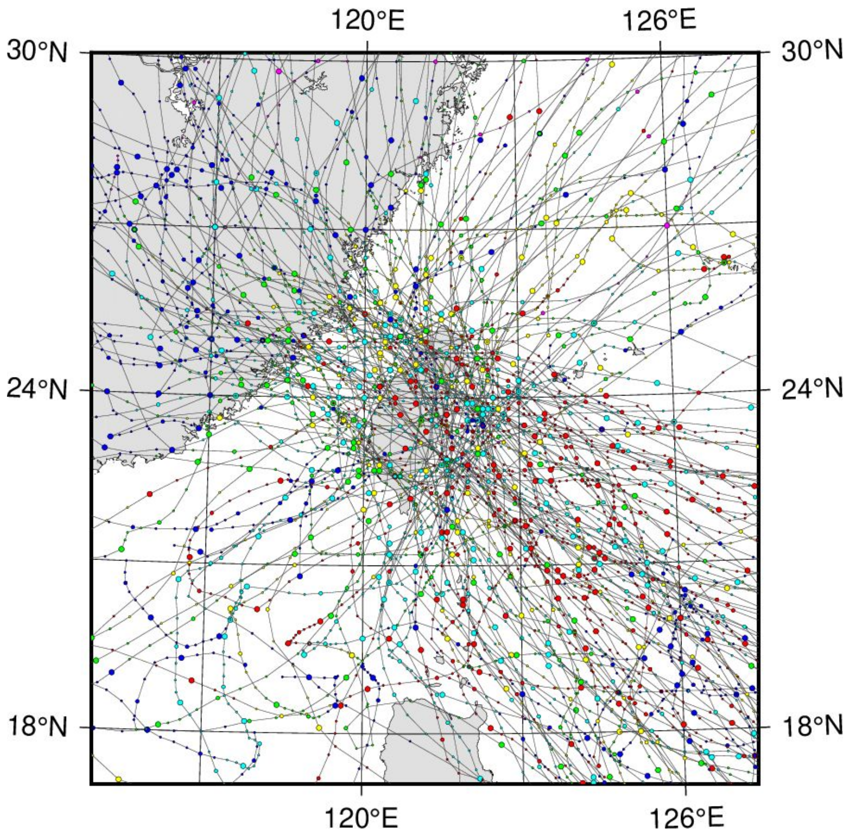
IMPERIAL

UNIVERSITY OF CAMBRIDGE

# Estimating Atmospheric Variables from Digital Typhoon Satellite Images via Conditional Denoising Diffusion Models

**Zhangyue Ling**
**Pritthijit Nath**
**César Quilodrán-Casas**

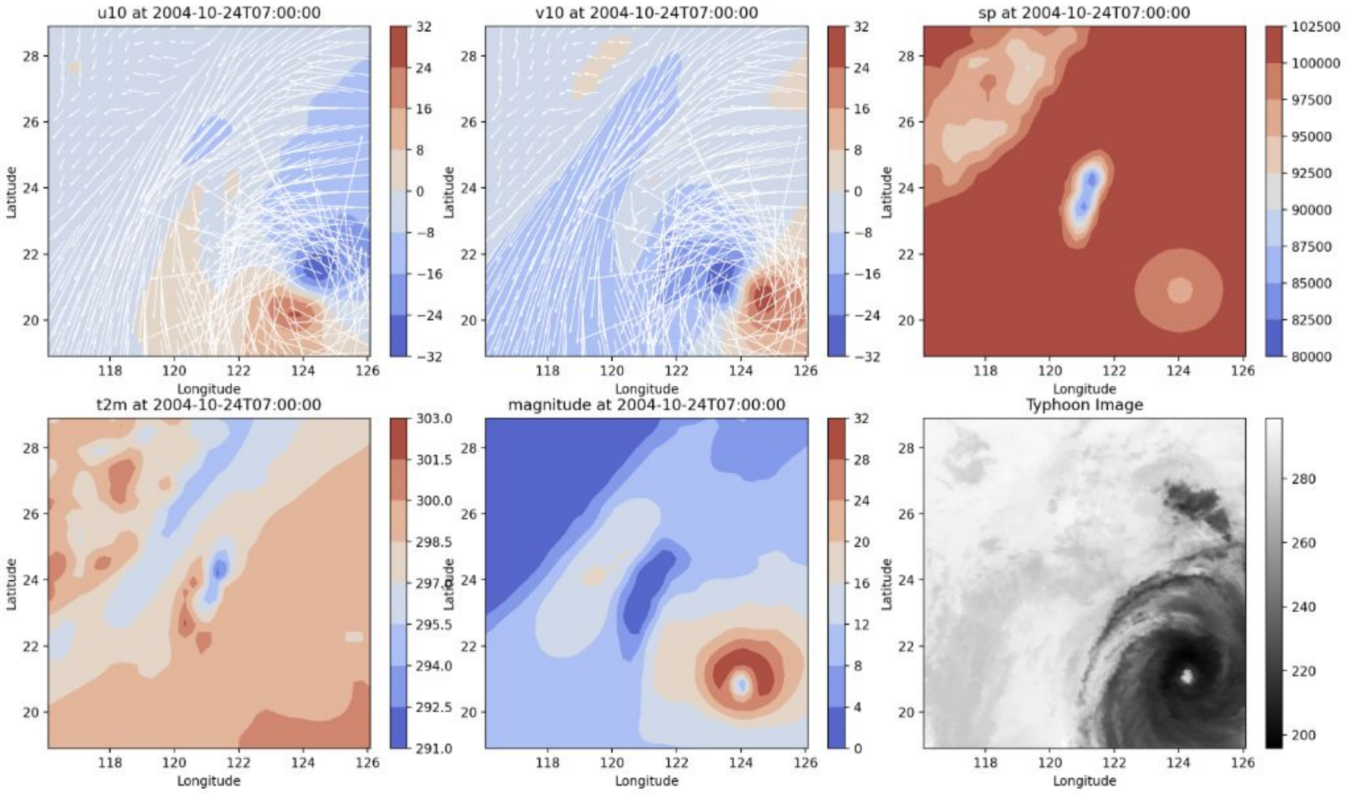
# Introduction
## Motivations




1. Typhoons have a significant impact on humans and society.
2. ML evolves rapidly, enabling systems to learn from data.
