Meteorological Super-Resolution vs Wind Representations

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Purpose

- Evaluate the impact of **different wind representations** on neural-based super-resolution for meteorological fields.
- Compare two **wind encodings**:
  - Orthogonal components u_{10}, v_{10}
  - Polar form: speed and direction (degrees from north)
- Use **ERA5** (*30 km*) and **VHR-REA** (*2.2 km*) datasets for training and testing.
- Assess which representation yields better performance and qualitative reconstruction.

Wind Field Representations

Cartesian Components

- u_{10}, v_{10}: zonal and meridional wind at 10m height
- Directly match ERA5 outputs

Polar Encoding

- speed $= \sqrt{u_{10}^2 + v_{10}^2}$
- direction $= (180 + \frac{180}{\pi} \arctan 2(-u_{10}, -v_{10})) \bmod 360$

Motivation: Representation may affect neural network learning and reconstruction quality.

Super-Resolution

Upscaling low-resolution fields to high-resolution targets using deep learning. This tecnique involves reconstructing high-resolution images from coarser data, with the aim of capturing finer and more complex atmospheric structures.

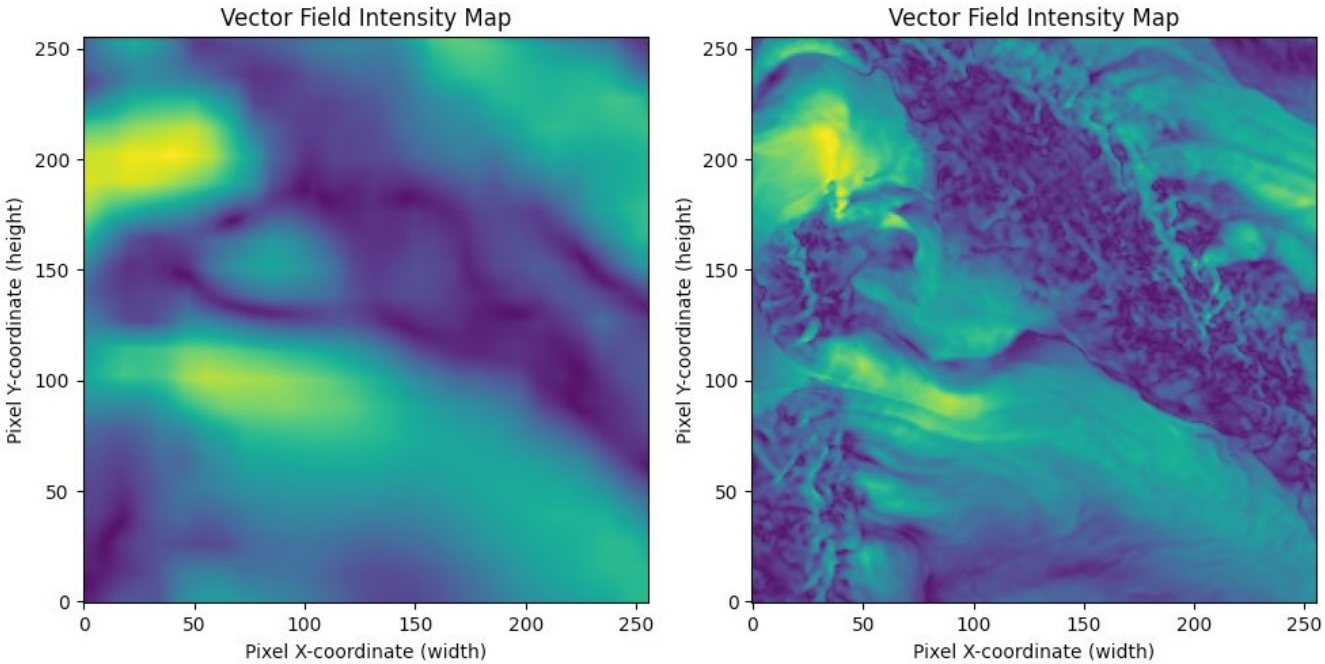


Figure: Super-resolution in the best case

U-Net Architecture

Encoder-decoder with skip connections for image-to-image tasks.

