中央氣象署114年第三十九屆天氣分析與預報研討會

基於深度學習應用於大臺北地區夏季強降水預報之研究

交通部中央氣象署 科技發展組　楊榮瑜、凌文海、劉正欽、陳新淦

Outline

Content Overview

Introduction

問題背景與重要性現有方法的局限性：

在夏季期間，大臺北地區常伴隨劇烈對流系統，造成短時強降水事件。這類降水不僅容易引發都市淹水，也有機率造成山區土石流等次生災害。故精確(量跟地點)的降水預報已是必要需求。

現有方法的局限性：

現有研究大多僅依賴單一來源：或是使用分析場[3]，或是依靠預報場[13]，因而未能充分結合兩者的互補資訊。本研究嘗試同時整合分析場與預報場作為訓練資料，提升模型對降水特徵的掌握。

Introduction

資料特性挑戰：

然而，強降水事件的發生頻率相對稀少，導致資料本身具有以下挑戰：

1. 嚴重類別不平衡：強降水樣本佔比極低，使模型傾向於低估降水發生。
2. 資料量較少：訓練資料較少容易造成模型過擬合，進而降低泛化能力。

貢獻：

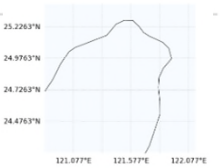
1. 方法創新：提出結合分析場與預報場作為訓練資料的 AI 模型。
2. 預報潛力：實驗結果顯示，本模型在部分評估指標上優於RWRF(中央氣象署對流尺度資料同化系統[14])，展現持續優化與應用的發展潛力。

Data Overview

RWRF Dataset

Spatial Information

Domain Coverage:
120.8274°N - 122.1343°N
24.2263°E - 25.4124°E



2km × 2km
Resolution

64 × 64
Grid Points

Vertical Structure

Pressure Levels (23 layers)

- 50 hPa
- 100-250 hPa
- 300-700 hPa
- 750-1000 hPa

↑ Upper Atmosphere　　Surface ↓

```
1000, 975, 950, 925, 900, 875, 850, 825, 800,
775, 750, 700, 650, 600, 550, 500, 400, 300,
250, 200, 150, 100, 50 hPa
Total: 23 vertical levels
```

Variables

Surface (9 vars)
- t2, u10, v10
- q2, sst, pw
- k_index, landmask, topography

Upper-air (6 vars)
- geopotential_height
- temperature, div
- u_wind, v_wind, water_vapor

15
Total Variables
per time step

Temporal Coverage

Training (6y)
2018年8月, 2019-2023年6、7、8月, 2024年6月

Validation (1m)
2024年7月

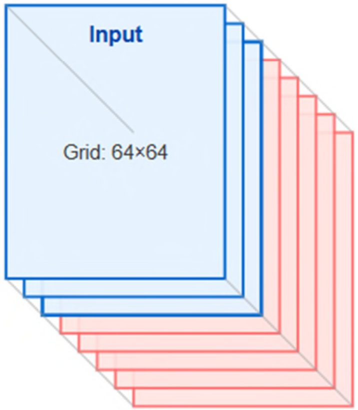
Testing (1m)
2024年8月

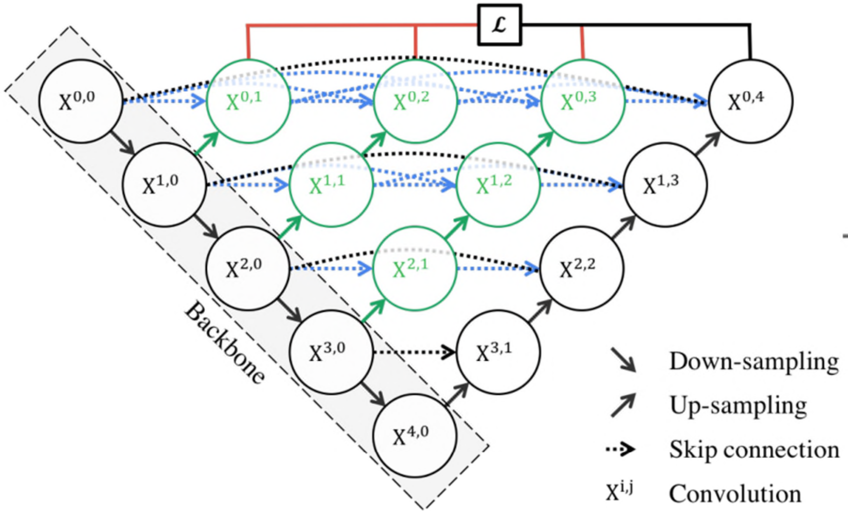
Focus on summer months (June-August) for heavy rainfall events