3. ML boosts typhoon prediction accuracy and efficiency.
4. Diffusion models enhance ML's weather prediction abilities.

# Introduction
## Data

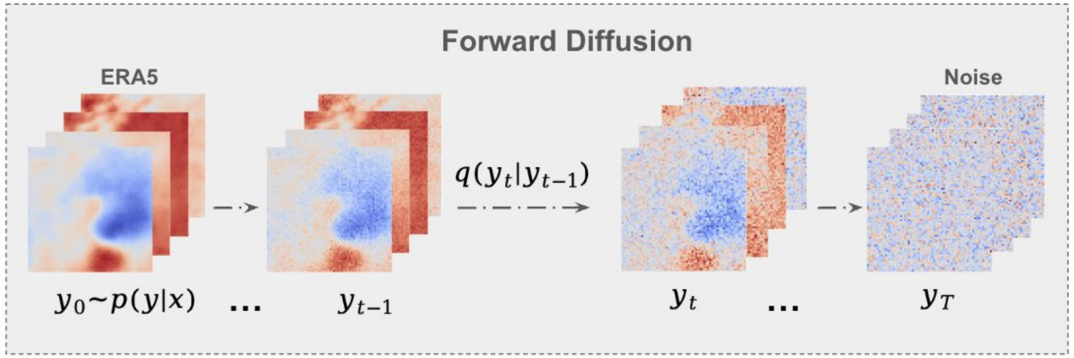
- Digital Typhoon (DT): The largest typhoon satellite image dataset covering the Western North Pacific region from 1978 to 2022.
- ERA5: The fifth generation ECMWF reanalysis atmospheric data for the global climate from 1940 onwards.