- Residual blocks to ease training.
- Multiscale features preserved via concatenation.

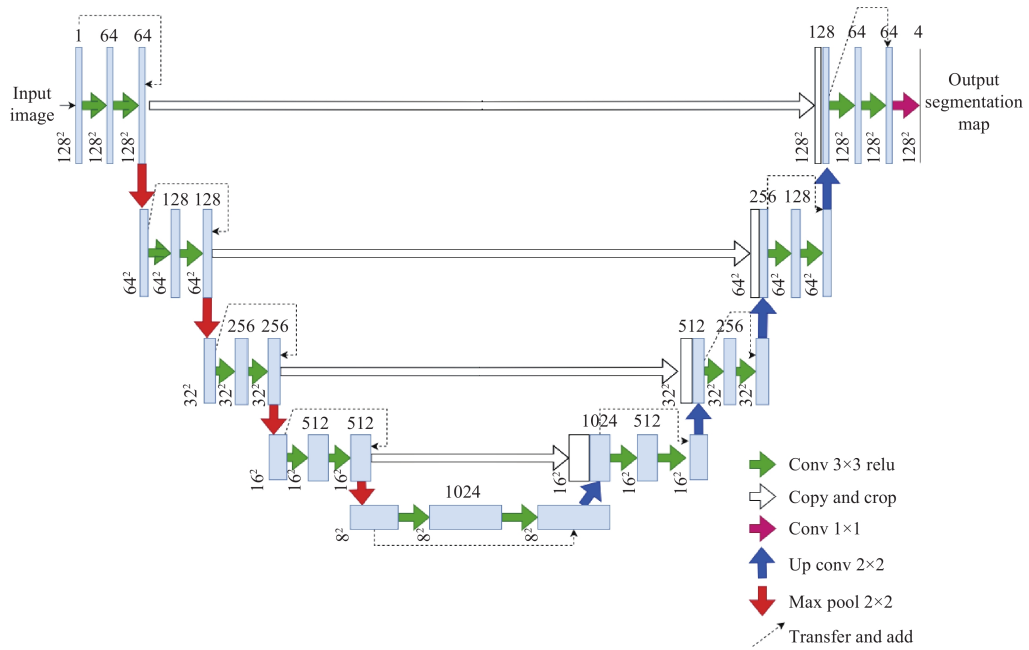


Figure: U-Net Standard Architecture

Datasets

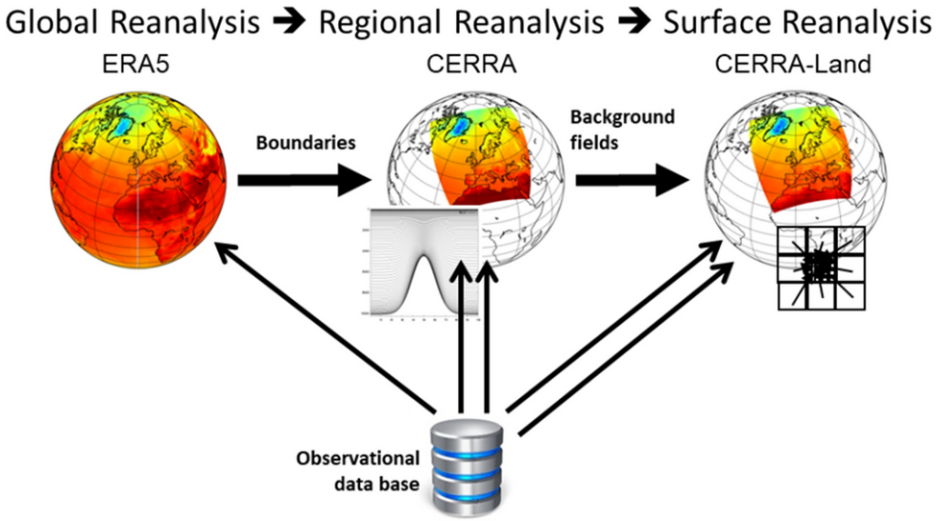
For the purpose of this project, the wind field representations are derived from the ERA5 and VHR–REA datasets.

