# Extreme Precipitation Nowcasting using Transformer-based Generative Models

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## Background

- **2 billion people affected by floods** from 1998 and 2017.
- Estimated **economic losses** of 656 billion USD [1].
- **Precipitation nowcasting** plays a crucial role in enabling timely responses to such rapid and extreme meteorological variations [2].

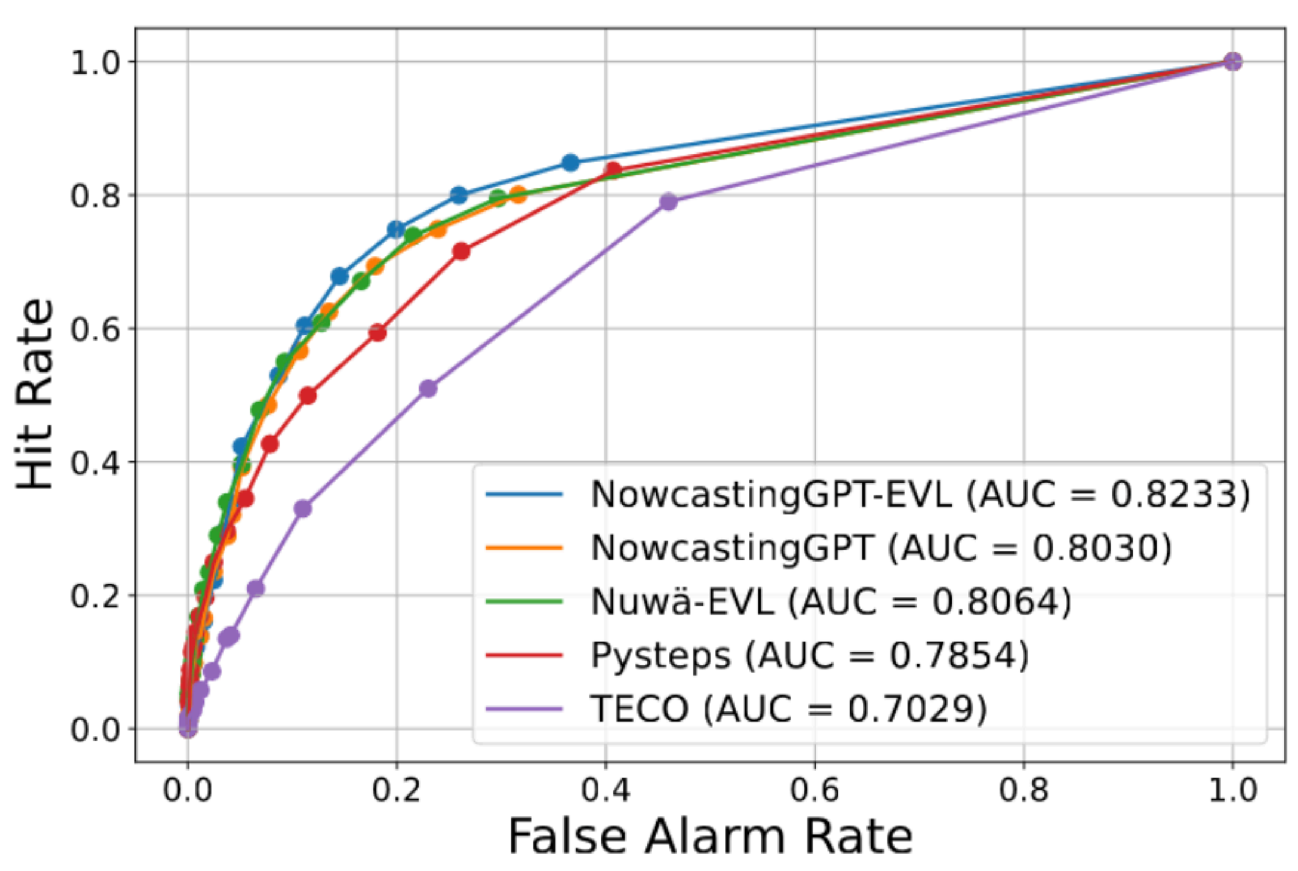
## Motivations

- **Extreme events** are not well represented and predicted by current models.
- Nuwä-EVL, the only SOTA model that uses an EVL regularizer, uses **fixed representations** for extreme events, leading to poor performances [3].
- Proposed DL-based Nowcasting SOTA models present **unfeasible** frame **generation time**.

