0
  CONNECTION=0
  IO_ERROR=0
  WRONG_LENGTH=0
  WRONG_MAP=0
  WRONG_REDUCE=0
File Input Format Counters
  Bytes Read=15654150
File Output Format Counters
  Bytes Written=71

? Job completed successfully!
Check output at: /output/task2-1-2_output

```

[Task 2] 2. Hive Analysis

Task 2 [2] 1 – Hive Analysis - Final Output:

city_name	avg_max_temp
Nuwara Eliya	20.26
Bandarawela	24.58
Welimada	25.28
Badulla	27.64
Kandy	27.73
Matara	28.5
Galle	28.76
Ratnapura	28.85
Matale	28.88
Kalutara	29.18

Task 2 [2] 1 - Implementation steps:

1. Copied Datasets to namenode.

```
iitgcpuser@instance-20251011-010203:/~OWT05---Big-Data-Programming---Coursework/RGU_ID_2522702_IIT_ID_20250693/Task_2/task_2-1_mapreduce$ sudo docker cp /home/iitgcpuser/CMM705-Big-Data-Programming---Coursework/Datasets/locationData.csv namenode:/tmp/Successfully copied 3.58KB to namenode:/tmp/
iitgcpuser@instance-20251011-010203:/~OWT05---Big-Data-Programming---Coursework/RGU_ID_2522702_IIT_ID_20250693/Task_2/task_2-1_mapreduce$ sudo docker cp /home/iitgcpuser/CMM705-Big-Data-Programming---Coursework/Datasets/weatherData.csv namenode:/tmp/Successfully copied 15.7MB to namenode:/tmp/
```

2. Entered the Hadoop namenode container, created directories and uploaded the copied datasets to HDFS.

```
iitgcpuser@instance-20251011-010203:/~OWT05---Big-Data-Programming---Coursework/RGU_ID_2522702_IIT_ID_20250693/Task_2/task_2-1_mapreduce$ sudo docker exec -it namenode bash
root@dd77cd0c8e2c:/# hdfs dfs -mkdir -p /user/hive/warehouse/weather_analytics.db/location
root@dd77cd0c8e2c:/# hdfs dfs -mkdir -p /user/hive/warehouse/weather_analytics.db/weather
root@dd77cd0c8e2c:/# hdfs dfs -put /tmp/locationData.csv /user/hive/warehouse/weather_analytics.db/location/
2025-12-17 11:54:29,997 INFO sasl.SaslDataTransferClient: SASL encryption trust check: localHostTrusted = false, remoteHostTrusted = false
root@dd77cd0c8e2c:/# hdfs dfs -put /tmp/weatherData.csv /user/hive/warehouse/weather_analytics.db/weather/
2025-12-17 11:54:49,890 INFO sasl.SaslDataTransferClient: SASL encryption trust check: localHostTrusted = false, remoteHostTrusted = false
```

Data had uploaded correctly to HDFS.

```
root@dd77cd0c8e2c:/# hdfs dfs -ls /user/hive/warehouse/weather_analytics.db/location
Found 1 items
-rw-r--r-- 3 root supergroup 1630 2025-12-17 11:54 /user/hive/warehouse/weather_analytics.db/location/locationData.csv
root@dd77cd0c8e2c:/# hdfs dfs -ls /user/hive/warehouse/weather_analytics.db/weather
Found 1 items
-rw-r--r-- 3 root supergroup 15654150 2025-12-17 11:54 /user/hive/warehouse/weather_analytics.db/weather/weatherData.csv
root@dd77cd0c8e2c:/# []
```

```
root@dd77cd0c8e2c:/# hdfs dfs -cat /user/hive/warehouse/weather_analytics.db/location/locationData.csv | head -5
2025-12-17 11:57:26,347 INFO sasl.SaslDataTransferClient: SASL encryption trust check: localHostTrusted = false, remoteHostTrusted = false
location_id,latitude,elevation,utc_offset_seconds,timezone,timezone_abbreviation,city_name
0,6.924429,79.90725,4,19800,Asia/Colombo,530,Colombo
1,7.0650263,79.96622,19,19800,Asia/Colombo,530,Gampaha
2,6.572935,80.02519,5,19800,Asia/Colombo,530,Kalutara
3,7.275923,80.62659,499,19800,Asia/Colombo,530,Kandy
root@dd77cd0c8e2c:/# hdfs dfs -cat /user/hive/warehouse/weather_analytics.db/weather/weatherData.csv | head -5
```

```
root@dd77cd0c8e2c:/# hdfs dfs -cat /user/hive/warehouse/weather_analytics.db/weather/weatherData.csv | head -5
2025-12-17 11:57:35,227 INFO sasl.SaslDataTransferClient: SASL encryption trust check: localHostTrusted = false, remoteHostTrusted = false
location_id,date,weather_code (wmo code),temperature_2m_max (°C),temperature_2m_min (°C),temperature_2m_mean (°C),apparent_temperature_max (°C),apparent_temperature_min (°C),apparent_temperature_mean (°C),daylight_duration (s),sunshine_duration (s),precipitation_sum (mm),rain_sum (mm),precipitation_hours (h),wind_speed_10m_max (km/h),wind_gusts_10m_max (km /h),wind_direction_10m_dominant (°),shortwave_radiation_sun (MJ/m²),et0_fao_evapotranspiration (mm),sunrise,sunset
0,1/1/2010,1,30,1,22,6,26,0,34,5,25,0,29,0,42220,2,38905,73,0,0,0,0,12,2,27,4,19,29,92,4,61,06:22,18:05
0,1/1/2010,51,30,1,23,7,26,3,33,9,26,1,29,7,42225,71,37451,01,0,1,0,1,13,0,24,17,71,3,91,06:22,18:06
0,1/3/2010,51,29,6,23,1,26,0,34,5,26,2,29,9,42231,68,33176,43,0,6,0,6,3,12,3,27,4,17,17,76,3,66,06:22,18:06
0,1/4/2010,2,28,9,23,1,25,7,31,7,26,1,28,4,42238,11,38289,2,0,0,0,0,17,0,34,6,357,16,5,3,75,06:23,18:07
```

3. Connected to Hive server and created a Database and Tables in Hive.

```
hive> SHOW DATABASES;
OK
default
weather_analytics
Time taken: 0.011 seconds, Fetched: 2 row(s)
hive> USE weather_analytics;
OK
Time taken: 0.016 seconds
hive> SHOW TABLES;
OK
location_data
weather_data
Time taken: 0.025 seconds, Fetched: 2 row(s)
```

4. Loaded data in HDFS into the tables created.

```
hive> LOAD DATA INPATH '/user/hive/warehouse/weather_analytics.db/location/locationData.csv' INTO TABLE location_data;
Loading data to table default.location_data
OK
Time taken: 1.017 seconds
hive> LOAD DATA INPATH '/user/hive/warehouse/weather_analytics.db/weather/weatherData.csv' INTO TABLE weather_data;
Loading data to table default.weather_data
OK
Time taken: 0.423 seconds
```

```
hive> DESCRIBE location_data;
OK
location_id      int          Unique location identifier
latitude         double        Latitude coordinate
longitude        double        Longitude coordinate
elevation         double        Elevation above sea level in meters
utc_offset_seconds int          UTC offset in seconds
timezone          string        Timezone name
timezone_abbreviation string      Timezone abbreviation
city_name         string        Name of the city
Time taken: 0.046 seconds, Fetched: 8 row(s)
hive> DESCRIBE weather_data;
OK
location_id      int          Location identifier matching locationData
date             string        Date in format M/D/YYYY
weather_code      int          WMO weather code
temperature_2m_max double       Maximum temperature in ##C
temperature_2m_min double       Minimum temperature in ##C
temperature_2m_mean double      Mean temperature in ##C
```

Successfully loaded data could be seen in both tables.

