Climate Adaptation-Aware Flood Prediction for Coastal Cities Using Deep Learning

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NEURAL INFORMATION PROCESSING SYSTEMS

Abstract

Rising sea levels threaten coastal regions, demanding efficient flood prediction methods. Traditional models are accurate but computationally expensive, limiting real-time use. We propose a deep learning framework for predicting coastal flooding under varying sea-level rise (SLR) scenarios and shoreline adaptations. Our model generalizes across diverse regions, achieving a 19.96% lower MAE for inundation prediction and a 0.55% improvement in non-flooded region accuracy over existing methods.

Introduction

Coastal flooding is intensifying due to climate change and sea-level rise (SLR), posing significant risks to urban areas, infrastructure, and economies [1]. Traditional hydrodynamic models provide accurate predictions but are computationally expensive, making real-time predictions impractical [2].

Deep learning (DL) approaches offer a promising alternative by accelerating predictions while maintaining accuracy [3]. However, existing methods often struggle with data scarcity, high-dimensional outputs, and limited generalization across different regions. We introduce a novel DL framework that leverages computer vision techniques to predict coastal flooding under various SLR scenarios and shoreline adaptation strategies [4]. Our model:

- Enables rapid, high-resolution flood mapping, supporting real-time flood risk management and climate adaptation planning.
- Generalizes across regions, using Abu Dhabi and San Francisco data.
- Outperforms state-of-the-art methods, reducing mean absolute error (MAE) by 19.96%.

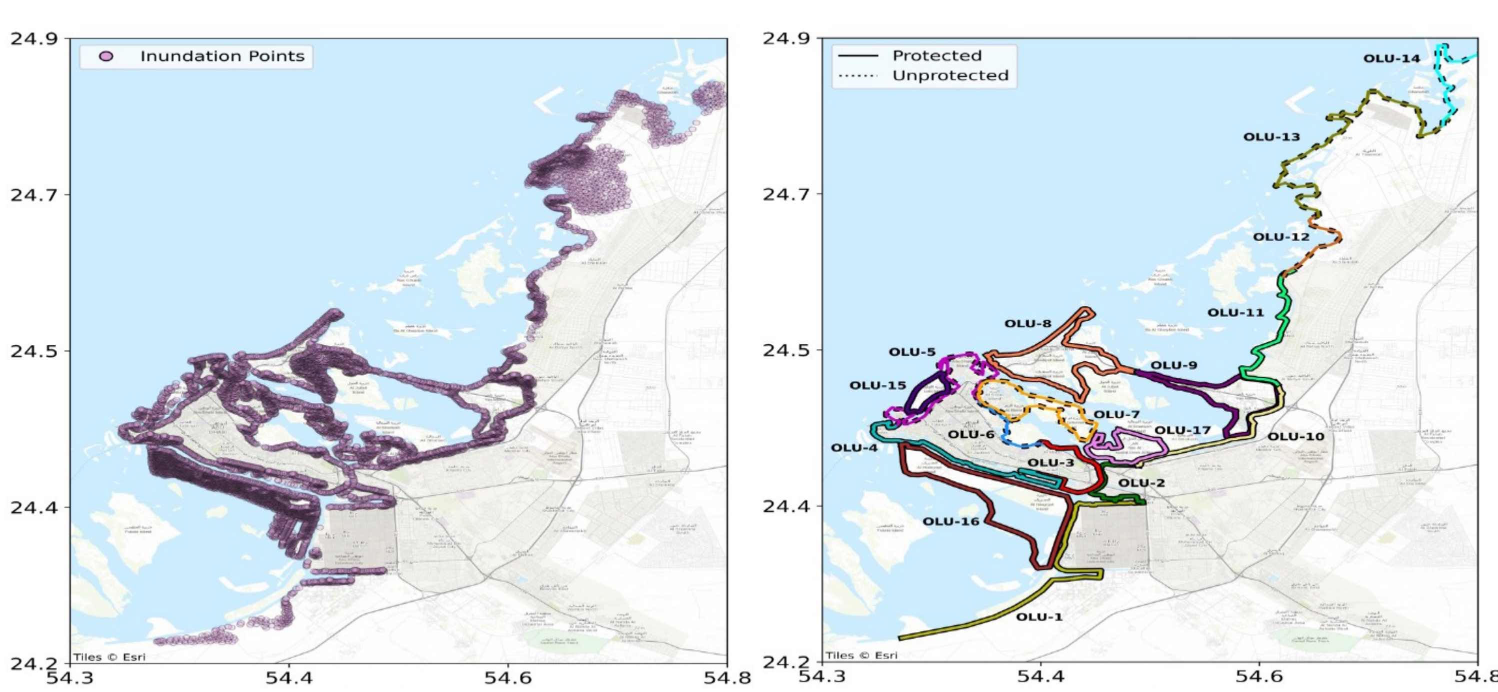

Figure 1. Abu Dhabi coastal region. (a) Inland inundation points under the 0.5 m SLR scenario for AD and 1.0 m SLR for SF. (b) OLU boundaries.