Model Architecture

U-Net++[1]

8 time steps × (23 levels × Upper-air variables + Surface variables) × spatial grid





Output

Predictions

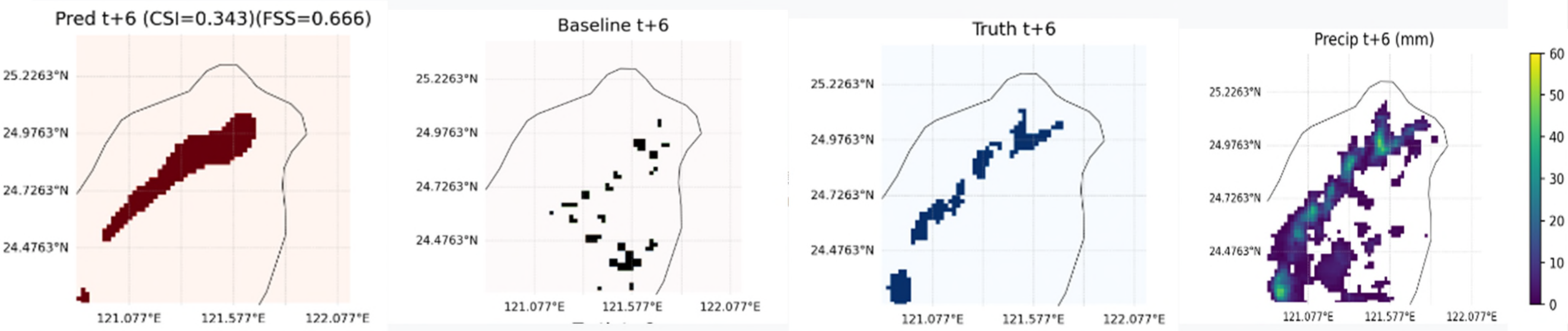
Input Temporal Information

- 分析場 (Analysis): t-2, t-1, t+0 (實際觀測)
- 預報場 (Forecast): t+2 ~ t+6 (模式預報)

• 時間解析度: 1小時 • 總時間跨度: 8小時 (t-2 到 t+6)

Output

預報未來二到六小時降雨超過門檻值之空間分布



門檻值設定

- 10 mm/hr
- 20 mm/hr

評估指標

- FSS (Fractions Skill Score): 空間預報技巧評分
- CSI (Critical Success Index): 臨界成功指數
- 數值範圍: 0 ~ 1 (越接近1表示預報越準確)

預測特點

- 空間解析度: 64×64 格點
- 時間解析度: 逐小時預測
- 預測範圍: t+2 至 t+6 (共5小時)

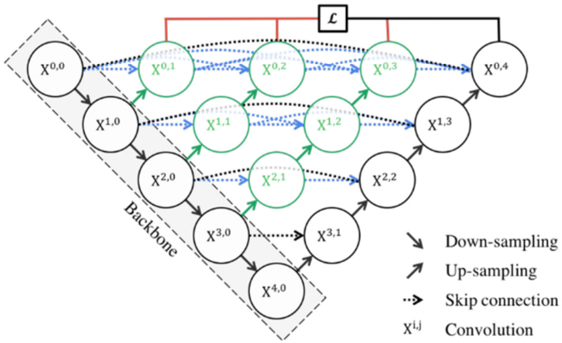
Method

1 Binary cross entropy + Dice loss [2]

類別不平衡

2 Focal SAM (Sharpness-Aware Minimization) [4]

資料不足



Experiments

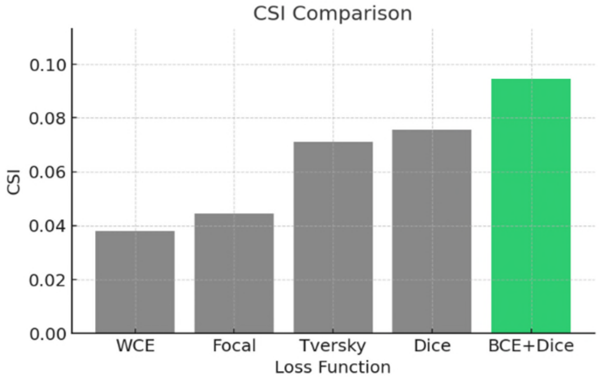
Binary cross entropy + Dice loss [2]