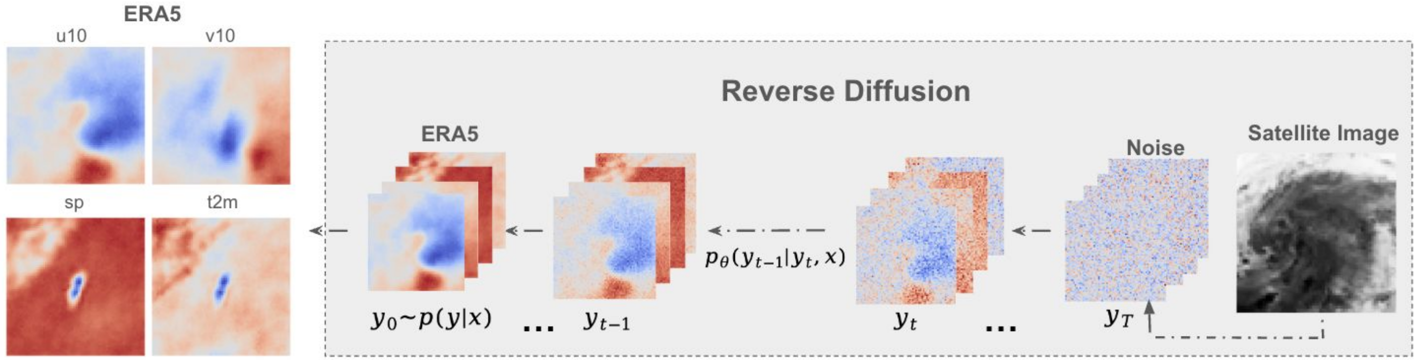



http://agora.ex.nii.ac.jp/digital-typhoon/index.html.en

# Methods

## Conditional Denoising Diffusion Models




| Stage | Input | Condition | Output |
|---|---|---|---|
| **Training** | Noisy ERA5 data ($y_t$) | Satellite Image DT ($x$) | Clean ERA5 data ($y_0$) |
| **Inference** | Random noise ($y_T$) | Satellite Image DT ($x$) | Clean ERA5 data ($y_0$) |

# Methods

## Conditional Denoising Diffusion Models

---

**Algorithm 1** Training a denoising model $f_\theta$[1]

---

**Input:** Noisy data $y_t$, condition $x$, initial parameters $\theta$
**Output:** Cleaned data $y_0$
**repeat**
  $(x, y_0) \sim p(x, y)$
  $\gamma \sim p(\gamma)$
  $\epsilon \sim \mathcal{N}(0, I)$
  Take a gradient descent step on

$$\nabla_\theta \| f_\theta(x, \sqrt{\gamma} y_0 + \sqrt{1-\gamma}\epsilon, \gamma) - \epsilon \|_p^p$$

**until** converged

---

[1] Chitwan Saharia et al.: Palette: Image-to-image diffusion models, in: ACM SIGGRAPH 2022 conference proceedings, 2022, pp. 1–10

# Methods

## Conditional Denoising Diffusion Models

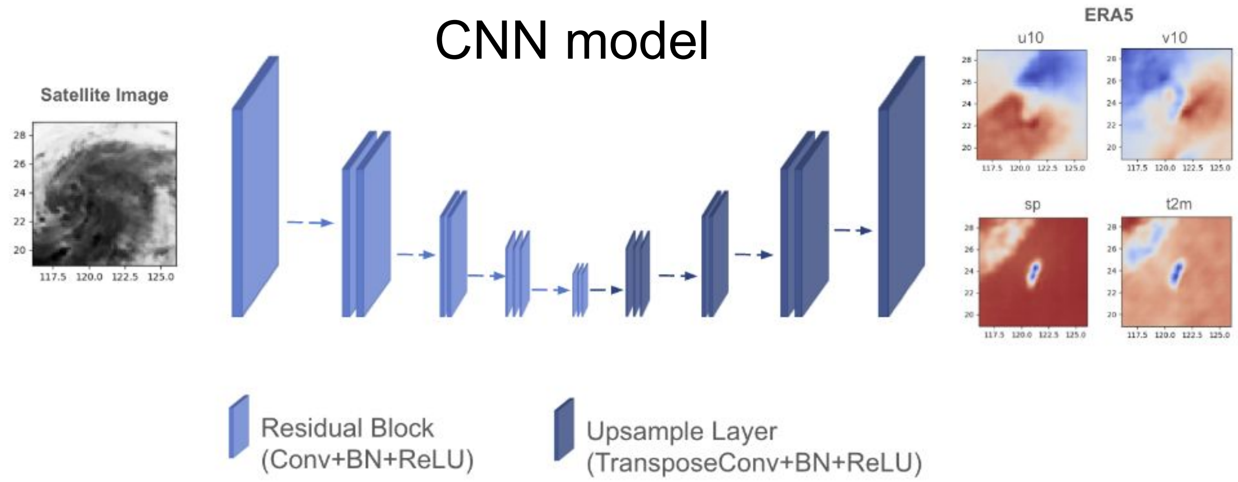
**Algorithm 2** Inference in $T$ iterative refinement steps[1]