## Contributions

- **NowcastingGPT**, a video prediction model composed by a VQVAE feature extractor, an autoregressive transformer dynamics module and an EVL regularizer to improve representation and prediction capabilities of extreme precipitation events
- A **new adaptive implementation** of the **EVL loss** that uses a latent transformer to compute extreme/not extreme probabilities on the fly
- We **benchmark TECO** [5] and evaluate the proposed model on the KNMI dataset which includes precipitation maps of the Netherlands between 2008 and 2021.

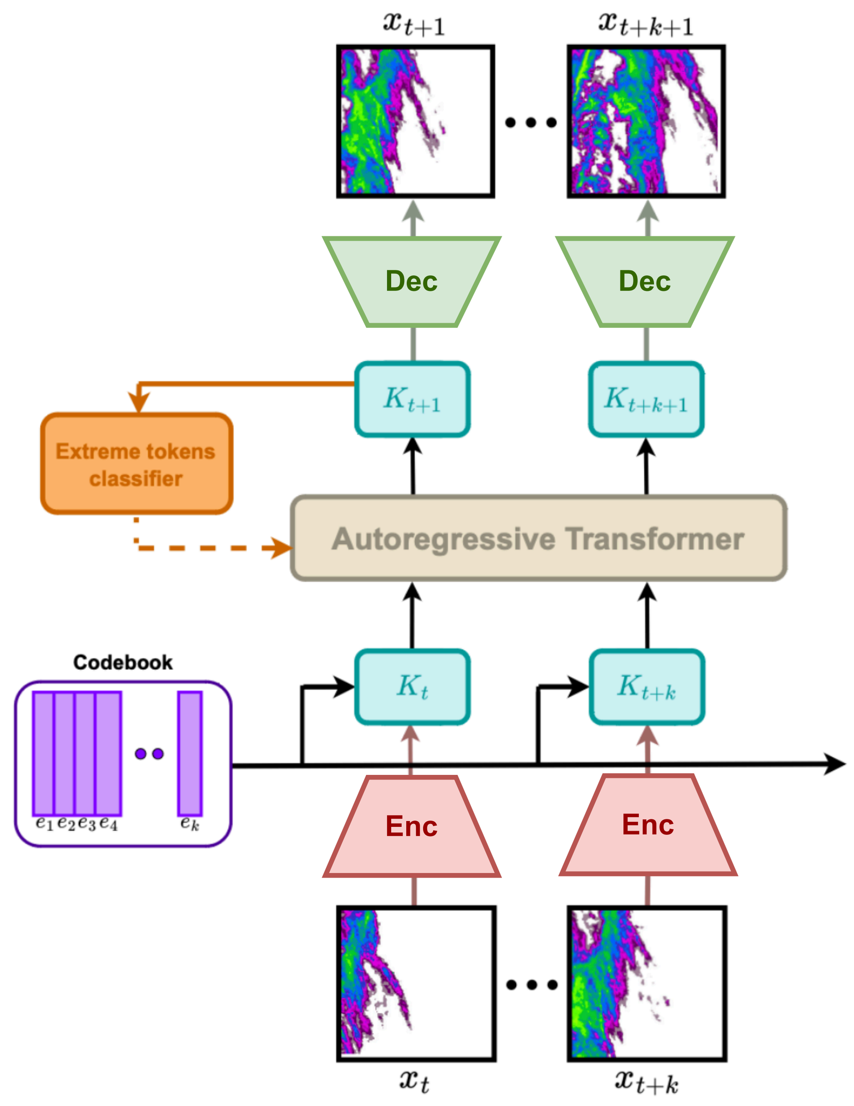
## Quantitative Results




| | Nuwä-EVL | NowcastingGPT | PySTEPS | TECO | NowcastingGPT-EVL |
|---|---|---|---|---|---|
| Number of parameters | 772,832 M | 402,735 M | - | 165,960 M | 520,374 M |
| Training time | 672h | 240h | - | 155h | 264h |
| Generation time | 322.86s | 38.90s | 9.34s | 0.51s | 43.10s |

