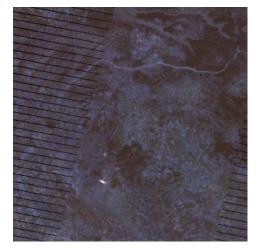


Convolutional Neural Processes for Inpainting Satellite Images Application to Water Body Segmentation

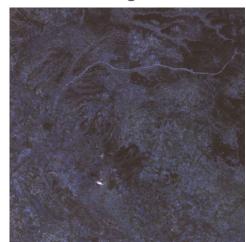
Alexander Pondaven*, Märt Bakler*, Donghu Guo, Hamzah Hashim, Martin Ignatov, Samir Bhatt, Seth Flaxman, Swapnil Mishra, Elie Alhajjar, Harrison Zhu Imperial College London

NeurIPS 2022 Workshop - Tackling Climate Change with Machine Learning









Our Contributions

- **☑** Repair LANDSAT 7 imagery with **Convolutional Neural Processes**
- ✓ State-of-the-art inpainting performance on in-distribution and **especially** out-of-distribution (OOD) inpainting
- ✓ Strong performance in climate **downstream** tasks

Satellite Imagery: LANDSAT 7

- LANDSAT 7 images collected by NASA/USGS via the LANDSAT programme
- High-resolution (30m) images publicly available (massive, terabytes!)
- Scanline corrector (SLC) failure on 31st May 2003
 → missing values at scanlines

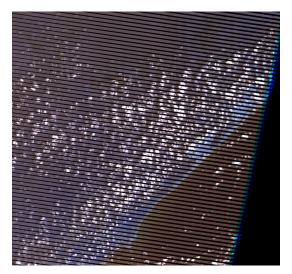


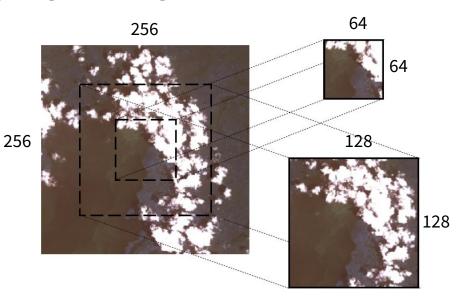
Figure 1: Snapshot in Kenya. Taken on 3rd January, 2005, after the SLC failure

Data from Google Earth Engine

- LANDSAT 7 Satellite images extracted using Google Earth Engine API (Gorelick et al. 2017)
- RGB channels/bands
- 256x256 images downloaded
- Cropped to 128x128 and 64x64 for training

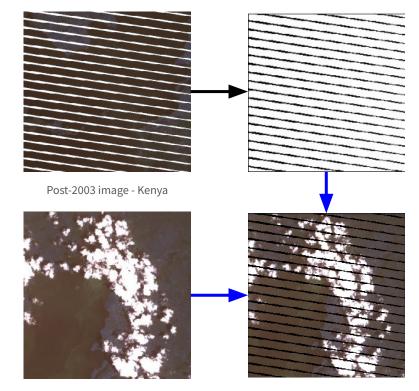
- In-distribution country
 - Kenya
- Out-of-distribution countries





Data Processing for Training

- Post-2003 images used to extract scanline bitmasks
- Pre-2003 uncorrupted images used for training



Pre-2003 image - Kenya

- Extract scanline from post-2003 images
- Apply scanline mask to pre-2003 images for training

Baselines

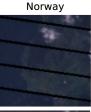
Corrupted



Kenya



Nepal





U-Net







Fast

No information sharing between images

Navier-Stokes







U-Net

Expressive and works quite well for a lot of problems

OOD requires large datasets and data augmentation

PartialConv







PartialConv

Convolution takes into account of masks/missing pixels

Requires large datasets and long training times

Original







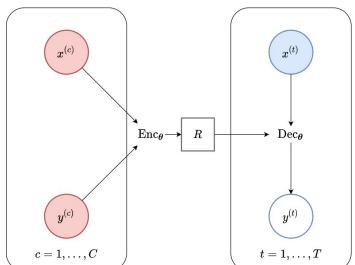
Neural Processes for Inpainting

- Satellite images are different regression problems
 - Different location and time
- Small dataset for each task





Context points are non-scanline pixels





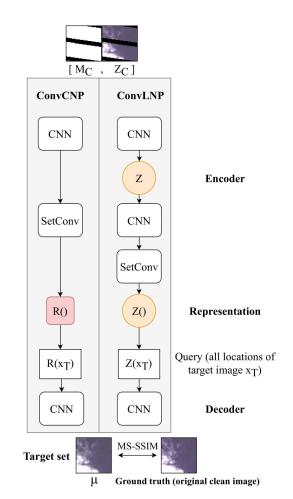
Target points are entire image (for continuity)

Convolutional Neural Processes

Translational equivariance

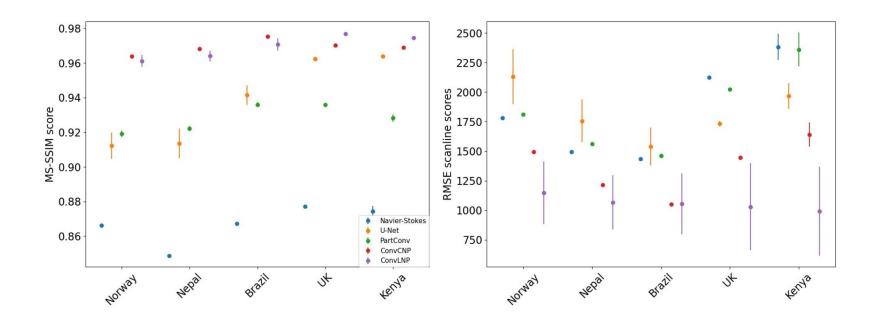
- Convolutional Conditional Neural Processes
- Convolutional Latent Neural Processes

- Trained using Maximum Likelihood
- Multi-Scale Structural Similarity (MS-SSIM) Loss (Wang et al. 2003) generates sharper images



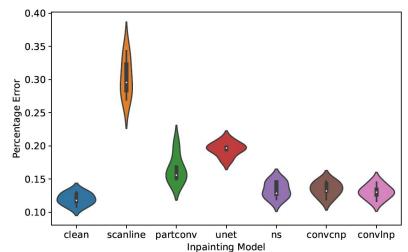
Inpainting results

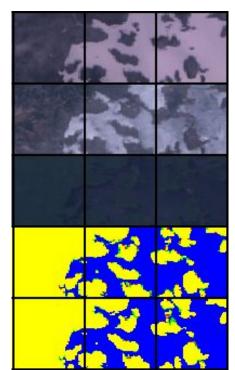
- **ConvNPs** perform well both for in and out-of-distribution images and outperform baselines
- **ConvLNP** performs the best on average when also compared to ConvCNP
- Good generalisability of Meta-Learning is a result of treating input images as different tasks



Experiment 2: Water Body Segmentation Downstream Task

- Image segmentation of seasonality of water in Canada
- Classify pixels into 3 classes based on 3 months of imputed satellite images
- UNet with 3D convolutions and masked cross entropy loss





Conclusion and Discussion

- ✓ ConvNPs successful at inpainting in-distribution and out-of-distribution
 - ✓ Take advantage of different spatiotemporal structure of satellite images
 - ✓ Global inpainter for LANDSAT 7 by only training small subset of locations



Bigger scanlines



Cloud removal



A wider array of downstream tasks

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