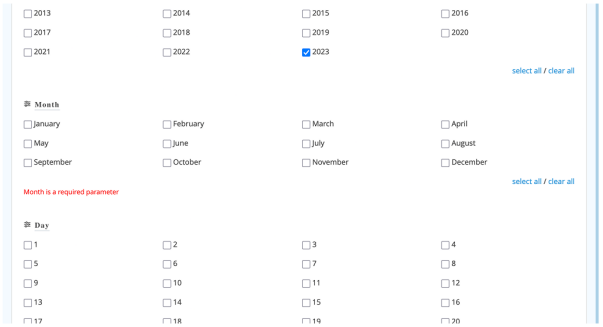
- **ERA5** is a global reanalysis dataset developed by ECMWF, providing hourly data since 1950 at a 0.25° (˜31 km) resolution.
- **VHR–REA** is a downscaled regional reanalysis for Italy based on the COSMO model, with a resolution of 2.2 km.

Both datasets are aligned temporally (06, 12, 18, 00 UTC) and spatially through reprojection.

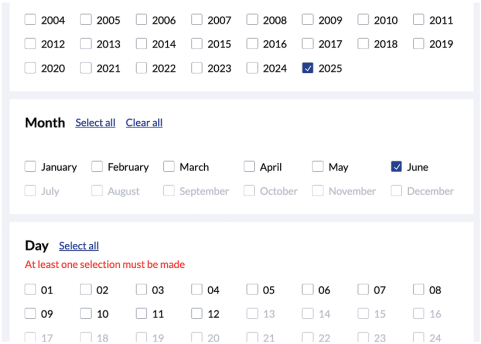
ERA5 acts as the low-resolution input; VHR–REA is used as the high-resolution target for training.

From Global to Surface Reanalysis





VHR-REA dataset download page



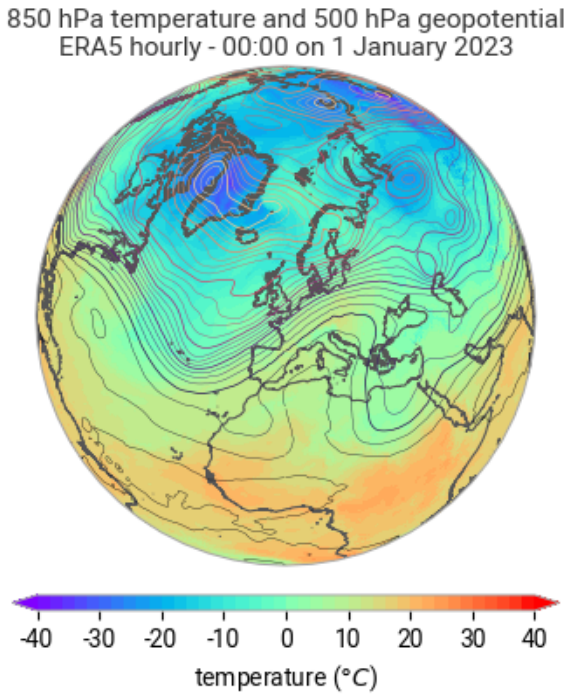
ERA 5 dataset download page

Datasets - ERA5

ERA5 is a global reanalysis dataset by ECMWF under the Copernicus Climate Change Service (C3S). It offers hourly data from 1950 at 0.25° resolution, replacing the older ERA-Interim.

Based on 4D-Var data assimilation, ERA5 integrates satellite, radiosonde, buoy, and aircraft observations, covering atmosphere, land, and ocean.

In this project, we use surface wind components `u10` and `v10` as low-resolution inputs for super-resolution modeling.