| | Nuwä-EVL | NowcastingGPT | PySTEPS | TECO | NowcastingGPT-EVL |
|---|---|---|---|---|---|
| PCC (↑) | 0.15 | $0.20 \pm 0.002$ | 0.14 | $0.10 \pm 0.002$ | $\mathbf{0.22} \pm 0.002$ |
| MSE (↓) | 4.85 | $3.60 \pm 0.02$ | 6.22 | $3.65 \pm 0.008$ | $\mathbf{3.45} \pm 0.02$ |
| MAE (↓) | 1.00 | $0.72 \pm 0.005$ | 0.93 | $\mathbf{0.68} \pm 0.001$ | $0.69 \pm 0.005$ |
| CSI(1mm) (↑) | **0.23** | $0.21 \pm 0.002$ | 0.21 | $0.07 \pm 0.001$ | $0.22 \pm 0.002$ |
| CSI(2mm) (↑) | **0.13** | $0.11 \pm 0.001$ | 0.12 | $0.03 \pm 0.001$ | $0.12 \pm 0.001$ |
| CSI(8mm) (↑) | 0.008 | $0.005 \pm 0.0005$ | **0.01** | $0.001 \pm 0.0009$ | $0.009 \pm 0.0005$ |
| FAR(1mm) (↓) | 0.61 | $0.59 \pm 0.002$ | **0.55** | $0.69 \pm 0.002$ | $0.59 \pm 0.002$ |
| FAR(2mm) (↓) | 0.76 | $0.71 \pm 0.0007$ | **0.70** | $0.78 \pm 0.004$ | $0.71 \pm 0.0007$ |
| FAR(8mm) (↓) | 0.85 | $0.59 \pm 0.003$ | 0.89 | $\mathbf{0.49} \pm 0.006$ | $0.52 \pm 0.003$ |
| FSS(1km) (↑) | 0.35 | $0.49 \pm 0.003$ | 0.32 | $0.49 \pm 0.003$ | $\mathbf{0.52} \pm 0.003$ |
| FSS(10km) (↑) | 0.42 | $0.55 \pm 0.004$ | 0.41 | $0.46 \pm 0.003$ | $\mathbf{0.58} \pm 0.004$ |
| FSS(20km) (↑) | 0.48 | $0.59 \pm 0.004$ | 0.47 | $0.42 \pm 0.003$ | $\mathbf{0.62} \pm 0.004$ |
| FSS(30km) (↑) | 0.52 | $0.62 \pm 0.004$ | 0.51 | $0.37 \pm 0.002$ | $\mathbf{0.65} \pm 0.004$ |