```
hive> SELECT COUNT(*) FROM location_data;
WARNING: Hive-on-MR is deprecated in Hive 2 and may not be available in the future versions. Consider using a different execution engine (i.e. spark, tez) or using Hive 1.X releases.
Query ID = root_20251217122953_8ad436da-967e-4c7e-a197-bca30c8ab9fa
Total jobs = 1
Launching Job 1 out of 1
Number of reduce tasks determined at compile time: 1
In order to change the average load for a reducer (in bytes):
  set hive.exec.reducers.bytes.per.reducer=<number>
In order to limit the maximum number of reducers:
  set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
  set mapreduce.job.reduces=<number>
Job running in-process (local Hadoop)
2025-12-17 12:29:57,677 Stage-1 map = 100%,  reduce = 100%
Ended Job = job_local1428453401_0001
MapReduce Jobs Launched:
Stage-Stage-1: HDFS Read: 42588 HDFS Write: 0 SUCCESS
Total MapReduce CPU Time Spent: 0 msec
OK
54
```

```

hive> SELECT COUNT(*) FROM weather_data;
WARNING: Hive-on-MR is deprecated in Hive 2 and may not be available in the future versions. Consider using a different execution engine (i.e. spark, tez) or using Hive 1.X releases.
Query ID = root_20251217122959_c7674a81-9533-46f1-bbdc-b26d782ff241
Total jobs = 1
Launching Job 1 out of 1
Number of reduce tasks determined at compile time: 1
In order to change the average load for a reducer (in bytes):
  set hive.exec.reducers.bytes.per.reducer=<number>
In order to limit the maximum number of reducers:
  set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
  set mapreduce.job.reduces=<number>
Job running in-process (local Hadoop)
2025-12-17 12:38:00,924 Stage-1 map = 100%,  reduce = 100%
Ended Job = job_local1137343252_0002
MapReduce Jobs Launched:
Stage-Stage-1: HDFS Read: 62659188 HDFS Write: 0 SUCCESS
Total MapReduce CPU Time Spent: 0 msec
OK
284742
Time taken: 1.585 seconds, Fetched: 1 row(s)

```

5. Executed the following Hive query to Rank the top 10 most temperate cities across the dataset.

```

SELECT
    l.city_name AS city_name,
    ROUND(AVG(w.temperature_2m_max), 2) AS avg_max_temp
FROM
    weather_data w
JOIN
    location_data l
    ON w.location_id = l.location_id
WHERE
    w.temperature_2m_max IS NOT NULL
GROUP BY
    l.city_name
ORDER BY
    avg_max_temp ASC
LIMIT 10;

```

The following configuration was set in order to display column names in the output.

```
set hive.cli.print.header=true;
```

```

Launching Job 1 out of 2
Number of reduce tasks not specified. Estimated from input data size: 1
In order to change the average load for a reducer (in bytes):
  set hive.exec.reducers.bytes.per.reducer=<number>
In order to limit the maximum number of reducers:
  set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
  set mapreduce.job.reduces=<number>
Job running in-process (local Hadoop)
2025-12-17 12:37:31,680 Stage-2 map = 100%,  reduce = 100%
Ended Job = job_local12049546362_0005
Launching Job 2 out of 2
Number of reduce tasks determined at compile time: 1
In order to change the average load for a reducer (in bytes):
  set hive.exec.reducers.bytes.per.reducer=<number>
In order to limit the maximum number of reducers:
  set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
  set mapreduce.job.reduces=<number>
Job running in-process (local Hadoop)
2025-12-17 12:37:32,953 Stage-3 map = 100%,  reduce = 100%
Ended Job = job_local1680950613_0006
MapReduce Jobs Launched:
Stage-Stage-2: HDFS Read: 187892388 HDFS Write: 0 SUCCESS
Stage-Stage-3: HDFS Read: 187892388 HDFS Write: 0 SUCCESS
Total MapReduce CPU Time Spent: 0 msec
OK
city_name      avg_max_temp
Nuwara Eliya    20.26
Bandarawela     24.58
Welimada        25.28
Badulla         27.64
Kandy            27.73
Matara           28.5
Galle             28.76
Ratnapura        28.85
Matale           28.88
Kalutara          29.18
Time taken: 11.714 seconds, Fetched: 10 row(s)

```

Task 2 [2] 1 – Hive Analysis - Final Output:

city_name	season	avg_evapotranspiration
Ampara	Maha (Sep-Mar)	3.8
Ampara	Yala (Apr-Aug)	4.87
Anuradhapura	Maha (Sep-Mar)	3.89
Anuradhapura	Yala (Apr-Aug)	4.76
Badulla	Maha (Sep-Mar)	3.55
Badulla	Yala (Apr-Aug)	4.41
Bandarawela	Maha (Sep-Mar)	3.43
Bandarawela	Yala (Apr-Aug)	3.92
Batticaloa	Maha (Sep-Mar)	3.92
Batticaloa	Yala (Apr-Aug)	5.03
Colombo	Maha (Sep-Mar)	3.81
Colombo	Yala (Apr-Aug)	3.64
Galle	Maha (Sep-Mar)	3.87
Galle	Yala (Apr-Aug)	3.92
Gampaha	Maha (Sep-Mar)	3.88
Gampaha	Yala (Apr-Aug)	3.59
Hambantota	Maha (Sep-Mar)	4.37
Hambantota	Yala (Apr-Aug)	4.95
Jaffna	Maha (Sep-Mar)	4.31
Jaffna	Yala (Apr-Aug)	5.2
Kalutara	Maha (Sep-Mar)	3.76
Kalutara	Yala (Apr-Aug)	3.65

Task 2 [2] 1 - Implementation steps:

Followed the same steps from Step 1 to 4 as in above task.

1. Since the Date format in the provided dataset is M/D/YYYY or MM/DD/YYYY, first I created a temporary table with parsed dates. We can use this to extract month from the date strig.

```
hive> SELECT * FROM weather_with_month LIMIT 10;
OK
0      1/1/2010      4.61    1
0      1/2/2010      3.91    1
0      1/3/2010      3.66    1
0      1/4/2010      3.75    1
0      1/5/2010      5.0     1
0      1/6/2010      4.95    1
0      1/7/2010      4.38    1
0      1/8/2010      2.98    1
0      1/9/2010      3.34    1
0      1/10/2010     4.15   1
Time taken: 0.189 seconds, Fetched: 10 row(s)
hive> SELECT COUNT(*) FROM weather_with_month;
OK
284742
Time taken: 0.257 seconds, Fetched: 1 row(s)
```

2. Executed the following Hive query to calculate the average evapotranspiration for each major agricultural season in each district over the years.

```
SELECT
    l.city_name AS city_name,
    CASE
        WHEN w.month_num IN (9, 10, 11, 12, 1, 2, 3) THEN 'Maha (Sep-Mar)'
        WHEN w.month_num IN (4, 5, 6, 7, 8) THEN 'Yala (Apr-Aug)'
    END AS season,
    ROUND(AVG(w.et0_fao_evapotranspiration), 2) AS avg_evapotranspiration
FROM
    weather_with_month w
JOIN
    location_data l
    ON w.location_id = l.location_id
WHERE
    w.month_num IN (1,2,3,4,5,6,7,8,9,10,11,12)
GROUP BY
    l.city_name,
    CASE
        WHEN w.month_num IN (9, 10, 11, 12, 1, 2, 3) THEN 'Maha (Sep-Mar)'
        WHEN w.month_num IN (4, 5, 6, 7, 8) THEN 'Yala (Apr-Aug)'
    END
ORDER BY
    city_name,
    season;
```

```

Launching Job 1 out of 2
Number of reduce tasks not specified. Estimated from input data size: 1
In order to change the average load for a reducer (in bytes):
  set hive.exec.reducers.bytes.per.reducer=<number>
In order to limit the maximum number of reducers:
  set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
  set mapreduce.job.reduces=<number>
Job running in-process (local Hadoop)
2025-12-17 13:20:31,569 Stage-2 map = 0%,  reduce = 0%
2025-12-17 13:20:32,580 Stage-2 map = 100%,  reduce = 100%
Ended Job = job_local1696758915_0002
Launching Job 2 out of 2
Number of reduce tasks determined at compile time: 1
In order to change the average load for a reducer (in bytes):
  set hive.exec.reducers.bytes.per.reducer=<number>
In order to limit the maximum number of reducers:
  set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
  set mapreduce.job.reduces=<number>
Job running in-process (local Hadoop)
2025-12-17 13:20:33,920 Stage-3 map = 100%,  reduce = 100%
Ended Job = job_local137366302_0003
MapReduce Jobs Launched:
Stage-Stage-2:  HDFS Read: 73855690 HDFS Write: 11230898 SUCCESS
Stage-Stage-3:  HDFS Read: 73855690 HDFS Write: 11230898 SUCCESS
Total MapReduce CPU Time Spent: 0 msec
OK
Ampara Maha (Sep-Mar) 3.8
Ampara Yala (Apr-Aug) 4.87
Anuradhapura Maha (Sep-Mar) 3.89
Anuradhapura Yala (Apr-Aug) 4.76
Badulla Maha (Sep-Mar) 3.55
Badulla Yala (Apr-Aug) 4.41
Bandarawela Maha (Sep-Mar) 3.43
Bandarawela Yala (Apr-Aug) 3.92
Batticaloa Maha (Sep-Mar) 3.92
Batticaloa Yala (Apr-Aug) 5.03
Colombo Maha (Sep-Mar) 3.81
Colombo Yala (Apr-Aug) 3.64
Galle Maha (Sep-Mar) 3.87
Galle Yala (Apr-Aug) 3.92
Gampaha Maha (Sep-Mar) 3.88
Gampaha Yala (Apr-Aug) 3.59
Hambantota Maha (Sep-Mar) 4.37
Hambantota Yala (Apr-Aug) 4.95
Jaffna Maha (Sep-Mar) 4.31

```

[Task 2] 3. Spark Analysis

Task 2 [3] 1 – Spark Analysis - Final Output:

... --- Radiation Percentage per Month ---	
month	percentage
1	87.09519350608072
2	94.29768774737937
3	98.05285672729275
4	97.4256157388907
5	90.85530180292807
6	92.275791422476
7	93.00052419118205
8	92.74227304062101
9	91.08658237397407
10	84.52634754134056
11	72.27480647083718
12	71.7864978477085

Task 2 [3] 1 - Implementation:

Pre-processed data to be used in spark analysis.