Datasets - VHR-REA

VHR–REA (Very High Resolution ReAnalysis) is produced by CMCC via dynamic downscaling of ERA5 using the COSMO model. It reaches a spatial resolution of 2.2 km, resolving convection in complex terrain.

This dataset is designed for high-resolution applications such as hydrology, renewable energy, and urban climate.

- Used as high-resolution target for training.
- Temporal coverage: 4 times daily for one full year.

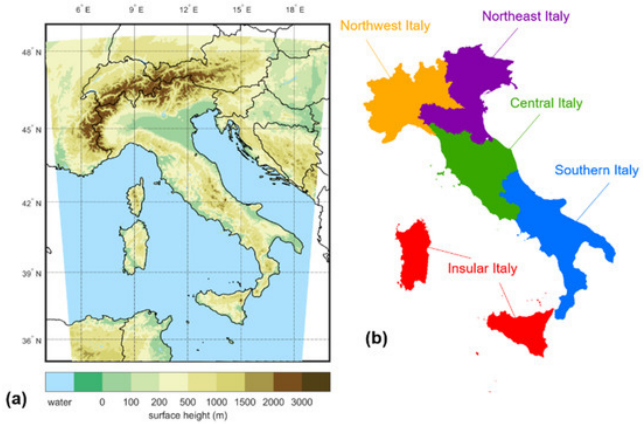


Figure: VHR–REA spatial coverage over Northern Italy

ERA5 & VHR–REA: Regridding Pipeline

ERA5 → VHR Reprojection Strategy

- ERA5 loaded with Dask chunking
- Target grid built from concatenated VHR quarters
- Bilinear regridding using `xesmf`
- Reuse of interpolation weights (caching)
- Post-rechunking to control memory usage

Data Output & Performance

- Lazy NetCDF writing with Dask
- Compute triggered with progress bar
- Output aligned with VHR spatial resolution

```
# Step 1: Load ERA5 with chunks
era5 = xr.open_dataset("era5.nc",
    chunks={"time": 10, "lat": 300, "lon":
        300})

# Step 2: Load and combine VHR target grid
vhr = xr.concat([
    xr.open_dataset("vhr_q1.nc"),
    xr.open_dataset("vhr_q2.nc")
], dim="time")

# Step 3: Create bilinear regridder
regridder = xe.Regridder(
    era5, vhr, method="bilinear",
    filename="weights.nc")

# Step 4: Apply regridding + rechunk
output = regridder(era5).chunk({
    "time": 10, "rlat": 100, "rlon": 100})

# Step 5: Save with progress bar
with ProgressBar():
    output.to_netcdf("regridded.nc")
```

Preprocessing

Spatial Alignment & Patch Extraction

- Center crop to 224×224 pixel patches
- Temporal synchronization verification
- Channel-wise data stacking (u10, v10 components)
- Custom PyTorch Dataset implementation

Data Pipeline Architecture

- ItalyWeatherDataset class for paired data loading
- Automatic temporal alignment checking
- Flexible normalizer integration
- Memory-efficient batch processing

Quality Assurance

- Index bounds verification
- Consistent tensor dimensions
- Error handling for misaligned datasets

```
def extract_region(self, data_tensor
    ):
    patch_h, patch_w = (224, 224)
    _, h, w = data_tensor.shape
    x = (w - patch_w) // 2
    y = (h - patch_h) // 2
    return data_tensor[:,
                       y:y+patch_h,
                       x:x+patch_w]

def __getitem[-]__(self, idx):
    era_slice = self.era5_dataset.
        isel(valid_time=idx)
    era_arrays = [era_slice[v].
        values
                  for v in self.
                      ERA5_VARIABLES
                      ]
    era_tensor = torch.from_numpy(
        np.stack(era_arrays, axis=0)
            ).float()
    era_tensor = self.extract_region
        (era_tensor)

    if self.era5_normalizer:
        era_tensor = self.
            era5_normalizer.
            normalize(era_tensor)
```