**Input:** Random noise $y_T$, Satellite Image DT $(x)$
**Output:** Clean ERA5 data $(y_0)$
$y_T \sim \mathcal{N}(0, I)$
**for** $t = T, \ldots, 1$ **do**
  **if** $t > 1$ **then**
    $z \sim \mathcal{N}(0, I)$
  **else**
    $z = 0$
  **end if**
  $y_{t-1} = \frac{1}{\sqrt{\alpha_t}}\left(y_t - \frac{1-\alpha_t}{\sqrt{1-\gamma_t}} f_\theta(x, y_t, \gamma_t)\right) + \sqrt{1-\alpha_t} z$
**end for**
**return** $y_0$

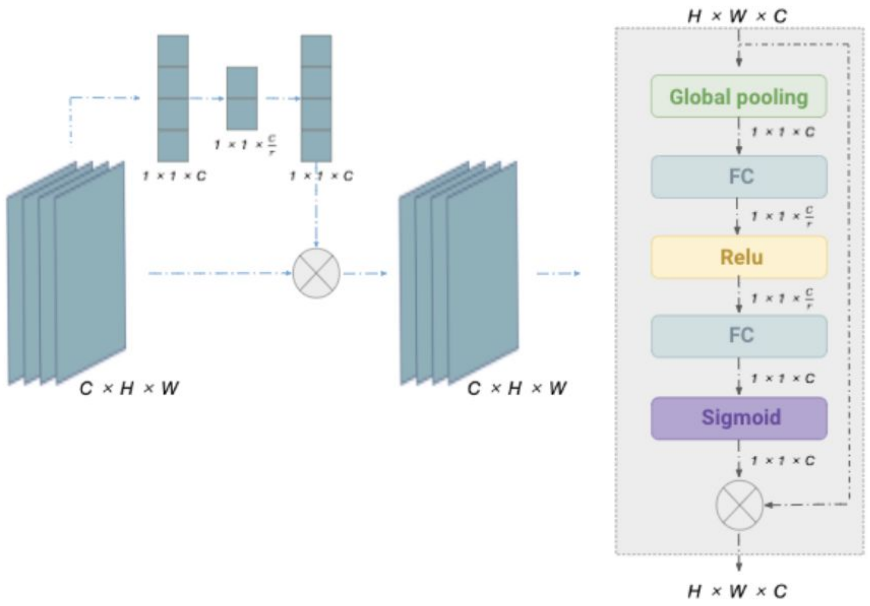
[1] Saharia et al.: Palette: Image-to-image diffusion models (see n. [1])