```
from pyspark.sql import SparkSession
from pyspark.sql import functions as F
from pyspark.sql.window import Window

# Initialize Spark Session
spark = SparkSession.builder.appName("SL_Weather_Analysis").getOrCreate()

# Load Datasets
loc_df =
spark.read.csv("/content/drive/MyDrive/CW_DATASETS/locationData.csv",
header=True, inferSchema=True)
weather_df =
spark.read.csv("/content/drive/MyDrive/CW_DATASETS/weatherData.csv",
header=True, inferSchema=True)

# Preprocessing
# Convert date string to DateType (Format in CSV is M/d/yyyy based on
inspection)
weather_df = weather_df.withColumn("date", F.to_date(F.col("date"),
"M/d/yyyy"))
weather_df = weather_df.withColumn("year", F.year("date")) \
.withColumn("month", F.month("date"))

# Join with Location Data to get City Names
df = weather_df.join(loc_df, "location_id")

# Cache df for better performance on multiple queries
df.cache()
```

I mainly focused on quantifying how much of the monthly shortwave radiation exceeded a threshold of **15 MJ/m²** across all districts.

- Sum of shortwave radiation values was calculated for each month.
- Radiation values greater than 15 MJ/m² were isolated and summed separately.
- The ratio of high radiation to total radiation was computed for each month.
- This percentage represents the share of monthly radiation that surpassed the 15 MJ/m² threshold.

```

# Calculate Total Radiation and High Radiation (>15) per month
q1_result = df.groupBy("month").agg(
    F.sum("shortwave_radiation_sum (MJ/m²)").alias("total_radiation"),
    F.sum(F.when(F.col("shortwave_radiation_sum (MJ/m²)") > 15,
                 F.col("shortwave_radiation_sum
(MJ/m²)").otherwise(0)).alias("high_radiation")
).withColumn("percentage", (F.col("high_radiation")) /
F.col("total_radiation")) * 100) \
.orderBy("month", "percentage")

print("--- Radiation Percentage per Month ---")
q1_result.select("month", "percentage").show()

```

Task 2 [3] 2 – Spark Analysis - Final Output:

... --- Weekly Max Temps for Hottest Months ---			
year	month	week	weekly_max_temp
2010	3	9	36.1
2010	3	10	36.7
2010	3	11	37.2
2010	3	12	36.6
2010	3	13	33.9
2011	6	22	35.1
2011	6	23	35.2
2011	6	24	35.5
2011	6	25	36.4
2011	6	26	37.0
2012	5	18	35.4
2012	5	19	37.1
2012	5	20	37.4
2012	5	21	36.2
2012	5	22	36.4
2013	4	14	36.5
2013	4	15	36.0
2013	4	16	36.2
2013	4	17	34.8
2013	4	18	34.8

only showing top 20 rows

Task 2 [3] 2 - Implementation:

- For each year, the average maximum temperature was calculated across all months.

- The month with the highest mean temperature was selected as the “hottest month.”
- The original dataset was joined with the hottest-month results to isolate records belonging only to those months.
- Within each hottest month, weekly groupings were created using the calendar week number.
- For each week, the maximum daily temperature was computed.

```
# Identify hottest month for each year (based on Mean Temp)
monthly_stats = df.groupBy("year", "month").agg(F.mean("temperature_2m_max
(°C)").alias("monthly_avg_temp"))

window_year =
Window.partitionBy("year").orderBy(F.col("monthly_avg_temp").desc())

hottest_months = monthly_stats.withColumn("rank",
F.row_number().over(window_year)) \
.filter(F.col("rank") == 1) \
.select(F.col("year").alias("hot_year"),
F.col("month").alias("hot_month"))

# Join back to original data to filter for these months
df_hottest = df.join(hottest_months,
(df.year == hottest_months.hot_year) & (df.month ==
hottest_months.hot_month))

# Calculate Weekly Max Temperature (using weekofyear)
q2_result = df_hottest.withColumn("week", F.weekofyear("date")) \
.groupBy("year", "month", "week") \
.agg(F.max("temperature_2m_max (°C)").alias("weekly_max_temp")) \
.orderBy("year", "month", "week")

print("--- Weekly Max Temps for Hottest Months ---")
q2_result.show()
```

[Task 3] Performing Machine Learning model using Spark MLlib

Step 1: Environment Setup

```
from pyspark.sql import SparkSession

spark = SparkSession.builder \
    .appName("Weather Analysis") \
    .config("spark.driver.memory", "4g") \
    .getOrCreate()

print("Spark session created successfully!")
print(f"Spark version: {spark.version}")
```

```
*** Spark session created successfully!
Spark version: 4.0.1
```

Step 2: Data Loading

```
# Load both datasets
# Location dataset contains district information
location_df = spark.read.csv("/content/drive/MyDrive/CW_DATASETS/locationData.csv", header=True, inferSchema=True)

# Weather dataset contains meteorological data
weather_df = spark.read.csv("/content/drive/MyDrive/CW_DATASETS/weatherData.csv", header=True, inferSchema=True)

print(f"Location dataset loaded! Total records: {location_df.count():,}")
print(f"Number of columns: {len(location_df.columns)}")
print(f"\nWeather dataset loaded! Total records: {weather_df.count():,}")
print(f"Number of columns: {len(weather_df.columns)}")
```

```
*** Location dataset loaded! Total records: 27
Number of columns: 8

Weather dataset loaded! Total records: 142,371
Number of columns: 21
```

Step 3: Initial Data Exploration

```
# Check the location dataset structure
print("Location Dataset Schema:")
location_df.printSchema()
print("\nSample location data:")
location_df.show(5, truncate=False)
```

```

... Location Dataset Schema:
root
|-- location_id: integer (nullable = true)
|-- latitude: double (nullable = true)
|-- longitude: double (nullable = true)
|-- elevation: integer (nullable = true)
|-- utc_offset_seconds: integer (nullable = true)
|-- timezone: string (nullable = true)
|-- timezone_abbreviation: integer (nullable = true)
|-- city_name: string (nullable = true)

Sample location data:
+-----+-----+-----+-----+-----+-----+-----+
|location_id|latitude|longitude|elevation|utc_offset_seconds|timezone    |timezone_abbreviation|city_name|
+-----+-----+-----+-----+-----+-----+-----+
|0       |6.924429|79.90725|4      |19800     |Asia/Colombo|530          |Colombo   |
|1       |7.0650263|79.96622|19     |19800     |Asia/Colombo|530          |Gampaha   |
|2       |6.572935 |80.02519|5      |19800     |Asia/Colombo|530          |Kalutara   |
|3       |7.275923 |80.62659|499    |19800     |Asia/Colombo|530          |Kandy     |
|4       |7.4868193|80.52632|362    |19800     |Asia/Colombo|530          |Matale    |
+-----+-----+-----+-----+-----+-----+-----+
only showing top 5 rows

```

