3D Convolutional Deep Learning for Coastal Fog Predictions

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Introduction

- The reduction of visibility adversely affects land, marine, and air transportation when considering the human and economic costs.
- The study site is the **Mustang Beach Airport in Port Aransas, Texas, USA (KRAS)**. We use KRAS measured visibility as a proxy for fog develops over the **Port of Corpus Christi Ship Channel (PCC).**
- Greater accuracy and skill in fog prediction over the PCC would provide significant economic benefits; the PCC is the 4th largest Port in the United States in terms of its annual tonnage.

In this study, we (1) predict fog visibility categories below 1600m, 3200m and 6400m by postprocessing 2D maps of numerical weather prediction model output and satellite-based sea surface temperature using a 3DConvolutional Neural Network (3D-CNN). In this specific 3D-CNN, a **dilated convolution** feature extraction strategy, spatial and variable-wise **dense blocks** have been designed to learn and extract the features from input variables. To magnify the importance of extracted information **double-branch attention mechanisms** have been applied.

The results of 3D-CNN for **6, 12- and 24-hour lead time** predictions are compared to probabilistic output from the **High-Resolution Ensemble Forecast (HREF)** system developed by the US National Weather Service. 3D-CNN outperformed HREF using 8 standard evaluation metrics.

Methodology: 3D-CNN

3D-CNN model designed in this work has 5 sections for 5 different input groups. Each consists of double branch feature extracting (spatial and spectral feature extraction branches) based on dense block, attention mechanism and dilated multiscale convolution shown in figure 2. MUR SST dimension reduction has been done by 3D convolutional before applying in 3D-CNN model.