Methodology

Dataset:

- **Coastal regions:** Abu Dhabi (AD) and San Francisco (SF).
- **Simulation Tool:** Delft3D, with high-resolution bathymetry, digital elevation models, and ERA5 climate data.
- **Flood Events:** Simulated under wind, wave, and tidal forcing for realistic inundation patterns.
- **SLR Scenarios:** 0.5m for AD and 1.0m for SF.
- **Shoreline Adaptations:** Modeled using Operational Landscape Units (OLUs) to assess the impact of protective measures.

Preprocessing:

- Inundation points mapped to a 1024×1024 grid for the DL model.
- Protection scenarios encoded as binary feature maps, with water depth values as targets.

CASPIAN-v2:

- Encoder-Decoder CNN network for flood prediction.
- Multi-Attention ResNeXt (MARX) blocks capture complex flood patterns.
- SLR-Enhanced Encoding (SEE) blocks integrate SLR levels dynamically.
- Skip connections & feature refinement improve spatial details.

Training & Optimization:

- **Loss Function:** A hybrid of Huber, Log-Cosh, and Quantile loss to balance accuracy and robustness.
- **Optimization:** Adam optimizer with learning rate 8×10^{-4}, batch size = 2, trained for 200 epochs with early stopping.
- **Data Augmentation:** Random cut-outs to enhance model generalization.