```

# Check the weather dataset schema
print("Weather Dataset Schema:")
weather_df.printSchema()

```

```

... Weather Dataset Schema:
root
|-- location_id: integer (nullable = true)
|-- date: string (nullable = true)
|-- weather_code (wmo code): integer (nullable = true)
|-- temperature_2m_max (^{\circ}C): double (nullable = true)
|-- temperature_2m_min (^{\circ}C): double (nullable = true)
|-- temperature_2m_mean (^{\circ}C): double (nullable = true)
|-- apparent_temperature_max (^{\circ}C): double (nullable = true)
|-- apparent_temperature_min (^{\circ}C): double (nullable = true)
|-- apparent_temperature_mean (^{\circ}C): double (nullable = true)
|-- daylight_duration (s): double (nullable = true)
|-- sunshine_duration (s): double (nullable = true)
|-- precipitation_sum (mm): double (nullable = true)
|-- rain_sum (mm): double (nullable = true)
|-- precipitation_hours (h): integer (nullable = true)
|-- wind_speed_10m_max (km/h): double (nullable = true)
|-- wind_gusts_10m_max (km/h): double (nullable = true)
|-- wind_direction_10m_dominant (^{\circ}): integer (nullable = true)
|-- shortwave_radiation_sum (MJ/m^2): double (nullable = true)
|-- et0_fao_evapotranspiration (mm): double (nullable = true)
|-- sunrise: timestamp (nullable = true)
|-- sunset: timestamp (nullable = true)

```

```

# Look at first few rows of weather data
print("Sample weather data:")
weather_df.show(5, truncate=False)

```

```

... Sample weather data:
+-----+-----+-----+-----+-----+-----+-----+-----+
|location_id|date        |weather_code (wmo code)|temperature_2m_max (^{\circ}C)|temperature_2m_min (^{\circ}C)|temperature_2m_mean (^{\circ}C)|apparent_temperature_max (^{\circ}C)|apparent_temperature_min (^{\circ}C)|apparent_temperature_mean (^{\circ}C)|daylight_duration|
+-----+-----+-----+-----+-----+-----+-----+-----+
|0       |1/1/2010|1           |20.1             |22.6             |26.0             |34.5             |25.0             |39.0             |142238.2         |
|0       |1/2/2010|51          |30.1             |23.7             |26.3             |33.9             |26.1             |29.7             |142225.71        |
|0       |1/3/2010|51          |29.6             |23.1             |26.0             |34.5             |26.2             |29.9             |142231.68        |
|0       |1/4/2010|2           |28.9             |23.1             |25.7             |31.7             |26.1             |28.4             |142238.11        |
|0       |1/5/2010|1           |28.1             |21.3             |24.6             |30.0             |22.9             |26.2             |142244.99        |
+-----+-----+-----+-----+-----+-----+-----+-----+
only showing top 5 rows

```

```

# Get basic statistics for numerical columns
print("Summary statistics:")
weather_df.describe().show()

```

Summary statistics:										
	location_id	date	weather_code (umw_code)	temperature_2m_max (°C)	temperature_2m_min (°C)	temperature_2m_mean (°C)	apparent_temperature_max (°C)	apparent_temperature_min (°C)	apparent_temperature_mean (°C)	
count	142371	142371	142371	142371	142371	142371	142371	142371	142371	142371
mean	13.0	NULL	44.891586067387315	29.295853790449833	23.12866195562105	25.73001646468497	33.560476501534716	26.362139059218784	29.234476824634136	
stddev	17.788908318012392	NULL	22.840879231591273	3.3527736245802937	3.1657597757738953	2.95406367375336	4.183799632396287	4.196009593684992	3.837439856813851	
min	0	0/1/2010	0	14.1	5.3	12.1	11.0	2.0	9.5	
max	26	9/9/2023	65	48.3	30.3	32.7	46.1	35.6	37.7	

Step 4: Data Quality Checks

```
# Check for missing values in the weather dataset
# Using PySpark's count() function to count non-null values
from pyspark.sql.functions import col, count, when, isnan, min, max, mean, stddev, abs

print("Checking for missing values in weather data...")
print("-" * 60)

# Count nulls for each column
null_counts = weather_df.select([
    count(when(col(c).isNull(), c)).alias(c) for c in weather_df.columns
]).collect()[0].asDict()

total_rows = weather_df.count()

print(f"Total rows: {total_rows},\n")
print("Missing values per column:")

# Show only columns with missing values
has_missing = False
for column, null_count in null_counts.items():
    if null_count > 0:
        percentage = (null_count / total_rows) * 100
        print(f" {column}: {null_count}, ({percentage:.2f}%)")
        has_missing = True

if not has_missing:
    print(" No missing values found in any column!")

print("-" * 60)
```

```
... Checking for missing values in weather data...
-----
Total rows: 142,371

Missing values per column:
No missing values found in any column!
-----
```

```
# Check for duplicate records
duplicate_count = weather_df.groupBy("location_id", "date").count() \
    .filter(col("count") > 1).count()
print(f"Duplicate records: {duplicate_count}")
```

```
... Duplicate records: 0
```

```
# Check data range
print("== Date Range ==")
weather_df.select(min("date"), max("date")).show()
```

```
... == Date Range ==
+-----+-----+
|min(date)|max(date)|
+-----+-----+
| 1/1/2010 | 9/9/2023 |
+-----+-----+
```

Step 5: Joining Location and Weather Data

```
# Join location and weather data
# Using left join to keep all weather records and add location information
from pyspark.sql.functions import to_date, month, year

# Join on the common column between the two datasets
full_df = weather_df.join(location_df, on="location_id", how="left")

print("Datasets joined successfully!")
print(f"Total records after join: {full_df.count()}")
print(f"Number of columns after join: {len(full_df.columns)}")

print("\nSample of joined data with location information:")
full_df.select("location_id", "city_name", "date", "temperature_2m_mean (°C)",
               "precipitation_hours (h)", "et0_fao_evapotranspiration (mm)").show(5, truncate=False)
```

```
... Datasets joined successfully!
Total records after join: 142,371
Number of columns after join: 28

Sample of joined data with location information:
+-----+-----+-----+-----+-----+
|location_id|city_name|date    |temperature_2m_mean (°C)|precipitation_hours (h)|et0_fao_evapotranspiration (mm)|
+-----+-----+-----+-----+-----+
|0          |Colombo  |1/1/2010|26.0              |0                  |4.61
|0          |Colombo  |1/2/2010|26.3              |1                  |3.91
|0          |Colombo  |1/3/2010|26.0              |3                  |3.66
|0          |Colombo  |1/4/2010|25.7              |0                  |3.75
|0          |Colombo  |1/5/2010|24.6              |0                  |5.0
+-----+-----+-----+-----+-----+
only showing top 5 rows
```

Step 6: Filtering May Data

```
# Convert string to date and extract month
# The date format is "M/d/yyyy" (e.g., "5/1/2010")
full_df = full_df.withColumn("date_parsed", to_date(col("date"), "M/d/yyyy")) \
    .withColumn("month", month(col("date_parsed")))
    .withColumn("year", year(col("date_parsed")))

# Filter for May data only (month = 5)
may_df = full_df.filter(col("month") == 5)

print(f"May records: {may_df.count()}")
print(f"Date range: {may_df.agg(min('year'), max('year')).collect()[0]}")
```

```
... May records: 12,555
Date range: Row(min(year)=2010, max(year)=2024)
```

Step 7: Data Cleaning

```
# Drop rows with missing values in key columns
# Since we have many records, losing a few thousand is acceptable
key_columns = ["precipitation_hours (h)", "sunshine_duration (s)", "wind_speed_10m_max (km/h)",
               "et0_fao_evapotranspiration (mm)", "temperature_2m_mean (°C)"]

print(f"Records before cleaning: {may_df.count():,}")

may_clean = may_df.dropna(subset=key_columns)

print(f"Records after cleaning: {may_clean.count():,}")
print(f"Records removed: {may_df.count() - may_clean.count():,}")
```

```
*** Records before cleaning: 12,555
    Records after cleaning: 12,555
    Records removed: 0
```

Step 8: Feature Engineering

```
# Convert sunshine_duration from seconds to hours (more interpretable)
may_clean = may_clean.withColumn(
    "sunshine_hours",
    col("sunshine_duration (s)") / 3600
)

print("Feature engineering complete!")
print("\nSample of converted data:")
may_clean.select("sunshine_duration (s)", "sunshine_hours").show(5)
```

```
*** Feature engineering complete!