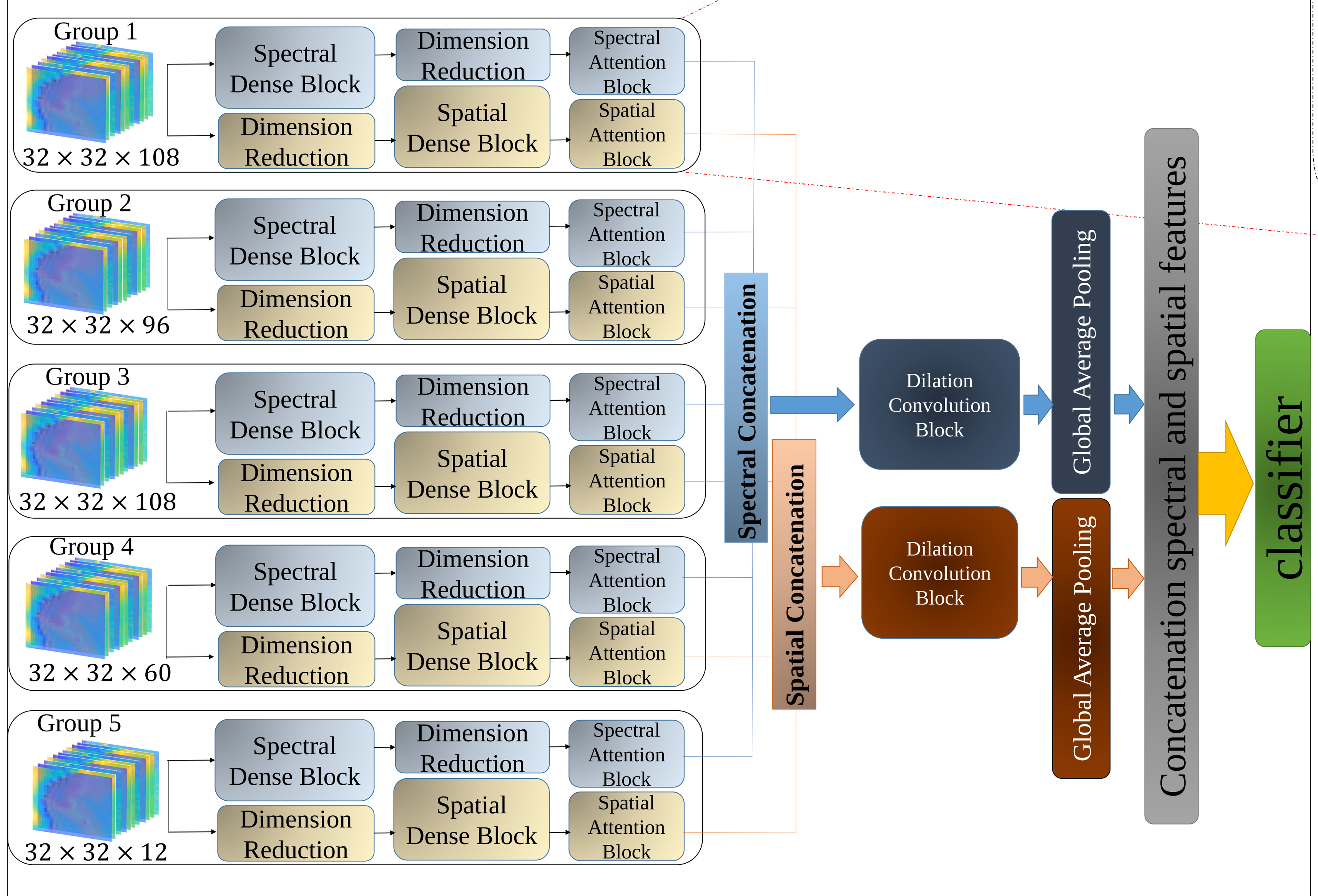
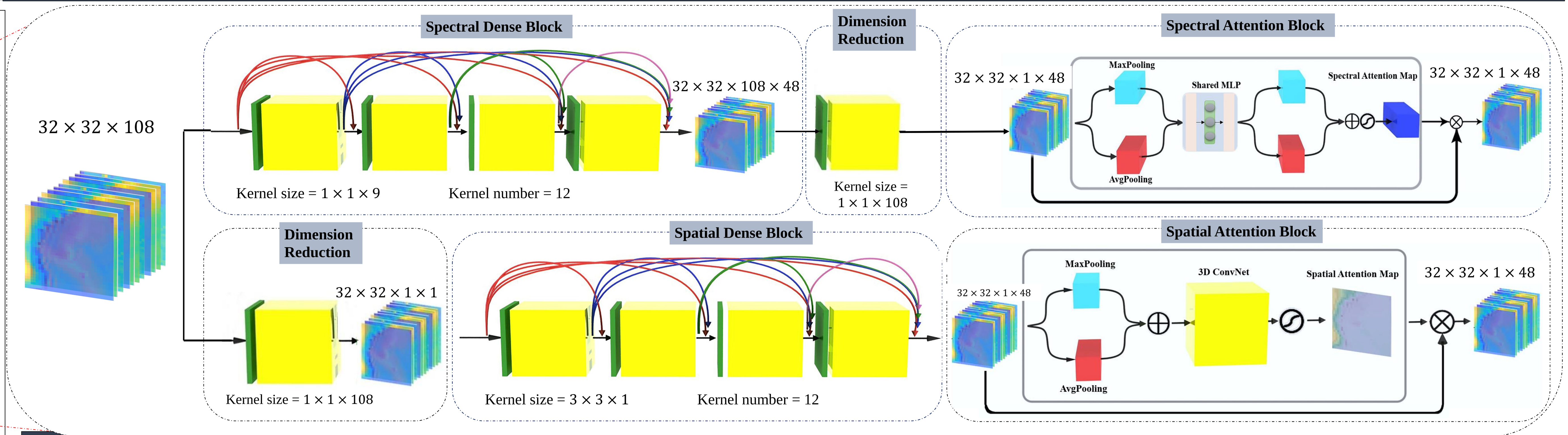


Figure 2: 3D-CNN architecture.