# Methods
## Baselines

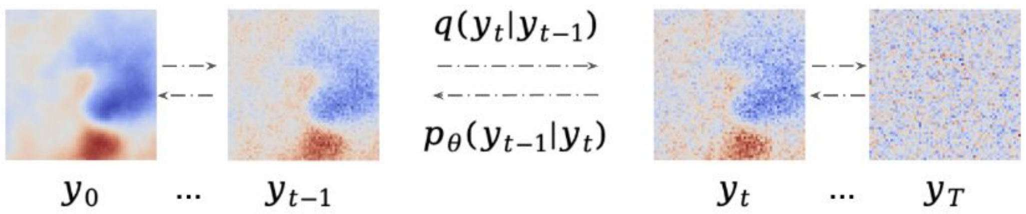
CNN model



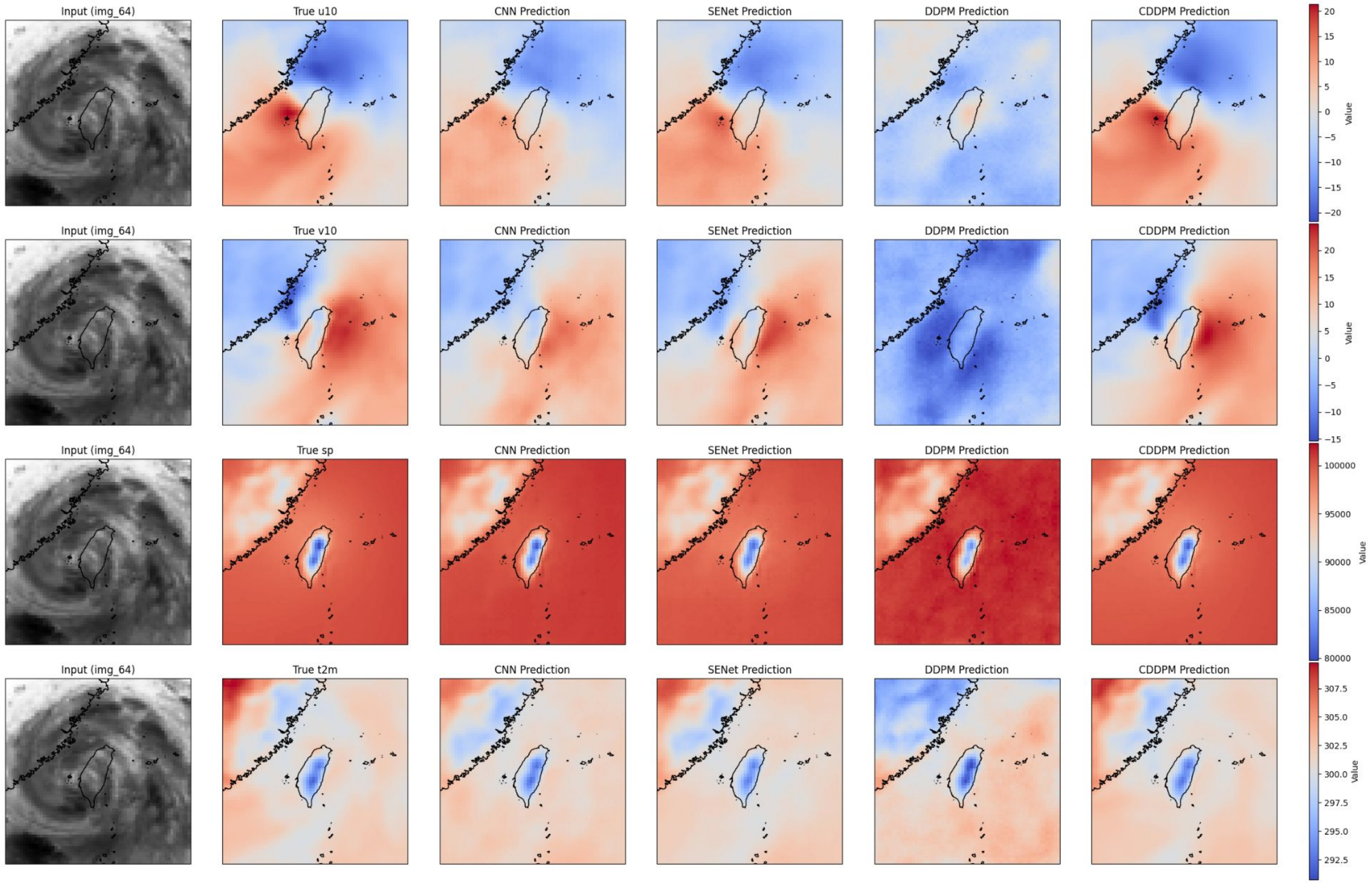

SENet




Denoising Diffusion Model



# Results
## Visual Results



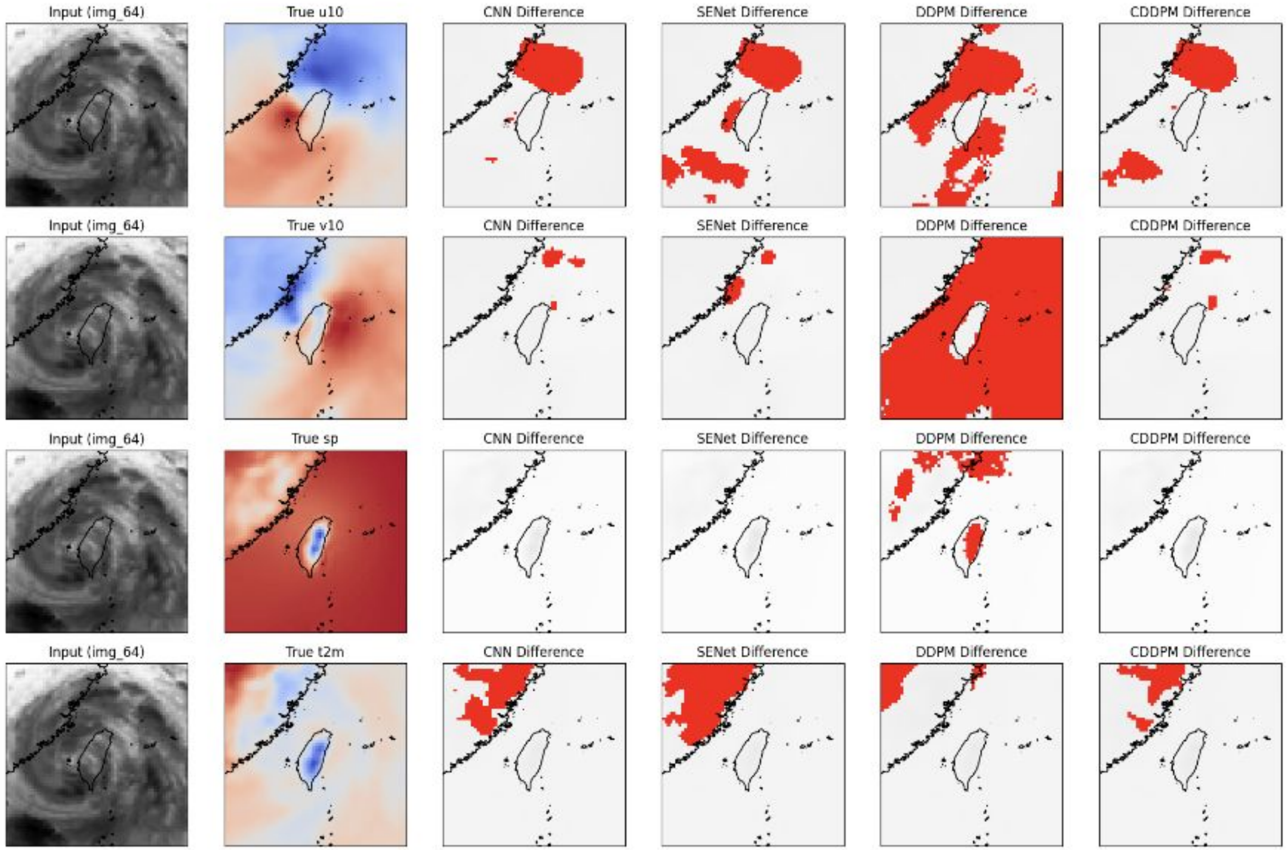
# Results
## Performance Metrics

| Model | Variable | KL-Div ↓ | RMSE ↓ | MAE ↓ | PSNR ↑ | SSIM ↑ | FID ↓ | LPIPS ↓ |
|---|---|---|---|---|---|---|---|---|
| CNN | u10 | 0.003 | 0.039 | 0.029 | 29.441 | 0.886 | 0.068 | 146.522 |
| | v10 | 0.004 | 0.043 | 0.032 | 28.955 | 0.872 | 0.064 | 135.013 |
| | t2m | 0.000 | 0.024 | 0.021 | 33.529 | 0.991 | 0.004 | 27.874 |
| | sp | 0.003 | 0.039 | 0.029 | 29.741 | 0.913 | 0.024 | 149.301 |
| | Average | **0.003** | 0.036 | 0.028 | 30.417 | 0.916 | 0.040 | 114.678 |
| SENet | u10 | 0.004 | 0.041 | 0.031 | 28.594 | 0.883 | 0.069 | 170.500 |
| | v10 | 0.004 | 0.044 | 0.034 | 28.305 | 0.869 | 0.063 | 148.516 |