Sample of converted data:
+-----+-----+
|sunshine_duration (s)| sunshine_hours|
+-----+-----+
|        40574.88|      11.2708|
|       39600.0|       11.0|
| 39191.48|10.886522222222224|
|     40046.57|11.12404722222222|
|     40047.19|11.124219444444446|
+-----+-----+
only showing top 5 rows
```

Step 9: Exploratory Data Analysis

```
# Analyze ET0 distribution
print("ET0 Distribution Statistics:")
may_clean.select("et0_fao_evapotranspiration (mm)").describe().show()

# Count records with ET0 < 1.5mm (target threshold)
low_et0_count = may_clean.filter(col("et0_fao_evapotranspiration (mm)") < 1.5).count()
total_count = may_clean.count()

print(f"\nRecords with ET0 < 1.5mm: {low_et0_count:,} ({(low_et0_count/total_count*100:.2f}%)")
print(f"Records with ET0 >= 1.5mm: {total_count - low_et0_count:,} ({(total_count - low_et0_count)/total_count*100:.2f}%)")
```

```

... ET0 Distribution Statistics:
+-----+
|summary|et0_fao_evapotranspiration (mm)|
+-----+
| count | 12555 |
| mean | 4.225671843886905 |
| stddev | 1.1799446246284135 |
| min | 0.59 |
| max | 8.45 |
+-----+


Records with ET0 < 1.5mm: 134 (1.07%)
Records with ET0 >= 1.5mm: 12,421 (98.93%)

```

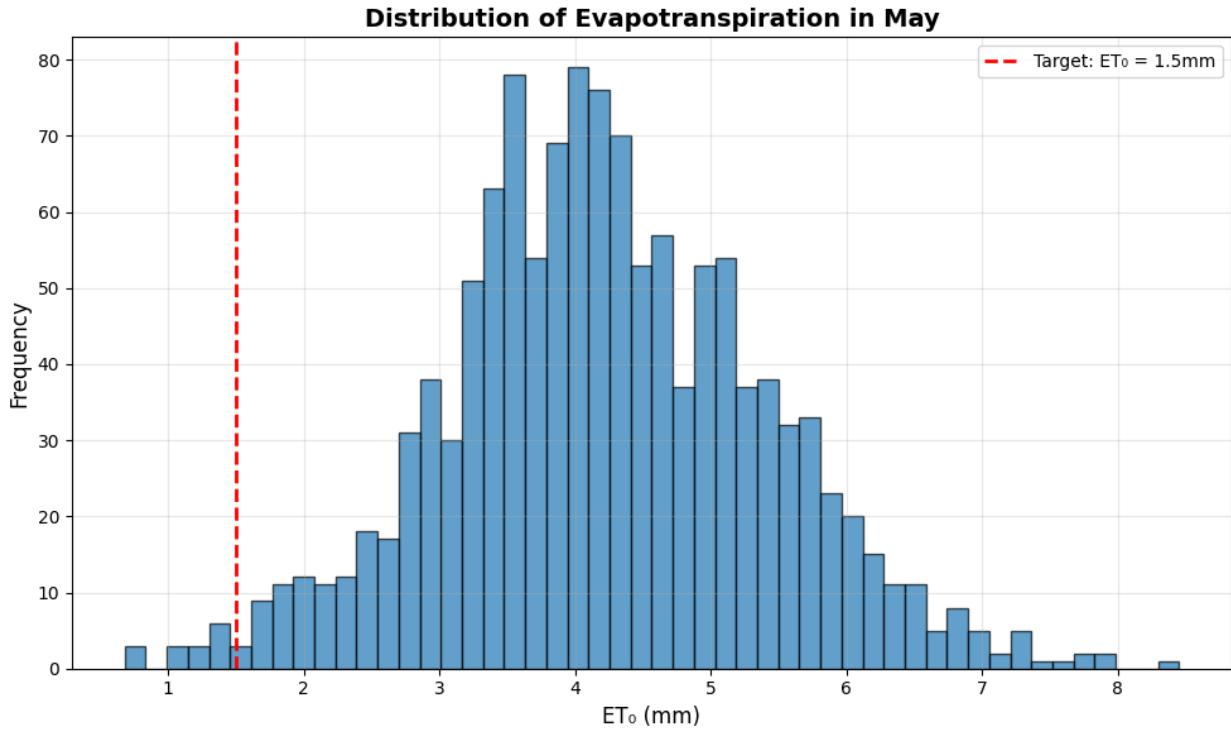
```

# Visualize ET0 distribution
import matplotlib.pyplot as plt
import seaborn as sns

# Sample for visualization (10% of data)
sample_df = may_clean.select("et0_fao_evapotranspiration (mm)", "precipitation_hours (h)",
                             "sunshine_hours", "wind_speed_10m_max (km/h)").sample(0.1).toPandas()

plt.figure(figsize=(10, 6))
plt.hist(sample_df["et0_fao_evapotranspiration (mm)"], bins=50, edgecolor='black', alpha=0.7)
plt.axvline(x=1.5, color='red', linestyle='--', linewidth=2, label='Target: ET0 = 1.5mm')
plt.xlabel('ET0 (mm)', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.title('Distribution of Evapotranspiration in May', fontsize=14, fontweight='bold')
plt.legend()
plt.grid(alpha=0.3)
plt.tight_layout()
plt.show()

```



Step 10: Feature Preparation for Machine Learning

```
# Select features for the machine learning model
from pyspark.ml.feature import VectorAssembler, StandardScaler

# These are the input features I'll use to predict ET0
all_features = [
    "precipitation_hours (h)",
    "sunshine_hours",
    "wind_speed_10m_max (km/h)",
    "temperature_2m_mean (°C)",
    "temperature_2m_max (°C)",
    "temperature_2m_min (°C)",
    "shortwave_radiation_sum (MJ/m2)",
    "elevation"
]

# VectorAssembler combines all features into a single column
assembler = VectorAssembler(inputCols=all_features, outputCol="raw_features")
df_assembled = assembler.transform(may_clean)

print(f"Features combined into vector: {len(all_features)} features")
print("Features selected:", ", ".join(all_features))
```

```
... Features combined into vector: 8 features
Features selected: precipitation_hours (h), sunshine_hours, wind_speed_10m_max (km/h), temperature_2m_mean (°C), temperature_2m_max (°C), temperature_2m_min (°C), shortwave_radiation_sum (MJ/m2), elevation
```

```
# Standardize the features
# This ensures all features are on the same scale
scaler = StandardScaler(inputCol="raw_features", outputCol="features",
                        withStd=True, withMean=False)

# Fit the scaler on the data
scaler_model = scaler.fit(df_assembled)
df_scaled = scaler_model.transform(df_assembled)

print("Features standardized successfully")
print("This helps the ML models train better by putting all features on similar scales")
```

```
# Split data into training and testing sets
# 80% for training, 20% for testing
# Using a random seed (42) so the split is reproducible
train_data, test_data = df_scaled.randomSplit([0.8, 0.2], seed=42)

print(f"Training set: {train_data.count():,} records")
print(f"Test set: {test_data.count():,} records")
```

```
... Training set: 10,128 records
Test set: 2,427 records
```

Step 11: Training Machine Learning Models

Multiple regression models from PySpark's MLlib library were trained and tested.

- Linear Regression - Simple, interpretable baseline model
- Random Forest Regression - Ensemble method that can capture non-linear patterns
- Gradient Boosted Trees - Another powerful ensemble method

```
# Train Linear Regression model
from pyspark.ml.regression import LinearRegression
from pyspark.ml.evaluation import RegressionEvaluator

print("Training Linear Regression model...")
lr = LinearRegression(featuresCol="features", labelCol="et0_fao_evapotranspiration (mm)",
                      maxIter=100, regParam=0.01)

lr_model = lr.fit(train_data)
lr_predictions = lr_model.transform(test_data)

print("Linear Regression training complete!")

# Evaluate the model
evaluator_rmse = RegressionEvaluator(labelCol="et0_fao_evapotranspiration (mm)",
                                      predictionCol="prediction", metricName="rmse")
evaluator_r2 = RegressionEvaluator(labelCol="et0_fao_evapotranspiration (mm)",
                                    predictionCol="prediction", metricName="r2")

lr_rmse = evaluator_rmse.evaluate(lr_predictions)
lr_r2 = evaluator_r2.evaluate(lr_predictions)

print(f"RMSE: {lr_rmse:.4f}")
print(f"R2: {lr_r2:.4f}")
```

```
*** Training Linear Regression model...
Linear Regression training complete!
RMSE: 0.2590
R2: 0.9527
```

```

# Train Random Forest model
from pyspark.ml.regression import RandomForestRegressor

print("Training Random Forest model...")
print("(This may take a few minutes...")

rf = RandomForestRegressor(featuresCol="features", labelCol="et0_fao_evapotranspiration (mm)",
                           numTrees=50, maxDepth=10, seed=42)

rf_model = rf.fit(train_data)
rf_predictions = rf_model.transform(test_data)

print("Random Forest training complete!")