Detail of 3DCNN Air-Sea Input Cube



ROC Curves

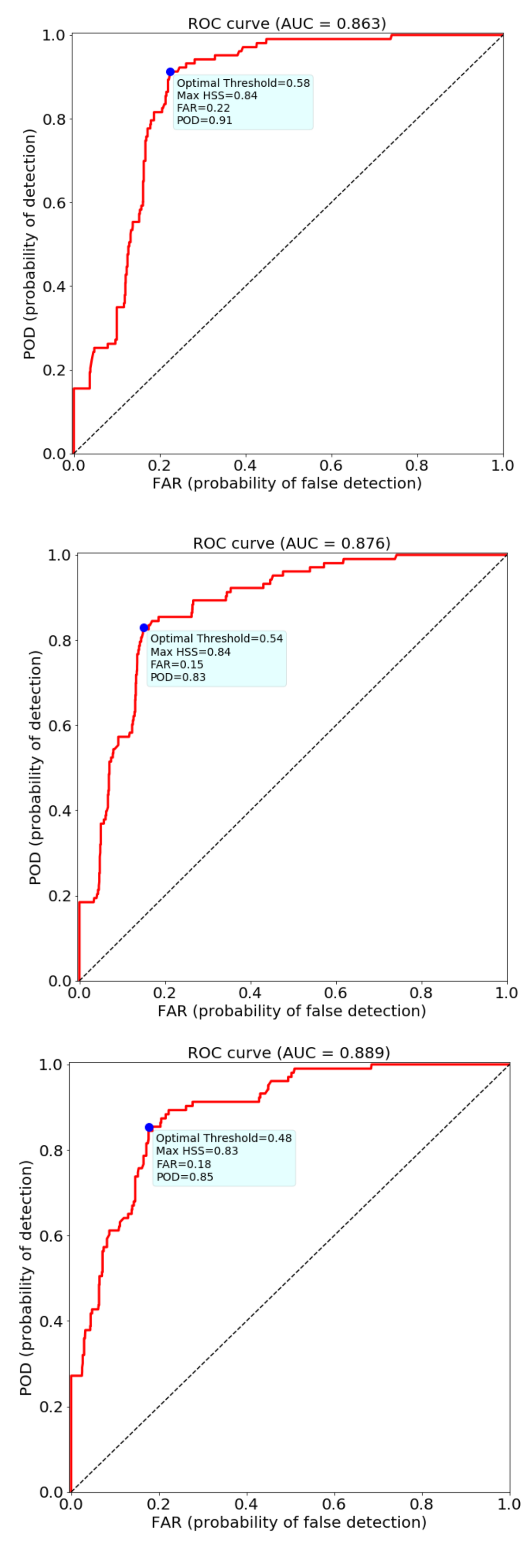


Figure 3: The area under curve for 6, 12 and 24 hours lead time prediction.

Results

Table 1: Results 6 Hours

	$\leq 1600m$		$\leq 3200m$		$\leq 6400m$	
Metrics	3D-CNN	HREF	3D-CNN	HREF	3D-CNN	HREF
POD	0.61	0.36	0.56	0.54	0.77	0.60
F	0.01	0.01	0.01	0.03	0.04	0.05
FAR	0.40	0.64	0.36	0.62	0.42	0.55
CSI	0.38	0.27	0.43	0.29	0.50	0.34
PSS	0.59	0.35	0.55	0.51	0.73	0.54
HSS	0.59	0.42	0.58	0.42	0.63	0.46
ORSS	0.98	0.96	0.98	0.94	0.97	0.92
CSS	0.58	0.51	0.62	0.36	0.56	0.42

Table 2: Results 12 Hours

	$\leq 1600m$		$\leq 3200m$		$\leq 6400m$	
Metrics	3D-CNN	HREF	3D-CNN	HREF	3D-CNN	HREF
POD	0.60	0.25	0.48	0.59	0.70	0.52
F	0.02	0.005	0.02	0.06	0.04	0.06
FAR	0.56	0.43	0.56	0.72	0.43	0.61
CSI	0.34	0.21	0.30	0.23	0.46	0.29
PSS	0.57	0.25	0.45	0.53	0.64	0.46
HSS	0.49	0.34	0.43	0.34	0.60	0.40
ORSS	0.96	0.97	0.94	0.91	0.96	0.88
CSS	0.42	0.55	0.41	0.26	0.54	0.35