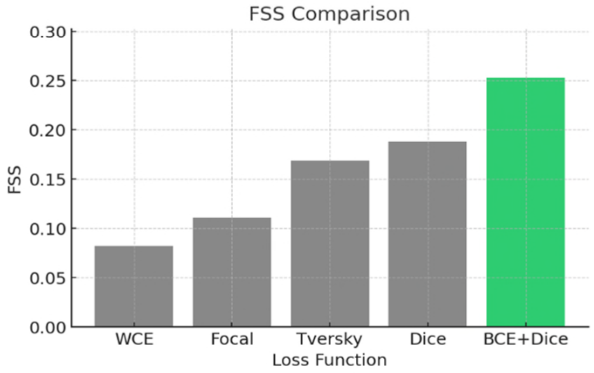
Loss Function Performance

Loss Function	CSI	FSS
Binary Cross Entropy [5]	0.0000	0.0001
Weighted Cross Entropy [6]	0.0381	0.0820
Focal Loss [7]	0.0444	0.1108
Tversky Loss [8]	0.0712	0.1691
Dice Loss [9]	0.0757	0.1878
BCE + Dice Loss	0.0945	0.2525

單純使用 cross entropy 容易偏向多數樣本，導致難以正確辨識強降水事件；
而 dice loss 則在降水預報中傾向高估降水範圍，產生過多假陽性 (false positive)。
因此，結合 cross entropy 與 dice loss 的混合損失函數，能兼顧不同情境並獲得最佳整體預報表現。

Visualization





Experiments

Focal SAM (Sharpness-Aware Minimization) [4]

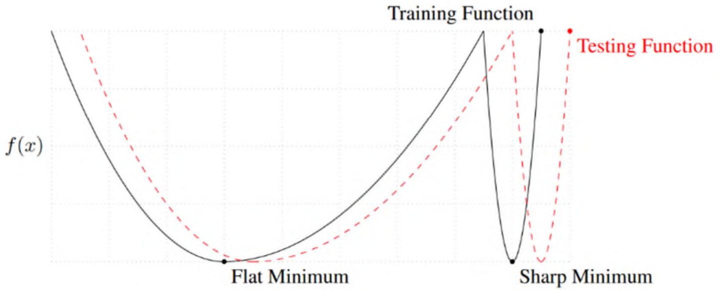


Figure 1: A Conceptual Sketch of Flat and Sharp Minima. The Y-axis indicates value of the loss function and the X-axis the variables (parameters)

Input: Training set $\mathcal{S} \triangleq \cup_{i=1}^{n}\{(\boldsymbol{x}_i, \boldsymbol{y}_i)\}$, Loss function $l : \mathcal{W} \times \mathcal{X} \times \mathcal{Y} \to \mathbb{R}_+$, Batch size b, Step size $\eta > 0$, Neighborhood size $\rho > 0$.
Output: Model trained with SAM
Initialize weights $\boldsymbol{w}_0$, $t = 0$;
while *not converged* **do**
  Sample batch $\mathcal{B} = \{(\boldsymbol{x}_1, \boldsymbol{y}_1), ...(\boldsymbol{x}_b, \boldsymbol{y}_b)\}$;
  Compute gradient $\nabla_{\boldsymbol{w}} L_{\mathcal{B}}(\boldsymbol{w})$ of the batch's training loss;
  Compute $\hat{\epsilon}(\boldsymbol{w})$ per equation 2;
  Compute gradient approximation for the SAM objective (equation 3): $\boldsymbol{g} = \nabla_w L_{\mathcal{B}}(\boldsymbol{w})|_{\boldsymbol{w}+\hat{\epsilon}(\boldsymbol{w})}$;
  Update weights: $\boldsymbol{w}_{t+1} = \boldsymbol{w}_t - \eta \boldsymbol{g}$;
  $t = t + 1$;
end
return $\boldsymbol{w}_t$

Algorithm 1: SAM algorithm

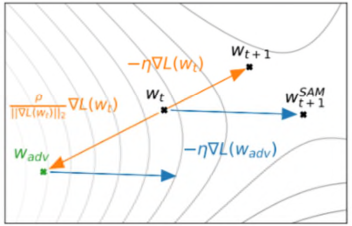
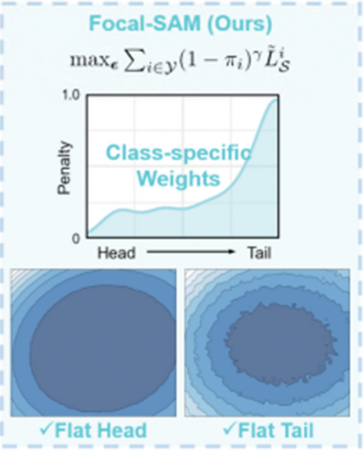


Figure 2: Schematic of the SAM parameter update.