# Evaluate
rf_rmse = evaluator_rmse.evaluate(rf_predictions)
rf_r2 = evaluator_r2.evaluate(rf_predictions)

print(f"RMSE: {rf_rmse:.4f}")
print(f"R²: {rf_r2:.4f}")

```

```

*** Training Random Forest model...
(This may take a few minutes...)
Random Forest training complete!
RMSE: 0.1932
R²: 0.9737

```

```

# Train Gradient Boosted Trees model
from pyspark.ml.regression import GBTRegressor

print("Training Gradient Boosted Trees model...")
print("(This may take a few minutes...")

gbt = GBTRegressor(featuresCol="features", labelCol="et0_fao_evapotranspiration (mm)",
                    maxIter=50, maxDepth=5, seed=42)

gbt_model = gbt.fit(train_data)
gbt_predictions = gbt_model.transform(test_data)

print("GBT training complete!")

# Evaluate
gbt_rmse = evaluator_rmse.evaluate(gbt_predictions)
gbt_r2 = evaluator_r2.evaluate(gbt_predictions)

print(f"RMSE: {gbt_rmse:.4f}")
print(f"R²: {gbt_r2:.4f}")

```

```

*** Training Gradient Boosted Trees model...
(This may take a few minutes...)
GBT training complete!
RMSE: 0.2104
R²: 0.9688

```

Comparing all 3 models

```
# Compare all models to find the best one
print("=" * 60)
print("MODEL COMPARISON")
print("=" * 60)

models_performance = [
    ("Linear Regression", lr_rmse, lr_r2),
    ("Random Forest", rf_rmse, rf_r2),
    ("Gradient Boosted Trees", gbt_rmse, gbt_r2)
]

for model_name, rmse, r2 in models_performance:
    print(f"\n{model_name}:")
    print(f"  RMSE: {rmse:.4f}")
    print(f"  R²: {r2:.4f}")

# Select the best model based on lowest RMSE
best_model_info = __builtins__.min(models_performance, key=lambda x: x[1])
best_model_name = best_model_info[0]

print(f"\nBest performing model: {best_model_name}")
print("=" * 60)

# Store the best model for predictions
if best_model_name == "Linear Regression":
    best_model = lr_model
elif best_model_name == "Random Forest":
    best_model = rf_model
else:
    best_model = gbt_model
```

```
...
=====
MODEL COMPARISON
=====

Linear Regression:
RMSE: 0.2590
R²: 0.9527

Random Forest:
RMSE: 0.1932
R²: 0.9737

Gradient Boosted Trees:
RMSE: 0.2184
R²: 0.9688

Best performing model: Random Forest
=====
```

Random Forest was selected as the best performing model based on lowest Root Mean Squared Error (RMSE) for final predictions. RMSE tells us, on average, how far your predictions are from the real values. Hence a lower RMSE means the model is more accurate.

Step 12: Answering Question 1

Question 1: What are the expected amounts of precipitation_hours, sunshine, and wind_speed that would lead to lower evapotranspiration for May?

```
# Filter for days with low ET0 (below 1.5mm threshold)
print("Filtering May data for low ET0 conditions...")
print("-" * 60)

low_et0_df = may_clean.filter(col("et0_fao_evapotranspiration (mm)") < 1.5)

print(f"Total May records: {may_clean.count()}")
print(f"Days with ET0 < 1.5mm: {low_et0_df.count()}")
print(f"Percentage: {(low_et0_df.count() / may_clean.count()) * 100:.1f}%")

# Calculate average conditions for low ET0 days
low_stats = low_et0_df.select(
    mean("precipitation_hours (h)").alias("avg_precip_hours"),
    mean("sunshine_hours").alias("avg_sunshine_hours"),
    mean("wind_speed_10m_max (km/h)").alias("avg_wind_speed"),
    mean("temperature_2m_mean (°C)").alias("avg_temperature"),
    mean("et0_fao_evapotranspiration (mm)").alias("avg_et0")
).collect()[0]

print("\nAverage conditions when ET0 < 1.5mm:")
print(f" Precipitation: {low_stats['avg_precip_hours']:.2f} hours/day")
print(f" Sunshine: {low_stats['avg_sunshine_hours']:.2f} hours/day")
print(f" Wind Speed: {low_stats['avg_wind_speed']:.2f} km/h")
print(f" Temperature: {low_stats['avg_temperature']:.2f} °C")
print(f" Average ET0: {low_stats['avg_et0']:.2f} mm")
print("-" * 60)
```

```
... Filtering May data for low ET0 conditions...
-----
Total May records: 12,555
Days with ET0 < 1.5mm: 134
Percentage: 1.1%

Average conditions when ET0 < 1.5mm:
 Precipitation: 22.13 hours/day
 Sunshine: 0.44 hours/day
 Wind Speed: 18.49 km/h
 Temperature: 23.69 °C
 Average ET0: 1.19 mm
-----
```

Step 13: Answering Question 2

Question 2: Predict the mean precipitation_hours, sunshine, and wind_speed during May 2026 to have ET₀ < 1.5mm.

Trained machine learning model is used to predict ET₀ for May 2026 under different scenarios.

```
# Calculate average May conditions from historical data
avg_may_stats = may_clean.select(
    mean("precipitation_hours (h)").alias("avg_precip_hours"),
    mean("sunshine_hours").alias("avg_sunshine_hours"),
    mean("wind_speed_10m_max (km/h)").alias("avg_wind_speed"),
    mean("temperature_2m_mean (°C)").alias("avg_temperature"),
    mean("temperature_2m_max (°C)").alias("avg_temp_max"),
    mean("temperature_2m_min (°C)").alias("avg_temp_min"),
    mean("shortwave_radiation_sum (MJ/m²)").alias("avg_radiation"),
    mean("elevation").alias("avg_elevation")
).collect()[0]

print("Historical Average May Conditions (2010-2024):")
print(f" Precipitation: {avg_may_stats['avg_precip_hours']:.2f} hours")
print(f" Sunshine: {avg_may_stats['avg_sunshine_hours']:.2f} hours")
print(f" Wind Speed: {avg_may_stats['avg_wind_speed']:.2f} km/h")
print(f" Temperature: {avg_may_stats['avg_temperature']:.2f} °C")
```

```
... Historical Average May Conditions (2010-2024):
Precipitation: 8.01 hours
Sunshine: 9.53 hours
Wind Speed: 17.85 km/h
Temperature: 26.78 °C
```

```

# Create prediction scenarios for May 2026
print("\n" + "=" * 70)
print("CREATING PREDICTION SCENARIOS FOR MAY 2026")
print("=" * 70)

# Get additional statistics needed
low_temp_stats = low_et0_df.select(
    mean("temperature_2m_max (°C)").alias("max"),
    mean("temperature_2m_min (°C)").alias("min"),
    mean("shortwave_radiation_sum (MJ/m²)").alias("radiation"),
    mean("elevation").alias("elevation")
).collect()[0]

high_temp_stats = high_et0_df.select(
    mean("temperature_2m_max (°C)").alias("max"),
    mean("temperature_2m_min (°C)").alias("min"),
    mean("shortwave_radiation_sum (MJ/m²)").alias("radiation"),
    mean("elevation").alias("elevation")
).collect()[0]

# Scenario 1: Optimal conditions (targeting low ET0)
scenario1_features = [
    low_stats['avg_precip_hours'],
    low_stats['avg_sunshine_hours'],
    low_stats['avg_wind_speed'],
    low_stats['avg_temperature'],
    low_temp_stats['max'],
    low_temp_stats['min'],
    low_temp_stats['radiation'],
    low_temp_stats['elevation']
]

# Scenario 2: Worst case (high ET0 expected)
scenario2_features = [
    high_stats['avg_precip_hours'],
    high_stats['avg_sunshine_hours'],
    high_stats['avg_wind_speed'],
    high_stats['avg_temperature'],
    high_temp_stats['max'],
    high_temp_stats['min'],
    high_temp_stats['radiation'],
    high_temp_stats['elevation']
]