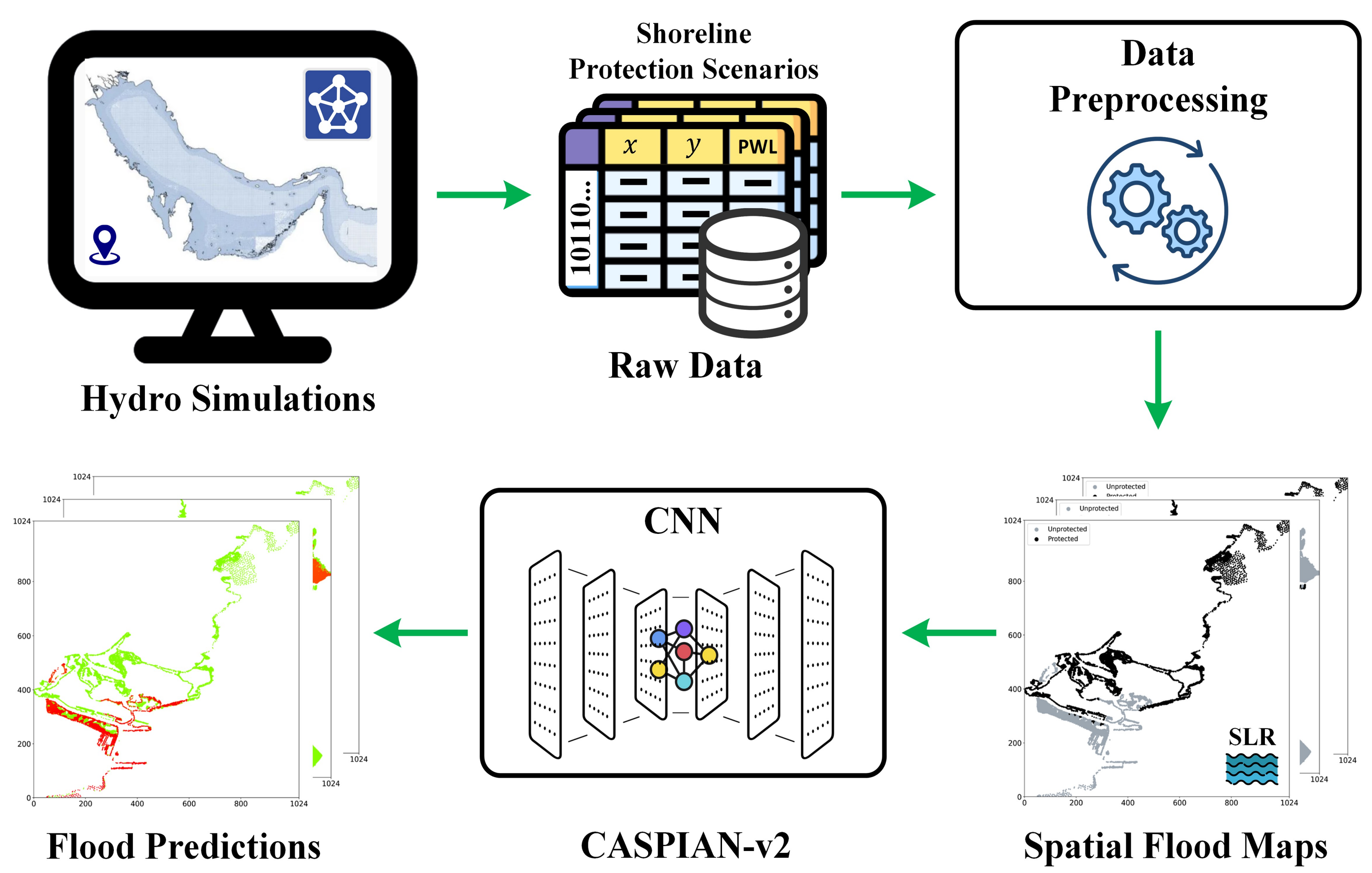

Figure 2. Proposed Framework for Coastal Flood Prediction

Results

Our proposed CASPIAN-v2 deep learning framework demonstrates high accuracy and strong generalization across diverse coastal regions.

- Predicted flood maps closely align with ground truth, capturing spatial variations effectively.
- Strong generalization results across AD and SF datasets.
- Surpasses traditional ML models and DL baselines.
- 19.96% lower MAE in predicting flood compared to existing models.
- 0.55% more accurate for non-flooded regions, reducing false positives.