	CSI	FSS
no SAM	0.0700	0.2041
SAM[10]	0.0915	0.2468
Focal SAM	0.0945	0.2525

Experiments

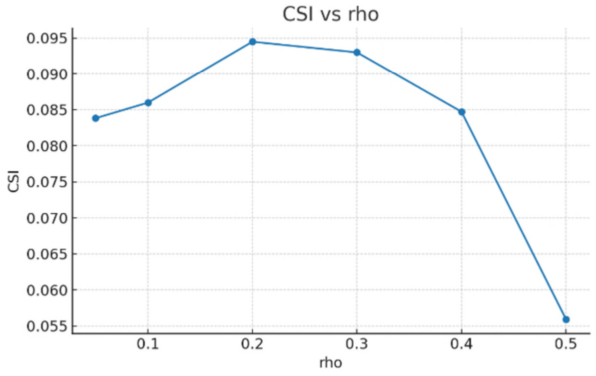
Focal SAM (Sharpness-Aware Minimization) [4]

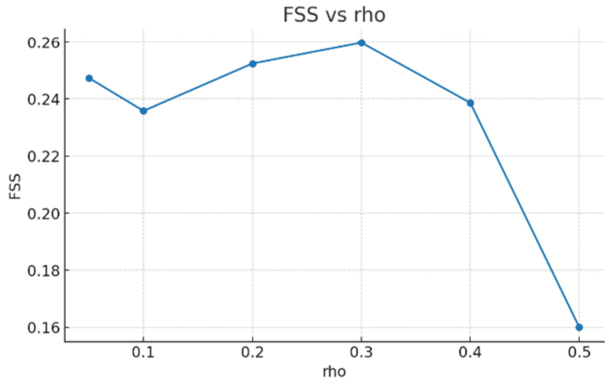
Focal SAM Results (ρ)

ρ (rho)	CSI	FSS
0.05	0.0838	0.2474
0.1	0.0860	0.2358
0.2	0.0945	0.2525
0.3	0.0930	0.2598
0.4	0.0847	0.2387
0.5	0.0559	0.1601

ρ (rho) 決定在權重空間中考慮的尖銳度範圍。
範圍越大 → 擾動越強，模型被迫在更廣鄰域內保持穩定；
範圍越小 → 擾動較弱，僅關注局部區域。

Visualization





Experiments

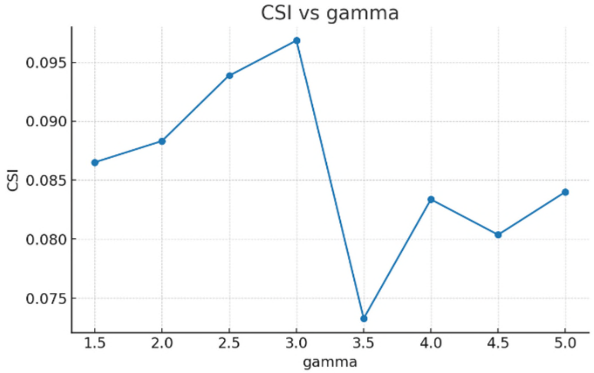
Focal SAM (Sharpness-Aware Minimization) [4]

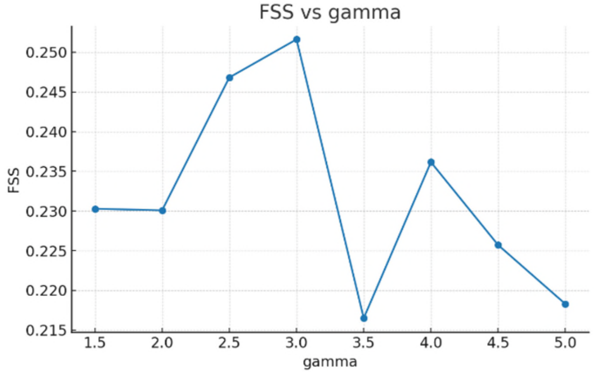
Focal SAM Results (α=1, γ sweep)

