Forecast and Classification of Dust Events in the East Mediterranean using Machine Learning



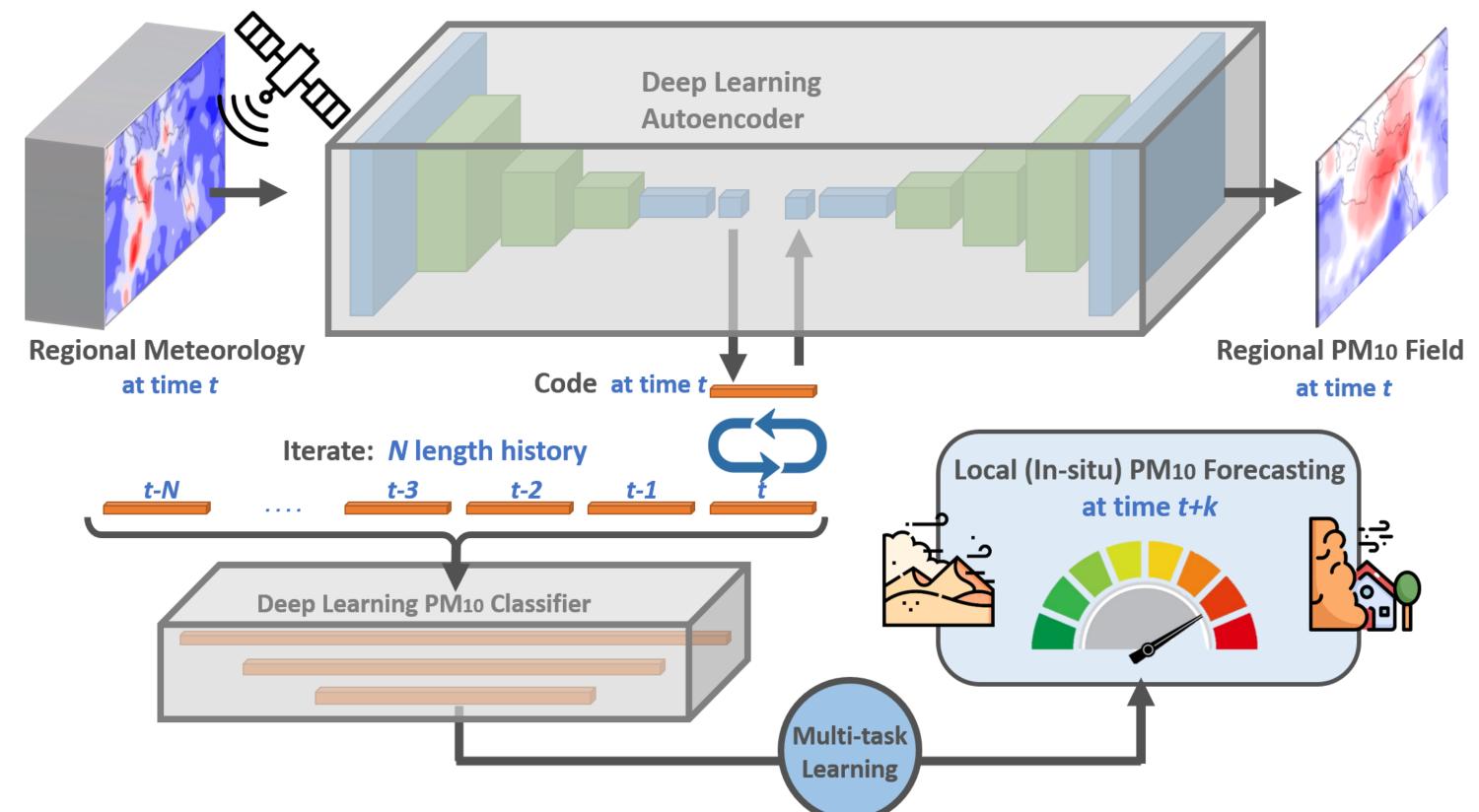
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Abstract

Dust events, presenting a health risk and an economic burden potentially exceeding hundreds of millions of dollars annually, necessitate a comprehensive understanding to facilitate precise and prompt forecasting. Such knowledge aids in impact mitigation and enhances societal safeguards. In this study, we offer an innovative climatological insight into the correlation between weather systems and dust transportation by methodically categorizing dust events. An 18-year compilation of ground PM₁₀ measurements in Israel, coupled with atmospheric reanalysis data, form the basis of our novel, unsupervised classification method for dust events in the Eastern Mediterranean. Further, we introduce a meteorological deep multi-task learning strategy for dust event forecasting. This approach integrates both the forecasting of local PM₁₀ (primary task) as observed in situ, and the simultaneous prediction of the satellite-assisted regional PM₁₀ (auxiliary task), thereby leveraging correlated task information.

