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# An Artificial Intelligence-Based Blending of Satellite products across Sicily, Italy using GPM-IMERG V06 Final Run

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**Abstract** - Precipitation is the key input variable to hydrological models and its monitoring plays a significant role in water resources planning and improving flood and drought forecasting, also under climate change impacts. In recent years, many precipitation satellite products have been developed and released to the public; among these, the Integrated Multi-satellitE Retrievals from Global Precipitation Measurement (IMERG) is designed to address limitations and uncertainties related to traditional methods.

The primary purpose of this study is to provide a comprehensive assessment of precipitation estimates retrieved from the IMERG v6 Final Run over the Mediterranean island of Sicily (Italy) at daily and half-hourly temporal and at 0.1° spatial resolution for the first time using a quality-controlled sub-hourly gauge dataset. Sicily, which is characterized by a Mediterranean climate and a complex orography, experiences rather frequent short duration and high intensity precipitation originating from the interaction of steep orography on the coasts with winds carrying humid air masses from the Mediterranean Sea.

Previous studies have highlighted that most of the available satellite-based precipitation products show poor performance for capturing rainfall events at high temporal resolution particularly in coastal areas. Based on these findings, there is a critical need to put much effort to improve retrieval algorithms to account for coastal and morphological effects, thus enhancing satellite-based precipitation estimations for those areas. With this regard, this work also aims to show that a combination of multiple products may result in more accurate estimations especially for short duration events. This merging technique, which has been carried out exploiting artificial intelligence (AI) techniques, is shown to successfully reduce the error based on the comparison with data from a local rain gauge network. The results of the study will demonstrate the proficiency of the AI based approaches for improving remote-sensed rainfall products even in coastal areas with complex orography.

## 1. Study area and data

- The Mediterranean Sea's island, Sicily, Italy
- Area: 25,000 km<sup>2</sup>
- Elevation ranging from 0 to 3,000 m above sea level

Figure (1). Map of elevation and the distribution of rain gauge network provided by the Servizio Informativo Agrometeorologico Siciliano (SIAS).

### 1.1 Ground Observations

- Source: Servizio Informativo Agrometeorologico Siciliano SIAS
- High temporal resolution, quality, and availability of up-to-date data
- Period: 2016 to 2020 as the observation dataset.
- Number of rain gauge stations: 104
- Temporal resolution: 10 minutes
- Sub-hourly data aggregated into daily aggregates for validation purposes.

### 1.2 Satellite Precipitation Estimations

- Source: The Integrated Multi-satellitE Retrievals for GPM (IMERG)
- Temporal resolution: half-hourly, daily
- Spatial resolution: 0.1°
- Version: IMERG-V06
- Latency: final run product
- Period: 2016 to 2020

### 1.3 Precipitable Water data

- Source: Advanced Microwave Scanning Radiometer 2 (AMSR-2)
- Product: Integrated water vapor (mm)
- Temporal resolutions : daily
- Spatial resolutions: 0.1° (rescaled)
- Period: 2016 to 2020.

## 2. Methodology

### 2.1 Flowchart of the improvement section

## 2.2 Evaluation Section

Table (1). List of the verification metrics applied in validation and evaluation

|                     | Metric | equation                                                                                                                                                               | Optimal Value |
|---------------------|--------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------|
| statistical metrics | CC     | $\frac{\sum_{i=1}^N (P_{O_i} - \overline{P_O})(P_{S_i} - \overline{P_S})}{\sqrt{\sum_{i=1}^N (P_{O_i} - \overline{P_O})^2 \sum_{i=1}^N (P_{S_i} - \overline{P_S})^2}}$ | 1             |
|                     | RMSE   | $\sqrt{\frac{\sum_{i=1}^N (P_{O_i} - P_{S_i})^2}{N}}$                                                                                                                  | 0             |
|                     | Rbias  | $\frac{\sum_{i=1}^N (P_{S_i} - P_{O_i})}{\sum_{i=1}^N P_{O_i}}$                                                                                                        | 0             |
|                     | MAE    | $\frac{1}{N} \times \sum_{i=1}^N  P_{O_i} - P_{S_i} $                                                                                                                  | 0             |
| categorical metrics | POD    | $\frac{H}{H + M}$                                                                                                                                                      | 1             |
|                     | FAR    | $\frac{F}{H + F}$                                                                                                                                                      | 0             |
|                     | CSI    | $\frac{H}{H + F + M}$                                                                                                                                                  | 1             |

## 2.3 Improvement Section

Objective: Improving the accuracy of satellite precipitation estimations  
Framework: Merging multisource satellite products (IMERG, TPW)  
Methods: 1) Multivariant Linear Regression (MLR)  
2) Artificial Neural Networks (ANN)

### 2.3.1 Multivariant Linear Regression

Steps: 1. standardizing variables using the mean and standard deviation

2. introducing a MLR model based on IMERG and TPW

$$P_{merge} = W_1 \cdot IMERG + W_2 \cdot TPW + b$$

3. hybrid optimization by Harmonic Search (HS) algorithm

controlled by: Harmonic Memory Consideration Rate (HMCR)