| | t2m | 0.000 | 0.014 | 0.012 | 38.101 | 0.991 | 0.004 | 41.946 |
| | sp | 0.003 | 0.041 | 0.029 | 29.404 | 0.916 | 0.025 | 135.948 |
| | Average | **0.003** | 0.035 | 0.026 | 31.101 | 0.915 | 0.040 | 124.227 |
| DDPM | u10 | 0.018 | 0.099 | 0.077 | 20.493 | 0.670 | 0.131 | 283.677 |
| | v10 | 0.023 | 0.138 | 0.114 | 17.655 | 0.608 | 0.159 | 263.575 |
| | t2m | 0.001 | 0.054 | 0.049 | 26.045 | 0.938 | 0.010 | 169.873 |
| | sp | 0.008 | 0.076 | 0.057 | 23.117 | 0.803 | 0.053 | 187.600 |
| | Average | 0.012 | 0.092 | 0.074 | 21.828 | 0.755 | 0.088 | 226.181 |
| CDDPM | u10 | 0.004 | 0.037 | 0.027 | 30.973 | 0.900 | 0.052 | 85.518 |
| | v10 | 0.004 | 0.041 | 0.031 | 30.199 | 0.891 | 0.051 | 91.219 |
| | t2m | 0.000 | 0.013 | 0.011 | 39.751 | 0.995 | 0.003 | 12.820 |
| | sp | 0.003 | 0.039 | 0.028 | 30.305 | 0.929 | 0.024 | 76.502 |
| | Average | **0.003** | **0.032** | **0.024** | **32.807** | **0.929** | **0.032** | **66.514** |