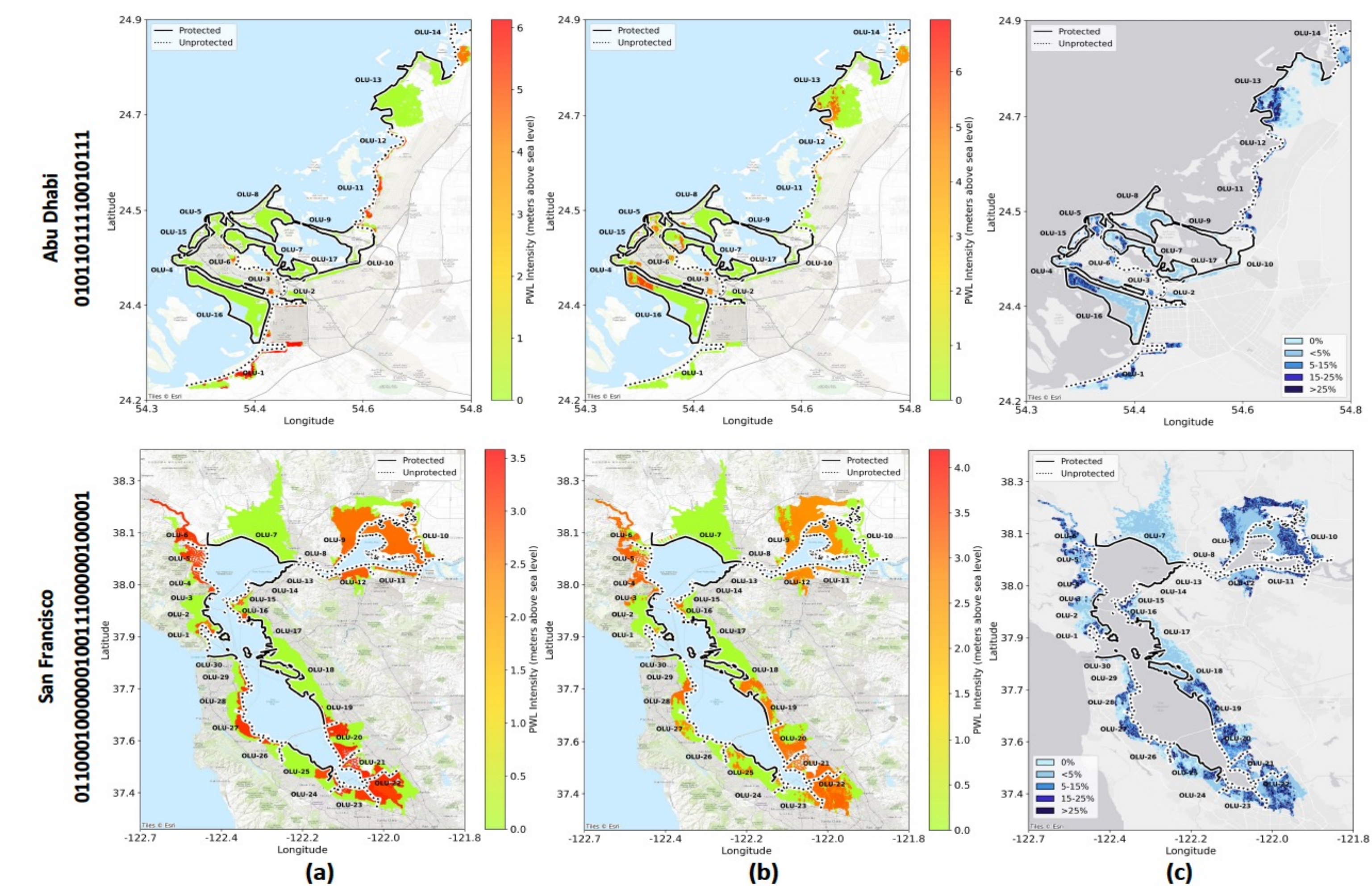

Figure 3. Qualitative evaluation of CASPIAN-v2 (a) Ground truth inundation maps for representative AD and SF scenarios. (b) Predicted inundation values. (c) Absolute error distributions of predicted inundation values.

Table 1. Performance comparison of the proposed CASPIAN-v2 model with SOTA ML and DL models. The best and second-best results are highlighted in red and blue, respectively.

Type	Model	Prediction Accuracy								Computational Efficiency		
		MAE ↓	RMSE ↓	RTAE ↓	$\delta > 0.5$ ↓	$\delta > 0.1$ ↓	R^2 ↑	Acc[0] ↑	DSC ↑	Param↓	TT ↓	IT ↓
Simulator	AD Pipeline†	*Served as the ground truth*								-	-	71–73h
	SF Pipeline°									-	-	3.5–6.0h
ML (1-D)	Naïve	1.53	3.54	1746.06	74.92%	80.11%	0.54	31.01%	0.38	-	62s	0.15s
	RF	0.54	0.73	264.95	36.77%	72.20%	0.79	34.19%	0.41	-	75s	0.18s
	Linear	0.12	0.19	64.98	7.87%	14.03%	0.94	59.28%	0.62	-	65s	0.16s
	XGBoost	0.25	0.24	164.16	16.27%	49.88%	0.93	44.10%	0.47	-	198s	0.21s
	SVR	0.20	0.24	72.31	9.24%	41.17%	0.92	45.46	0.48	-	79s	0.19s
	Lasso Poly	0.09	0.12	28.15	4.47%	15.04%	0.96	55.78%	0.64	-	72s	0.17s
	Kriging	0.10	0.24	39.90	5.22%	11.59%	0.94	62.88%	0.63	-	76s	0.18s
DL (1-D)	MLP	0.64	2.72	524.17	32.82%	41.94%	0.65	36.91%	0.43	0.01M	14h	5.03s
	CCT	0.90	2.32	843.54	48.08%	64.63%	0.66	34.01%	0.42	11.05M	18h	0.26s
DL (2-D)	Atten-Unet	0.10	0.37	11.82	3.14%	16.70%	0.91	95.26%	0.73	12.07M	46h	0.24s
	Atten-Unet*	0.10	0.36	11.65	3.31%	15.62%	0.92	94.99%	0.74	12.07M	47h	0.27s
	Swin-Unet	0.06	0.27	6.72	1.47%	12.94%	0.95	98.10%	0.80	8.29M	26h	0.24s
	CASPIAN	0.05	0.36	5.85	1.01%	4.79%	0.92	98.84%	0.82	0.36M	22h	0.22s
	Ours	0.04	0.30	6.54	0.89%	3.55%	0.93	99.39%	0.84	0.38M	22h	0.22s

Conclusion

We present CASPIAN-v2, a DL-based framework for predicting coastal flooding under various SLR scenarios and shoreline adaptation strategies. By treating flood prediction as a computer vision task, our model efficiently captures high-resolution inundation patterns while significantly improving accuracy and computational efficiency over traditional methods.

References

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