α	γ	CSI	FSS
1	1.5	0.0865	0.2303
1	2	0.0883	0.2301
1	2.5	0.0939	0.2468
1	3	0.0969	0.2516
1	3.5	0.0733	0.2165
1	4	0.0834	0.2362
1	4.5	0.0804	0.2257
1	5	0.0840	0.2183

$$\tilde{L}_S^{FS}(\boldsymbol{w}) = \max_{\|\boldsymbol{\epsilon}\|_2 \leq \rho} \sum_{i=1}^{C} (1-\pi_i)^{\gamma} \tilde{L}_S^i(\boldsymbol{w}, \boldsymbol{\epsilon}), \qquad (5)$$

Visualization





Experiments

Setup Comparison

Legend: ✓ used ✗ not used

Experiment	Binary cross entropy + Dice loss	Focal SAM (Sharpness-Aware Minimization)	CSI	FSS
(a)	✓	✓	0.0945	0.2525
(b)	✗	✓	0.0000 (-99.95%)	0.0002 (-99.93%)
(c)	✓	✗	0.0700 (-25.92%)	0.2041 (-19.15%)

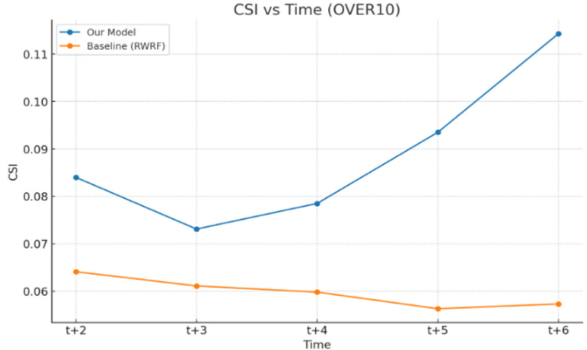
若未使用 BCE + Dice loss，模型幾乎無法學習到強降水事件；
引入 BCE + Dice loss 後，預報能力有明顯提升；
不用Focal SAM則會減少約20%上下的效果

Conclusion and Future Works

Performance Summary of OVER10 Model

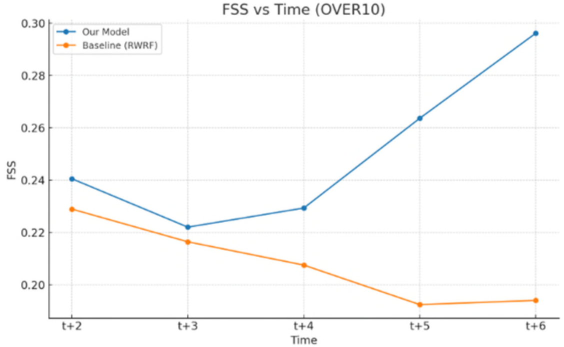
CSI Comparison (OVER10)

Time	Our Model	Baseline (RWRF)
Avg	0.0930	0.0594
t+2	0.0840	0.0641
t+3	0.0731	0.0611
t+4	0.0785	0.0598
t+5	0.0935	0.0563
t+6	0.1143	0.0573