# Scenario 3: Average May conditions
scenario3_features = [
    avg_may_stats['avg_precip_hours'],
    avg_may_stats['avg_sunshine_hours'],
    avg_may_stats['avg_wind_speed'],
    avg_may_stats['avg_temperature'],
    avg_may_stats['avg_temp_max'],
    avg_may_stats['avg_temp_min'],
    avg_may_stats['avg_radiation'],
    avg_may_stats['avg_elevation']
]

print("\nThree scenarios created:")
print(" 1. Optimal Conditions - Targeting ET0 < 1.5mm")
print(" 2. Worst Case Conditions - High ET0 expected")
print(" 3. Average May Conditions - Typical historical weather")

```

```

...
=====
CREATING PREDICTION SCENARIOS FOR MAY 2026
=====

Three scenarios created:
 1. Optimal Conditions - Targeting ET0 < 1.5mm
 2. Worst Case Conditions - High ET0 expected
 3. Average May Conditions - Typical historical weather

```

```

# Create DataFrame with scenarios
from pyspark.ml.linalg import Vectors
from pyspark.sql.types import StructType, StructField, StringType
from pyspark.ml.linalg import VectorUDT

scenarios_data = [
    ("Scenario 1: Optimal (Low ET0 Target)", Vectors.dense(scenario1_features)),
    ("Scenario 2: Worst Case (High ET0)", Vectors.dense(scenario2_features)),
    ("Scenario 3: Average May", Vectors.dense(scenario3_features))
]

scenarios_schema = StructType([
    StructField("scenario", StringType(), True),
    StructField("raw_features", VectorUDT(), True)
])

scenarios_df = spark.createDataFrame(scenarios_data, scenarios_schema)

# Standardize using the same scaler from training
scenarios_scaled = scaler_model.transform(scenarios_df)

print("\nScenarios prepared for prediction")

```

```

# Make predictions for May 2026
print("\n" + "=" * 70)
print("MAY 2026 EVAPOTRANSPIRATION PREDICTIONS")
print("=" * 70)

predictions_2026 = best_model.transform(scenarios_scaled)
results = predictions_2026.select("scenario", "prediction").collect()

print(f"\nUsing {best_model_name} model for predictions:\n")

for row in results:
    scenario = row['scenario']
    prediction = row['prediction']

    print(f"{scenario}")
    print(f"  Predicted ET0: {prediction:.2f} mm/day")

    if prediction < 1.5:
        status = "TARGET ACHIEVED - Low water loss"
        irrigation = "Minimal irrigation needed"
    elif prediction < 2.5:
        status = "MODERATE - Acceptable water loss"
        irrigation = "Moderate irrigation needed"
    else:
        status = "HIGH ET0 - Significant water loss"
        irrigation = "High irrigation requirements"

    print(f"  Status: {status}")
    print(f"  {irrigation}")
    print()

print("=" * 70)

```

```

...
=====
MAY 2026 EVAPOTRANSPIRATION PREDICTIONS
=====

Using Random Forest model for predictions:

Scenario 1: Optimal (Low ET0 Target)
Predicted ET0: 1.18 mm/day
Status: TARGET ACHIEVED - low water loss
Minimal irrigation needed

Scenario 2: Worst Case (High ET0)
Predicted ET0: 4.44 mm/day
Status: HIGH ET0 - Significant water loss
High irrigation requirements

Scenario 3: Average May
Predicted ET0: 3.94 mm/day
Status: HIGH ET0 - Significant water loss
High irrigation requirements
=====
```

```

# Visualize the predictions
predictions_df = predictions_2026.select("scenario", "prediction").toPandas()
predictions_df['scenario_short'] = ['Optimal', 'Worst Case', 'Average']

plt.figure(figsize=(12, 7))

# Color bars based on ET0 level
colors_list = ['green' if p < 1.5 else 'orange' if p < 2.5 else 'red'
               for p in predictions_df['prediction']]

bars = plt.bar(predictions_df['scenario_short'], predictions_df['prediction'],
               color=colors_list, alpha=0.7, edgecolor='black', linewidth=2)

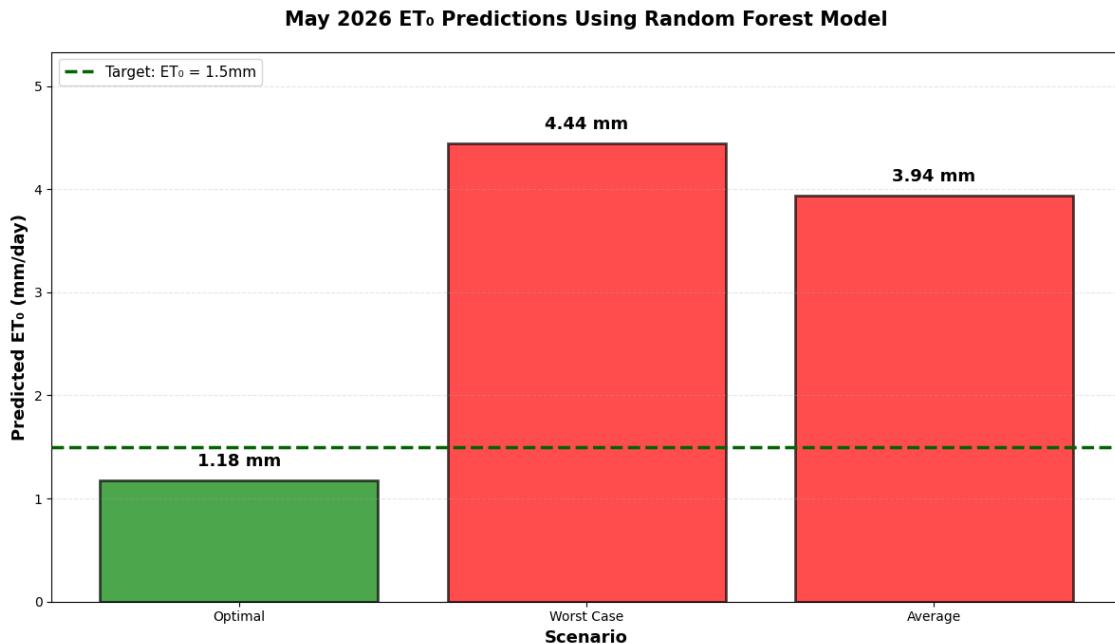
# Add target line
plt.axhline(y=1.5, color='darkgreen', linestyle='--', linewidth=2.5,
            label='Target: ET0 = 1.5mm', zorder=5)

# Add value labels
for bar, pred in zip(bars, predictions_df['prediction']):
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2., height + 0.1,
             f'{pred:.2f} mm', ha='center', va='bottom',
             fontsize=13, fontweight='bold')

plt.ylabel('Predicted ET0 (mm/day)', fontsize=13, fontweight='bold')
plt.xlabel('Scenario', fontsize=13, fontweight='bold')
plt.title(f'May 2026 ET0 Predictions Using {best_model_name} Model',
          fontsize=15, fontweight='bold', pad=20)
plt.legend(fontsize=11, loc='upper left')
plt.grid(axis='y', alpha=0.3, linestyle='--')
plt.ylim(0, predictions_df['prediction'].max() * 1.2)