## NowcastingGPT Visualization



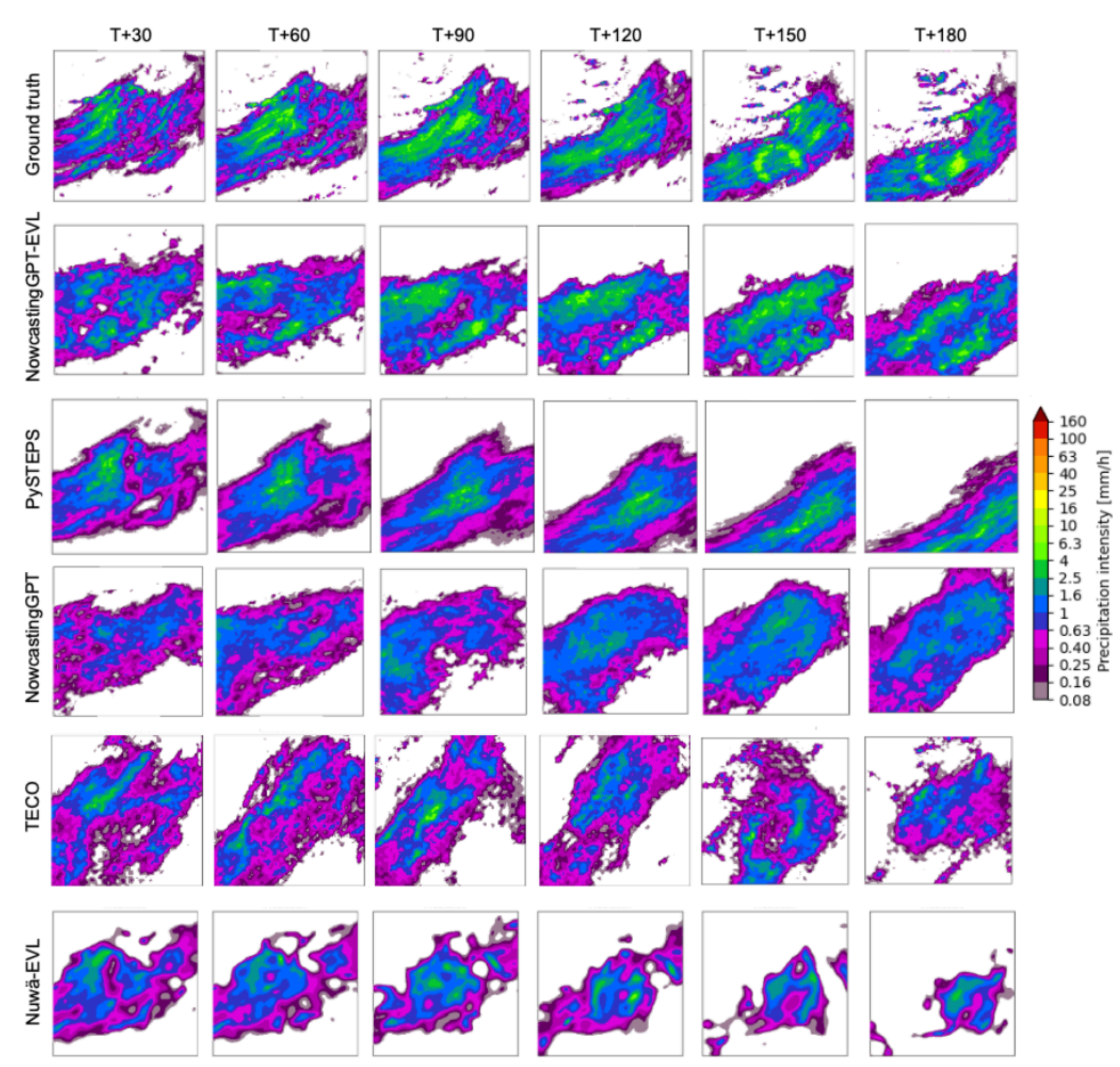

## Extreme Value Loss Framework

When dealing with **imbalanced data**, the standard cross-entropy loss often falls short, particularly when classifying extreme events. To address this, the Extreme Value Loss (EVL) [4] has been introduced as a more effective alternative, designed to **balance** the **disparities between extreme** and **non-extreme cases** in time series data:

$$\mathrm{EVL}(u_t, v_t) = -\beta_1 \left[1 - \frac{u_t}{\gamma}\right]^{\gamma} v_t \log(u_t) - \beta_0 \left[1 - \frac{1 - u_t}{\gamma}\right]^{\gamma} (1 - v_t) \log(1 - u_t).$$

where $v_t$ represents the ground truth labels (extreme/not extreme), $u_t$ the predicted probabilities, $\gamma$ is a hyperparameter of the related Generalized Extreme Value (GEV) distribution, and $\beta_0$ and $\beta_1$ reflect the proportions of non-extreme and extreme tokens.

## Qualitative Results




## References

[1] Spatial and temporal evaluation of radar rainfall nowcasting techniques, R.O.Imhoff et al, 2020.

[2] Global projections of river flood risk in a warmer world, L. Alfieri et al, 2017.

[3] Nowcasting of extreme precipitation using deep generative models, H. Bi et al, 2023.

[4] Modeling extreme events in time series prediction, D. Ding et al, 2019.

[5] Temporally consistent transformers for video generation, W. Yan et al, 2023.