Normalization & Coordinate Transformation

MinMax Normalization Strategy

- Training-based statistics computation
- Per-channel normalization across spatial dimensions
- Feature range scaling to [0, 1]
- Epsilon handling for division-by-zero cases
- Serializable normalizer objects

Coordinate System Transformation

- **Option 1**: Cartesian coordinates (u, v)
- **Option 2**: Polar coordinates (magnitude, direction)
- $magnitude = \sqrt{u^2 + v^2}$
- $direction = 180 + \frac{180}{\pi} \arctan 2(-u, -v) \bmod 360$

Dataset Management

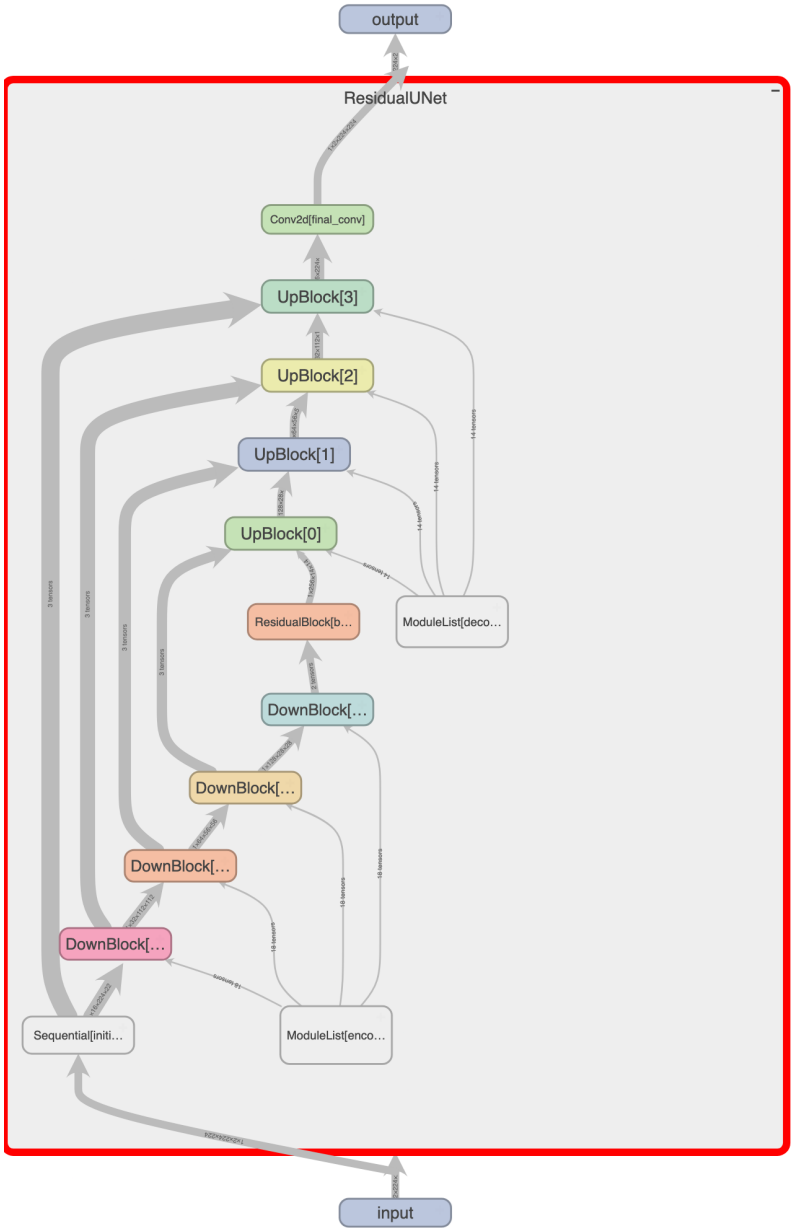
- 80-20 train-test split with fixed seed (42)
- Separate normalization preservation
- Batch processing with memory optimization

```
class MinMaxNormalizer:
    def compute_stats(self, data_tensor):
        # Min/max per channel across (N,H,W)
            dims
        self.min_val = data_tensor.amin(
            dim=(0, 2, 3), keepdim=True)
        self.max_val = data_tensor.amax(
            dim=(0, 2, 3), keepdim=True)

        # Handle division by zero
        diff = self.max_val - self.min_val
        epsilon = 1e-7
        self.max_val[diff < epsilon] = \
            self.min_val[diff < epsilon] +
                epsilon
    def normalize(self, x):
        return (x - self.min_val) / \
               (self.max_val - self.min_val)

# Coordinate transformation to polar
if COORDINATES == "1":
    u_squared = tensor[0, :, :]**2
    v_squared = tensor[1, :, :]**2
    magnitude = torch.sqrt(u_squared + v_squared
        )
    direction = (180 + (180/math.pi) *
                 torch.atan2(-u_squared, -
                     v_squared)) % 360
    tensor = torch.stack([magnitude, direction],
          axis=0)
```