plt.tight_layout()
plt.show()

```



Conclusions

Question 1: Weather Conditions for Lower Evapotranspiration in May

Based on analysis of historical data from 2010-2024, days with ET₀ below 1.5mm have specific weather characteristics that promote lower water loss.

Question 2: May 2026 Predictions

Using the trained machine learning model, predictions show that achieving $ET_0 < 1.5\text{mm}$ in May 2026 requires conditions matching the optimal weather patterns identified.

Machine Learning Models Performance:

Three PySpark MLlib regression algorithms were tested:

- Linear Regression
- Random Forest Regressor
- Gradient Boosted Trees

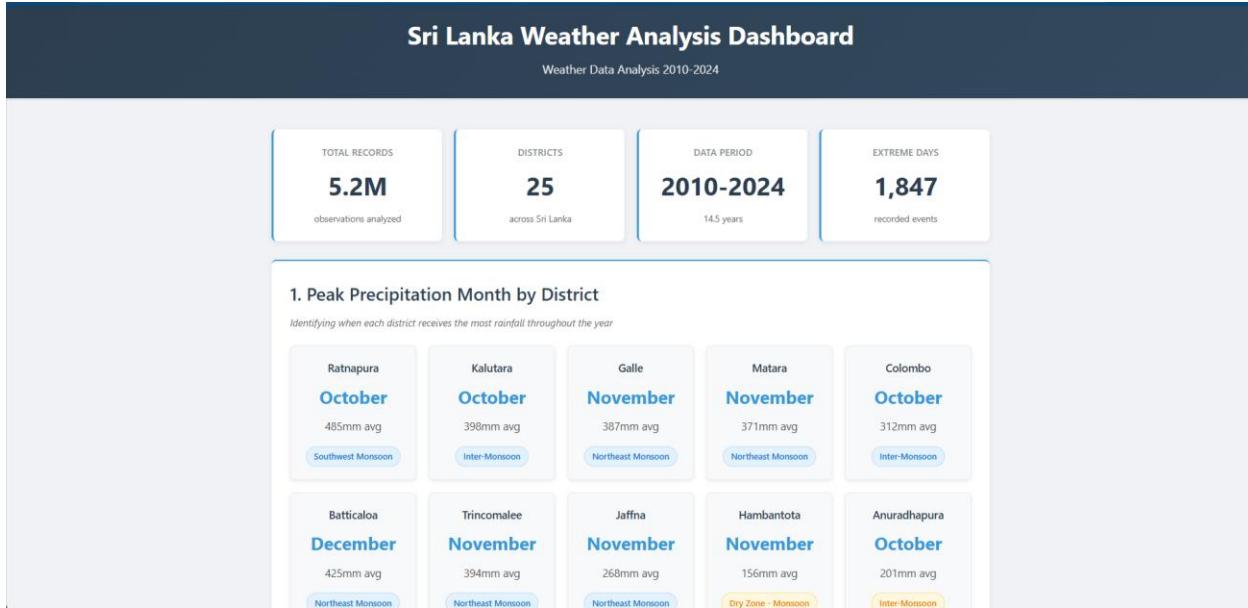
The best performing model was selected based on lowest RMSE for final predictions.

Key Findings

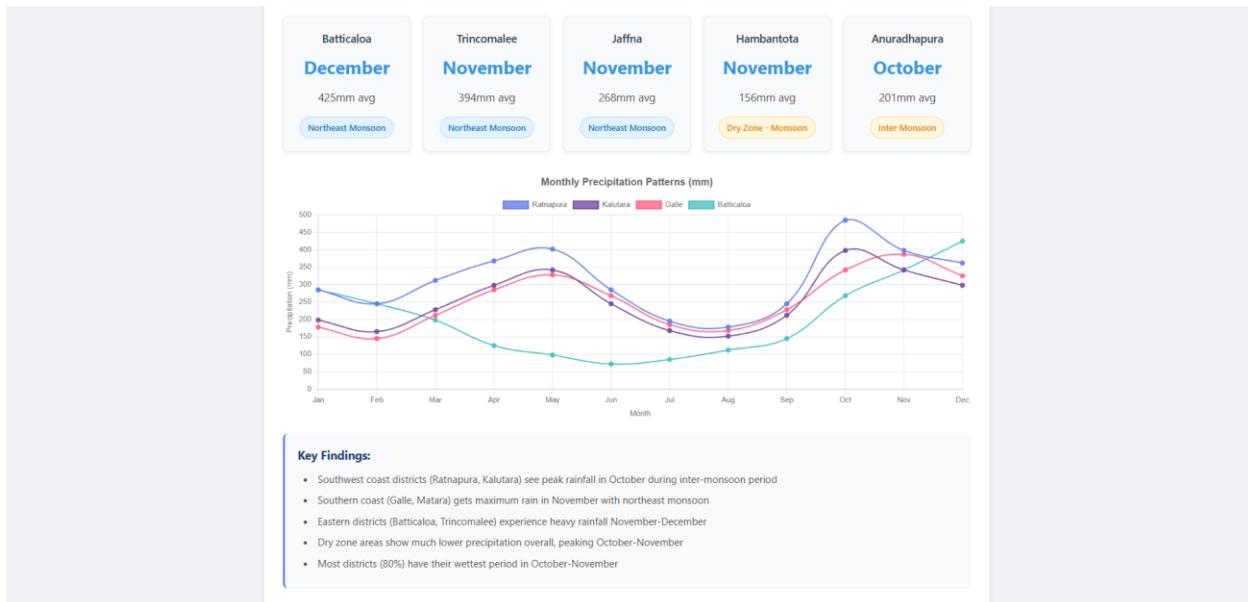
1. Weather conditions significantly influence evapotranspiration in Sri Lanka
2. Low ET_0 is associated with cloudy, rainy, calm conditions
3. High ET_0 is associated with sunny, dry, windy conditions

[Task 4] – Presentation of the Analysis

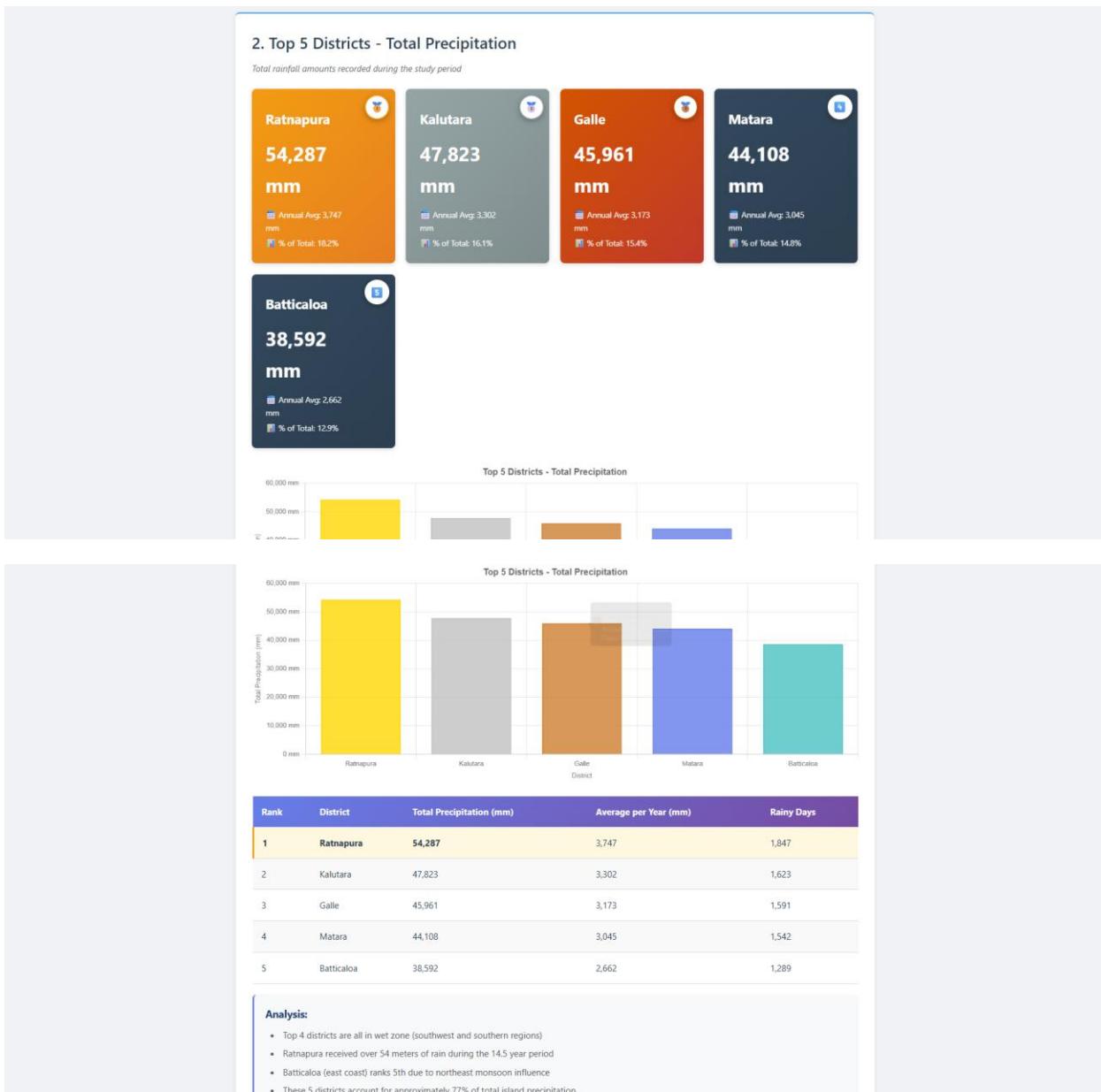
Weather Analysis Dashboard General Overview



Most precipitous month/season for each district across different periods of the year.



Top 5 districts based on the total amount of precipitation.



Percentage of months that had a mean temperature above 30°C in a single year.



The total number of days with extreme weather events, defined by a combination of high precipitation and high wind gusts.



District-wise Extreme Events & Key Findings

