衛星遙測雨量深度學習模式：

結合混和專家模型之季節模型整合應用

Deep Learning Model for Satellite Rainfall Estimation: Seasonal Model Integration with Mixture of Experts

蔡宗育[1]、彭彥璁[2]、蔡政達[1]、陳雲蘭[3]、劉豫臻[3]、方偉庭[3]

資拓宏宇國際股份有限公司[1]、國立政治大學資訊科學系[2] 、

中央氣象署科技發展組[3]

摘要

利用地球同步衛星資料進行降雨估算，對於短期的極端降水與長期的氣候監測至關重要。本計畫開發的 AIQPE 深度學習模型，專注於提升降雨推估的時空解析度與準確性。2024 年，透過調整輸入變數、優化訓練超參數以及替換損失函數等實驗設計，本計畫成功建立了適用於夏季的降雨估算模型，並在此基礎上進一步建構了冬季推估模型，確立了多季節降雨估算的核心架構。

然而，在實際應用中，各季節模型需根據時序及天氣型態自動切換，以形成全年一致且穩定的作業流程。為解決人工切換模型的操作負擔與潛在錯誤風險，本計畫於 2025 年引入了混和專家模型（Mixture of Experts, MoE）架構。該方法透過門控神經網路自動判斷每個時間點應使用的季節模型，使系統能根據輸入特徵自適應選擇最適合的專家模型，提升整體作業效率與彈性。

初步實驗結果顯示，採用 MoE 架構的模型在不同季節皆能維持穩定且具有一致性的降雨估算表現。相較於單一季節模型或靜態切換策略，MoE 模型展現出更高的泛化能力與操作便利性。本研究的技術架構與評估結果將於本次研討會中報告，期望為衛星降雨估算模型的全年應用提供更完善的解決方案與實務依據。

關鍵字：深度學習, 氣象衛星遙測, 降雨推估, 混和專家模型

Abstract

Geostationary satellite-based precipitation estimation plays a vital role in both short-term extreme rainfall monitoring and long-term climate monitoring. This project developed the AIQPE (AI-based Quantitative Precipitation Estimation) deep learning model to enhance the spatial and temporal resolution and accuracy of rainfall prediction. In 2024, by adjusting input variables, optimizing training hyperparameters, and experimenting with alternative loss functions, we successfully established a summer-specific precipitation estimation model. Building upon this foundation, a corresponding winter model was developed, completing the core framework for multi-seasonal rainfall estimation.

In practical applications, the seasonal models need to switch automatically based on seasonal shifts and weather conditions to support a consistent and reliable year-round operational workflow. To address the limitations of manual

model switching and reduce the risk of operational errors, the project introduced the Mixture of Experts (MoE) architecture in 2025. By employing a gating neural network, the system can automatically determine the appropriate seasonal model for each time point, enabling adaptive model selection based on input features and significantly improving operational efficiency and flexibility.

Preliminary validation results indicate that the MoE-based system maintains consistent and reliable estimation performance across different seasons. Compared to static switching or single-season models, the MoE approach demonstrates superior generalization capability and ease of use. The technical framework and evaluation results of this study will be presented at this conference, aiming to provide a more robust and practical solution for year-round satellite-based precipitation estimation.

Keywords: Deep learning, satellite remote sensing, precipitation estimation, mixture of experts