Deep Auxiliary-Task Learning Forecasting



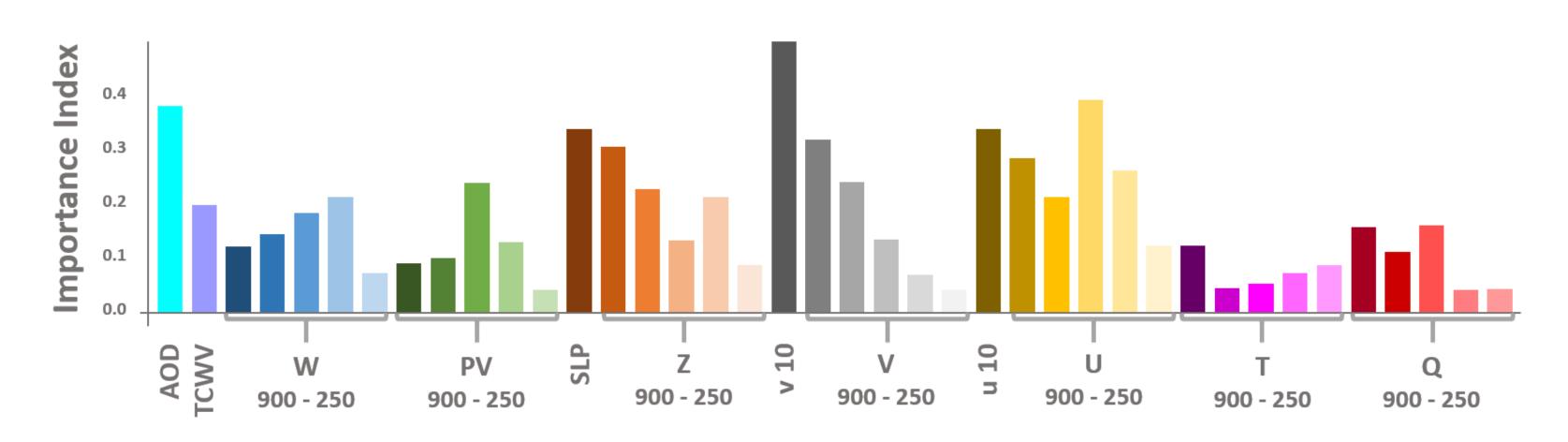
0.8 0.7 0.6 0.5 0.4 — Recall Recall (Dec-Apr) Precision 0.2 --- Precision (Dec-Apr) Shallow (Recall+Precision)/2 0.1 Naive (Recall+Precision)/2 ····· Event Rate 0.0 24 72 Lead Time [Hours]

Figure 1. At each timestamp, a meteorological input tensor, time feature, and in-situ PM_{10} level are channeled into an encoder network, which consequently generates a code. These codes are then forwarded to the decoder network, yielding regional PM_{10} predictions. Simultaneously, the classifier network utilizes the codes to generate a local dust level forecast.

Figure 3. This is a Dust-Forecast Variable Importance Index, which is derived by integrating the meteorological attribution towards the model's dust event prediction over both time and space, thereby using integrated gradients.

(b) Dimensionality Reduction

Figure 2. Recall and precision of local dust event $(PM_{10}>65.2)$ forecast for increasing lead time.



(d) Composite Analysis

Machine-Learning based Classification

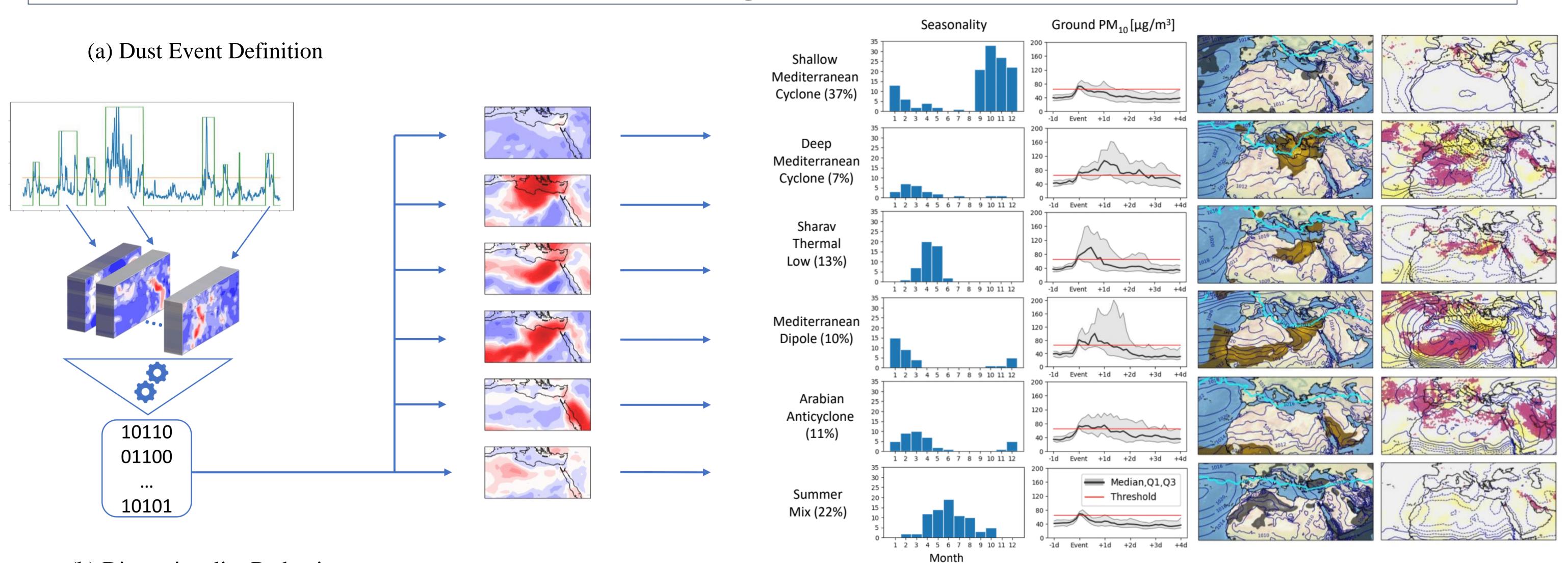


Figure 4. Unsupervised classification method's overview: A. dust event definition yielding 356 event; B. compression of the events' CAMS PM₁₀ map timeseries; C. clustering and labeling of the compressed timeseries; and D. composite examination of the clustered events

(c) Clustering & Labeling