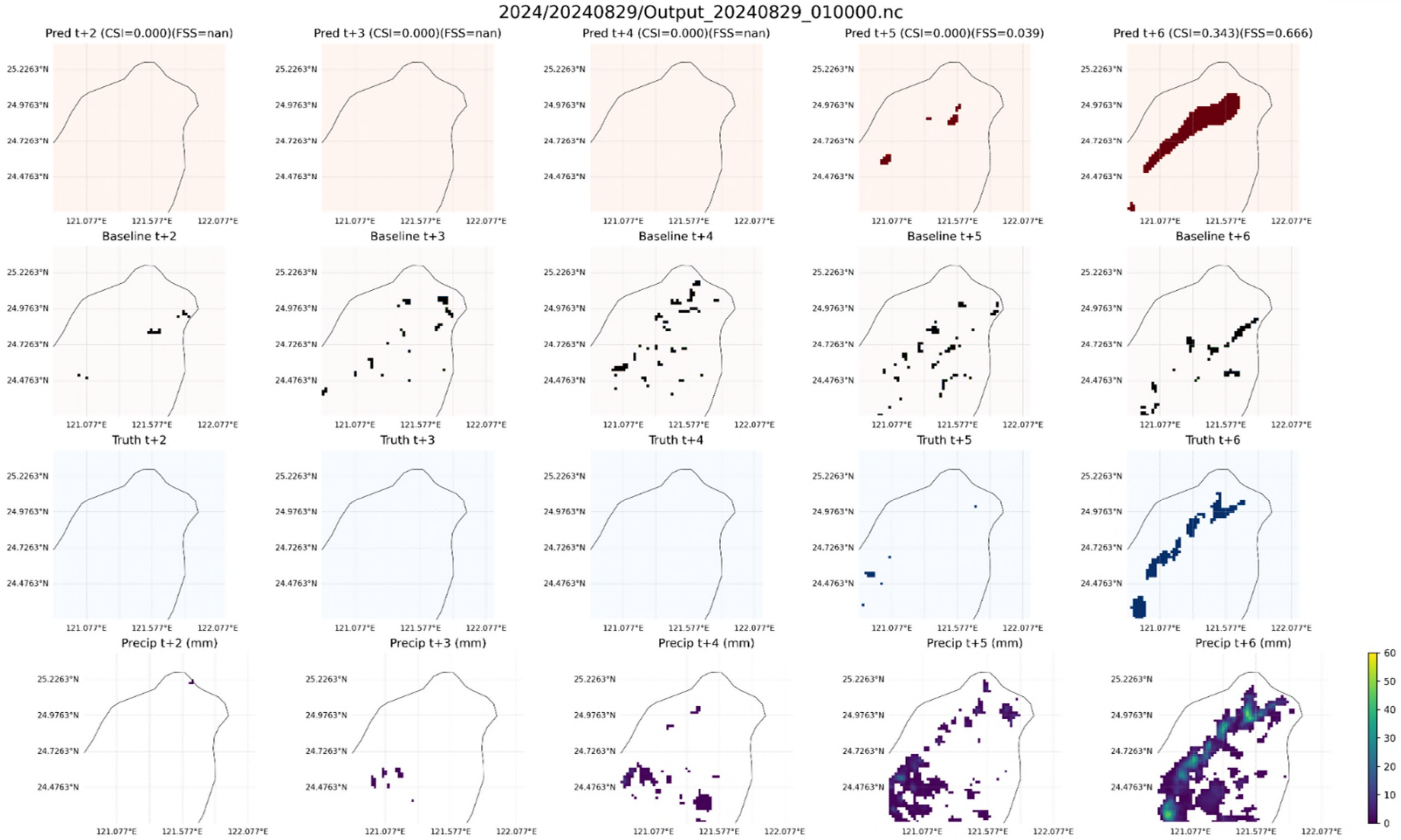
FSS Comparison (OVER10)

Time	Our Model	Baseline (RWRF)
Avg	0.2598	0.2058
t+2	0.2405	0.2289
t+3	0.2220	0.2164
t+4	0.2293	0.2075
t+5	0.2636	0.1924
t+6	0.2961	0.1940



Conclusion and Future Works

Performance Summary of OVER10 Model



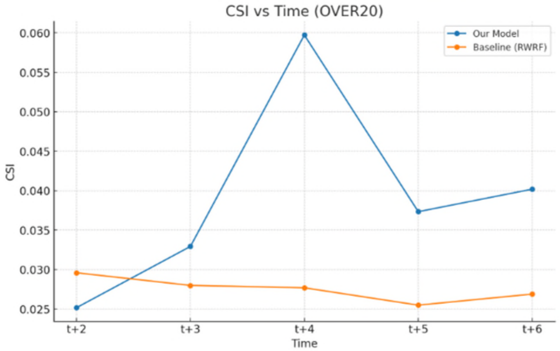
左圖顯示模型成功學習到地形作用，特別是雪山山脈沿線的強降雨特徵

Conclusion and Future Works

Performance Summary of OVER20 Model

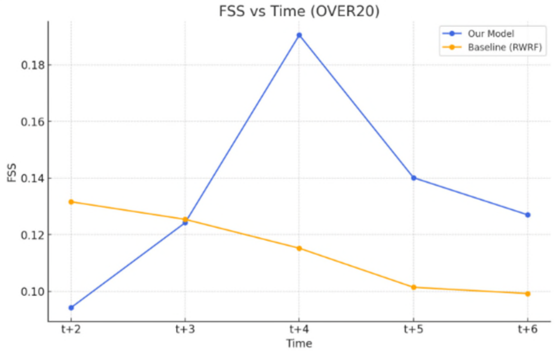
CSI Comparison (OVER20)