# Results
## Pixel Difference

| Model | u10 | v10 | t2m | sp | Average |
|---|---|---|---|---|---|
| CNN | 149.539 | 222.422 | 4.865 | 197.252 | 143.520 |
| SENet | 151.089 | 234.270 | 0.887 | 214.000 | 150.061 |
| DDPM | 1128.631 | 1829.025 | 219.908 | 568.504 | 936.517 |
| CDDPM | 181.326 | 225.301 | 1.684 | 205.004 | 153.329 |

# Results
## Pixel Difference

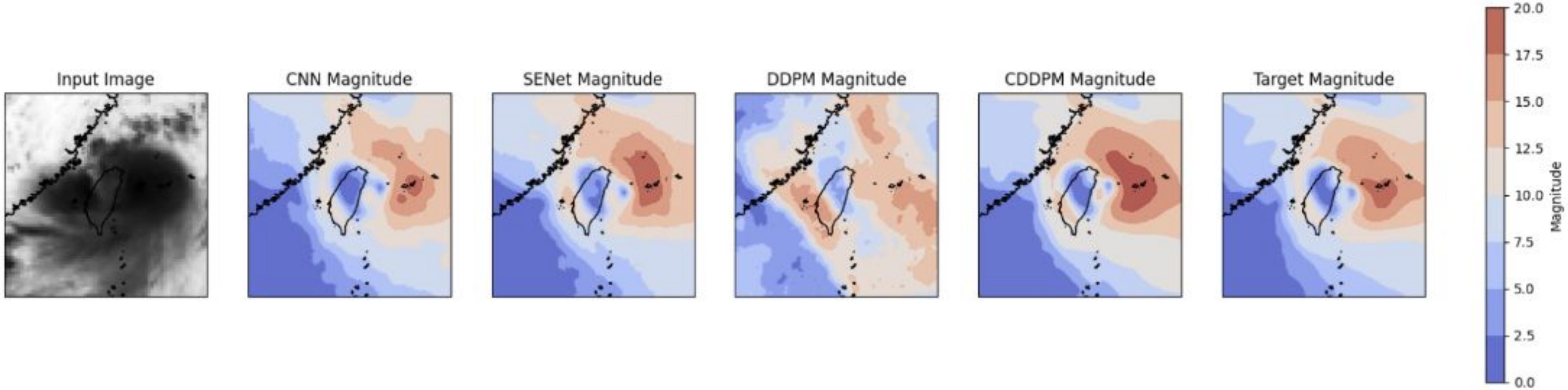



https://github.com/dmtrKovalenko/odiff

# Results
## Magnitude Prediction

The magnitude is calculated by:

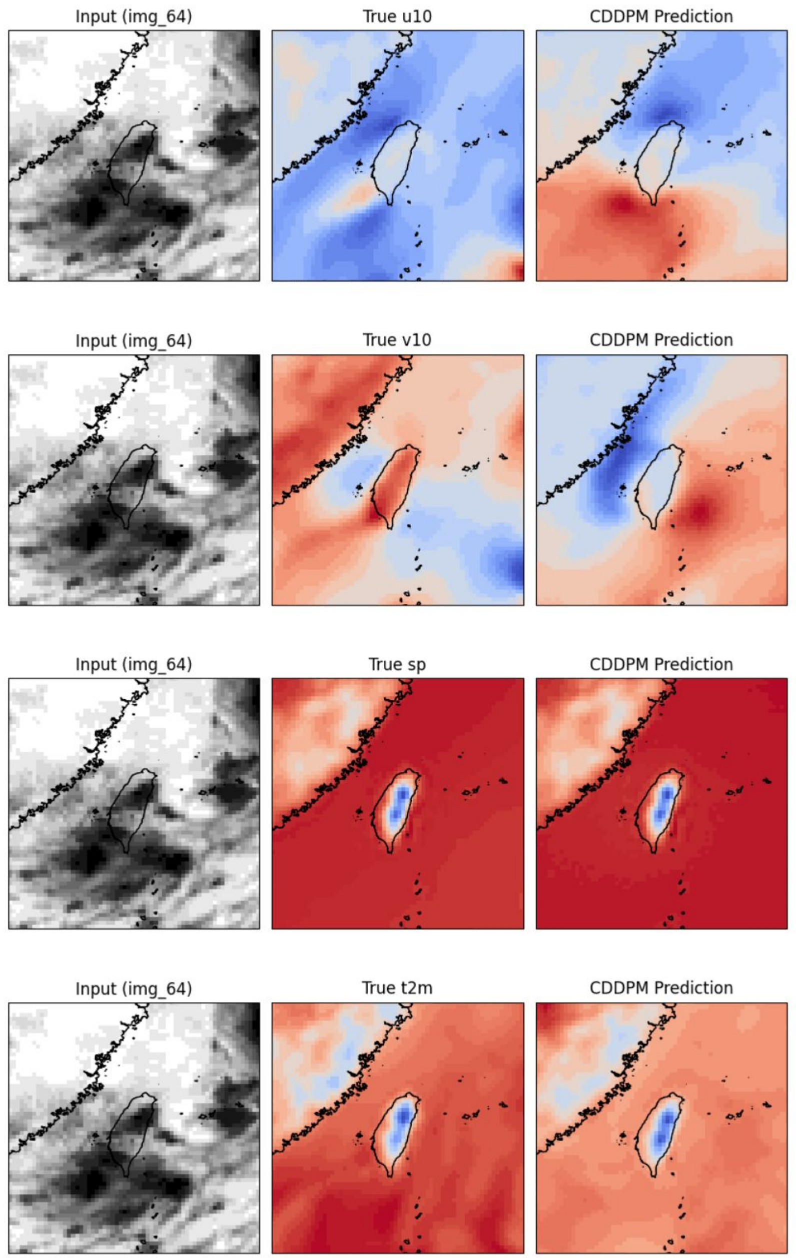
$$M = \sqrt{u_{10}^2 + v_{10}^2}$$



# Results

## Case study: Typhoon Muifa September 2022 Category 3 (170 km/h sustained winds)

| Time | Predicted | CMA | JMA | KMA |
|---|---|---|---|---|
| 2022-09-10 12:00:00 | 1005 | 955 | 965 | 970 |
| 2022-09-10 18:00:00 | 1003 | 950 | 960 | 960 |
| 2022-09-11 09:00:00 | 999 | 940 | 950 | 953 |
| 2022-09-11 21:00:00 | 994 | 948 | 965 | 953 |
| 2022-09-12 00:00:00 | 997 | 955 | 965 | 955 |
| 2022-09-12 21:00:00 | 995 | 958 | 965 | 960 |
| 2022-09-13 06:00:00 | 1003 | 955 | 955 | 955 |
| 2022-09-14 00:00:00 | 1006 | 955 | 955 | 955 |
| 2022-09-14 03:00:00 | 1005 | 945 | 955 | 955 |
| 2022-09-14 06:00:00 | 1002 | 945 | 955 | 955 |



# Conclusion
## Key Takeaways

1. **Development of a Customised Typhoon Dataset:** Match the DT and ERA5 meteorological data for any given region.
2. **Advancement in the Use of CDDPM:** Demonstrate CDDPM to consistently outperformed other three models across multiple reanalysis variables.
3. **Providing Supplementary Meteorological Data:** Demonstrate the ability to generate additional high-quality reanalysis data from satellite images, which can be used both for forecasting and to fill in gaps in existing reanalysis datasets.
4. **Ability of Multi-Variable Prediction:** The ability to predict multiple meteorological variables simultaneously, including u10, v10, t2m, sp.

# Conclusion
## Future Study

Due to the current limitations faced, a few areas that can be researched in the future include:

1. More case studies
2. Consider Temporal Dynamic
3. Explore Multimodal Models
4. Explore Downscaling Applications

IMPERIAL

UNIVERSITY OF CAMBRIDGE

# THANKS!

Ling, Z. (2024). Estimating Atmospheric Variables from Digital Typhoon Satellite Images via Conditional Denoising Diffusion Models. arXiv preprint arXiv:2409.07961