Table 3: Results 24Hours

	$\leq 1600m$		$\leq 3200m$		$\leq 6400m$	
Metrics	3D-CNN	HREF	3D-CNN	HREF	3D-CNN	HREF
POD	**0.54**	0.34	0.57	0.40	0.67	0.52
F	**0.02**	0.04	0.03	0.05	0.04	0.06
FAR	**0.50**	0.80	0.58	0.76	0.41	0.61
CSI	**0.35**	0.15	0.32	0.18	0.45	0.28
PSS	**0.52**	0.30	0.54	0.37	0.63	0.45
HSS	**0.50**	0.23	0.46	0.27	0.59	0.40
ORSS	**0.97**	0.85	0.95	0.84	0.96	0.88
CSS	**0.48**	0.18	0.40	0.26	0.56	0.35

Model Domain and Input Feature Dataset

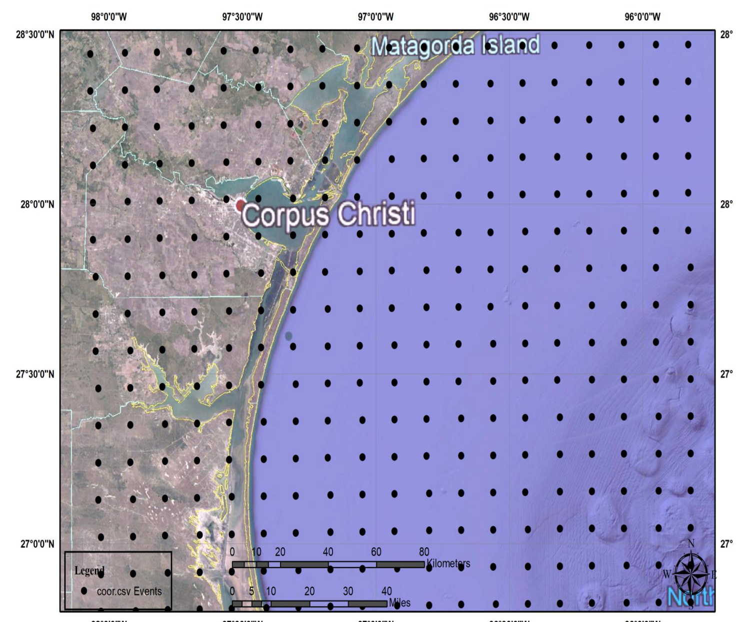


Figure 1: Study area.

The features originated from the North American Mesoscale Modeling System (**NAM**) from **2009 − 2020** with a **32 × 32** horizontal **12-km** grid; and sea surface temperature from the NASA Multiscale Ultra Resolution (**MUR**) dataset, a **384 × 384** grid with **1 km** grid spacing.

Within the 3D-CNN architecture used in this study, the features are arranged in 5 groups with each group possessing a similar physical relationship to fog:

1. Wind-related features FRICV SURFACE, U10-METERS, V10-METERS, U[975:25:700] mb, and V[975:25:700] mb (Koracin et al., 2014).
2. TKE[975:25:700] mb and Q[975:25:700] mb (Toth et al., 2010).
3. TMP2-METERS, TMP[975:25:700], DPT2-METERS, RH2-METERS, and RH [975:25:700] mb which describe the thermodynamic profile of the lower atmosphere (Koracin et al. ˇ , 2014).
4. Surface visibility (VIS), surface features QSURFACE, TMP2-METERS-DPT2-METERS (dew point depression) that correlate with VIS, and TLCL and VVEL975-700 that also correlate with VIS.
5. SST, DPT2-METERS-SST, and TMP2-METERS-SST, related to advection fog (Li et al., 2016).

Conclusions

- 3D CNN architecture combines SST map and atmospheric predictions over nearshore coastal region to produce significant improvement in coastal visibility predictions as compared to the operational HREF ensemble predictions.
- Future work includes comparisons with SDAE and VAE predictions and applying explainable AI methods to better understand what parts of the input are most important for model performance during coastal fog events.

References

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