Time	Our Model	Baseline (RWRF)
Avg	0.0399	0.0274
t+2	0.0252	0.0296
t+3	0.0329	0.0280
t+4	0.0597	0.0277
t+5	0.0373	0.0255
t+6	0.0402	0.0269



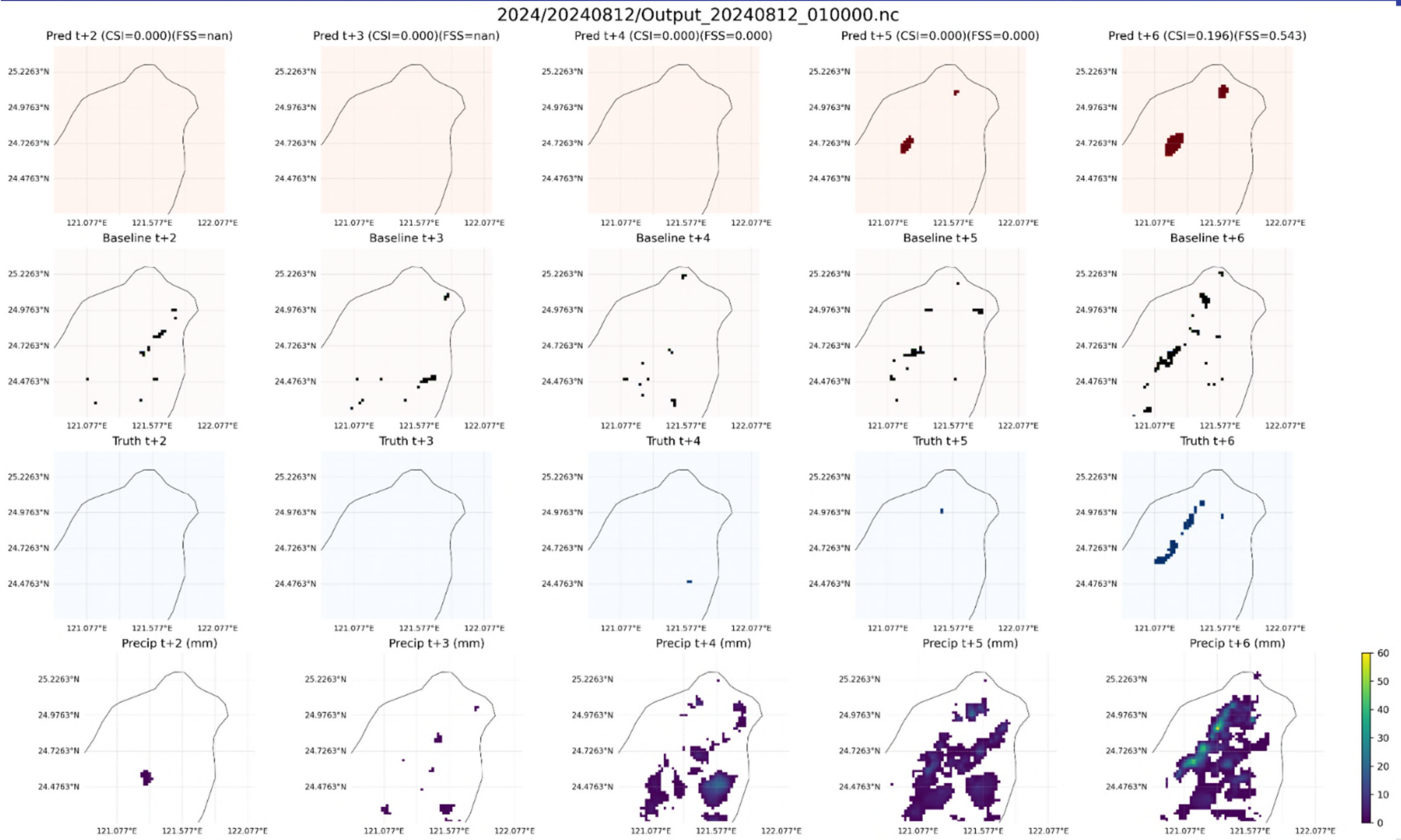
FSS Comparison (OVER20)

Time	Our Model	Baseline (RWRF)
Avg	0.1370	0.1128
t+2	0.0942	0.1316
t+3	0.1242	0.1254
t+4	0.1905	0.1152
t+5	0.1401	0.1014
t+6	0.1270	0.0992



Conclusion and Future Works

Performance Summary of OVER20 Model



同over10模型結果

模型成功學習到地形作用，
特別是雪山山脈沿線的強降雨特徵

Conclusion and Future Works

結論:

1. 採用 BCE + Dice loss 能讓模型更好地關注少數樣本，有效緩解類別不平衡問題。
2. 引入 Focal-SAM 後，CSI 與 FSS 指標均有進一步提升，顯示其在增強模型泛化能力與處理不平衡問題上具有效果。
3. 實驗結果顯示，本模型在部分評估指標上優於 RWRF，展現持續優化與應用的發展潛力。

未來工作:

1. 擴充資料量，以降低過擬合風險並提升泛化能力。
2. 探索全局注意力(global attention)機制，以增強模型對全局特徵的捕捉。
3. 針對加權損失函數(如 Dice loss)可能過度強調少數樣本，導致提前過擬合，未來可以考慮發展自適應損失函數或解耦學習。

THANK YOU

Reference

[1]Zongwei Zhou, Md Mahfuzur Rahman Siddiquee, Nima Tajbakhsh, and Jianming Liang. Unet++: A nested u-net architecture for medical image segmentation. In Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support, pages 3–11. Springer, 2018.
[2]Adrian Galdran, Gustavo Carneiro, and Miguel A. González Ballester. On the optimal combination of cross-entropy and soft dice losses for lesion segmentation with out-of-distribution robustness. In Moi Hoon Yap, Connah Kendrick, and Bill Cassidy, editors, Diabetic Foot Ulcers Grand Challenge, pages 40–51. Springer International Publishing, Cham, 2023.
[3]Zhanwei Li, Konstantinos Kamnitsas, and Ben Glocker. Analyzing overfitting under class imbalance in neural networks for image segmentation. IEEE Transactions on Medical Imaging, vol. 40, no. 3, pp. 1065–1077, March 2021.
[4]Sicong Li, Qianqian Xu, Zhiyong Yang, Zitai Wang, Linchao Zhang, Xiaochun Cao, and Qingming Huang. Focal-sam: Focal sharpness-aware minimization for long-tailed classification. In International Conference on Machine Learning, 2025.
[5] Ma Yi-de, Liu Qing, and Qian Zhi-Bai. Automated image segmentation using improved pcnn model based on cross-entropy. In Proceedings of 2004 International Symposium on Intelligent Multimedia, Video and Speech Processing, 2004., pages 743–746. IEEE, 2004.
[6] Vasyl Pihur, Susmita Datta, and Somnath Datta. Weighted rank aggregation of cluster validation measures: a monte carlo cross-entropy approach. Bioinformatics, 23(13):1607–1615, 2007.

Reference

[7] TY Lin, P Goyal, R Girshick, K He, and P Dollar. Focal loss for dense ´ object detection. arxiv 2017. arXiv preprint arXiv:1708.02002, 2002.
[8] Seyed Sadegh Mohseni Salehi, Deniz Erdogmus, and Ali Gholipour. Tversky loss function for image segmentation using 3d fully convolutional deep networks. In International Workshop on Machine Learning in Medical Imaging, pages 379–387. Springer, 2017.
[9] Carole H Sudre, Wenqi Li, Tom Vercauteren, Sebastien Ourselin, and M Jorge Cardoso. Generalised dice overlap as a deep learning loss function for highly unbalanced segmentations. In Deep learning in medical image analysis and multimodal learning for clinical decision support, pages 240–248. Springer, 2017.
[10] Pierre Foret, Ariel Kleiner, Hossein Mobahi, and Behnam Neyshabur. Sharpness-aware minimization for efficiently improving generalization. In International Conference on Learning Representations, 2021.
[11] Nitish Shirish Keskar, Dheevatsa Mudigere, Jorge Nocedal, Mikhail Smelyanskiy, and Ping Tak Peter Tang. On large-batch training for deep learning: Generalization gap and sharp minima. arXiv preprint arXiv:1609.04836, 2016.
[12] Shruti Jadon. A survey of loss functions for semantic segmentation. In 2020 IEEE Conference on Computational Intelligence in Bioinformatics and Computational Biology (CIBCB), pages 1–7, Via del Mar, Chile, 2020.

Reference

[13] O. Sharma, D. Trivedi, S. Pattnaik, V. Hazra and N. B. Puhan, "Improvement in District Scale Heavy Rainfall Prediction Over Complex Terrain of North East India Using Deep Learning," in IEEE Transactions on Geoscience and Remote Sensing, vol. 61, pp. 1-8, 2023

[14]7-2-7.pdf