Pitch Adjustment Rate (PAR)

4. Validating model by statistical and categorical metrics

- Results/ hyper parameters and assumptions in table (3)

### 2.3.2 Artificial Neural Network

Steps: 1. Variable rescaling

2. Introducing a Multilayer Perceptron (MLP); Loss Function:

$$SE = \sum_{i=1}^N (P_O(i) - P_S(i))^2$$

3. training model using the Back-propagation error algorithm

4. Validating model by statistical and categorical metrics

- Results/Number of hidden layers and neurons in table (4)

## 3. Results

### 3.1 Daily and Half-Hourly Evaluation

Table (2). Performance metrics associated with IMERG-V06 products provided separately in each temporal resolutions.

| Metric\Period | Half-Hourly data evaluation separated by period |        |        |        |              | Daily |
|---------------|-------------------------------------------------|--------|--------|--------|--------------|-------|
|               | 2017                                            | 2018   | 2019   | 2020   | 2017 to 2020 |       |
| CC (%)        | 27                                              | 20     | 21     | 22     | 22           | 63    |
| RBias         | -12.26                                          | -13.14 | -10.92 | -11.05 | -12.10       | 2.47  |
| MAE (mm)      | 12.07                                           | 13.12  | 10.10  | 11.07  | 12.09        | 2.53  |
| RMSE (mm)     | 25.62                                           | 23.75  | 24.63  | 25.56  | 24.64        | 7.30  |
| POD (%)       | 42                                              | 46     | 40     | 42     | 43           | 85    |
| FAR (%)       | 66                                              | 70     | 71     | 70     | 70           | 32    |
| CSI (%)       | 23                                              | 22     | 20     | 21     | 22           | 61    |

- Assessment Period: 2017 to 2020
- Half-Hourly threshold>0.2 mm
- Daily threshold> 1 mm

### 3.2 Results of validation of the MLR model

Table (3). Summery of the evaluation criteria for MLR model  
Harmony Search assigned hyper parameters

| Model | Pitch | HMCR | PAR | Iteration | $W_1$ | $W_2$ | b     | CC   | RMSE (mm) | Rbias | POD (%) | FAR (%) | CSI (%) |
|-------|-------|------|-----|-----------|-------|-------|-------|------|-----------|-------|---------|---------|---------|
| MLR   | 0.1   | 0.7  | 0.8 | 800       | 2.041 | 0.167 | 0.152 | 0.63 | 6.88      | 2.11  | 86      | 32      | 61      |

### 3.3 Results of validation of the ANN model

Table (4). Summary of the evaluation criteria for the ANN model  
number of hidden layers, number of nodes in each hidden layer for the ANN

| Model | $l_1$ | $l_2$ | $l_3$ | $l_4$ | $l_5$ | $l_6$ | $l_7$ | $l_8$ | $l_9$ | CC   | RMSE (mm) | Rbias | POD (%) | FAR (%) | CSI (%) |
|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|------|-----------|-------|---------|---------|---------|
| ANN   | 25    | 27    | 27    | 24    | 22    | 19    | 15    | 17    | 20    | 0.67 | 6.05      | 1.98  | 87      | 38      | 62      |

### 3.4 Results of validation of the ANN model

Figure (2). Bar chart of average monthly precipitation estimations derived by SIAS, individual IMERG product, calculated by MLR and ANN models from 2016-2020

- Average annual precipitation height in Sicily: 830 mm

## 4. Discussion and conclusion

- Reasonable and great performance of categorical metrics in discriminating precipitation events from non-precipitation ones in half-hourly and daily temporal resolution respectively
- Slight overestimations in daily estimations while considerable underestimations in half-hourly estimations
- Rigorous performance of daily products in terms of statistical indices
- Expected large error in light rainfall values corresponded to fine temporal resolution of half-hourly
- Slight improvement of MLR compared to ANN model
- A potential possibility of improving the accuracy of satellite precipitation estimations by blending more atmospheric and ground variables from space sources
- Effects of the training data size on feeding an ANN model; case of inadequate five years
- Larger error in wet and dry months corresponded to heavy and light rainfalls
- Superiority of estimations from merged model compared to individual IMERG estimations

## References

- Yang, X. S. (2009). Harmony search as a metaheuristic algorithm. In *Music-inspired harmony search algorithm* (pp. 1-14). Springer, Berlin, Heidelberg.
- Khan RS, Bhuiyan MAE. 2021. Artificial intelligence-based techniques for rainfall estimation integrating multisource precipitation datasets. *Atmos.* 12(10):1239.
- S. Wang et al., "Intercomparison of Total Precipitable Water Derived From COSMIC-2 and Three Different Microwave Radiometers Over the Ocean," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1-10, 2022, Art no. 4107610, doi: 10.1109/TGRS.2022.3160020.