Model and hyperparameters - General differences



Interesting points in our implementation:

- `Conv2d` with `stride=2` for downsampling.
- `BatchNorm` to reduce internal covariate shift. This improves speed and stability of the training.

But there's more...

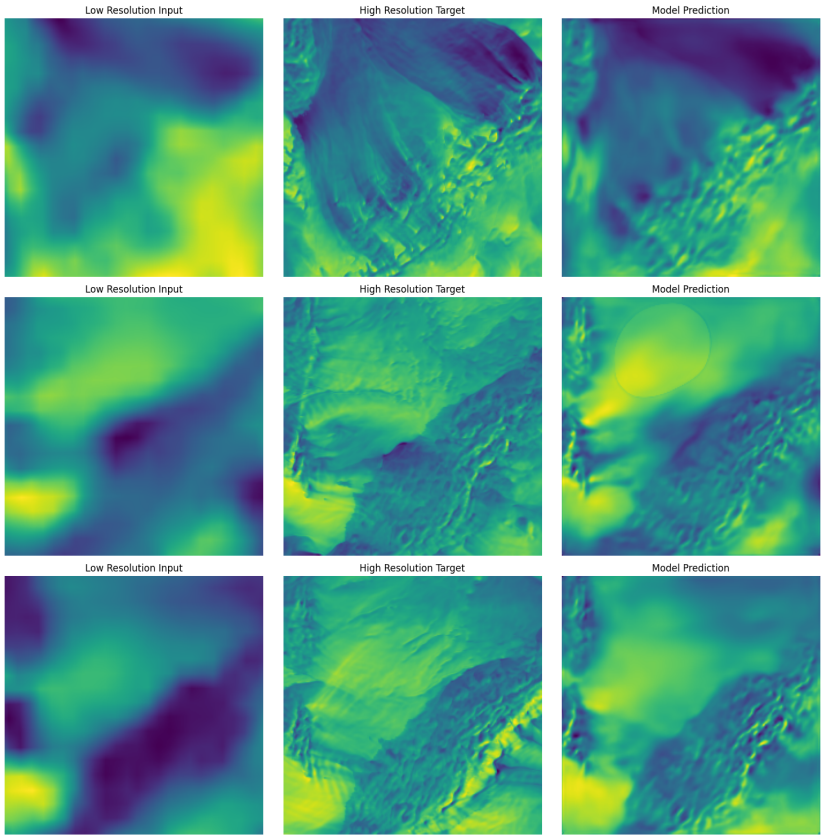
Model and hyperparameters - Transposed vs Bilinear

Network Type	Parameters Count	Training Time	Test Loss	Test SSIM
Transposed Conv	13,041,922 (13.0 M)	54:03 16.22s/it	0.19775	0.70910
Bilinear Interp	3,607,586 (3.6 M)	08:04 2.42s/it	0.17166	0.74983

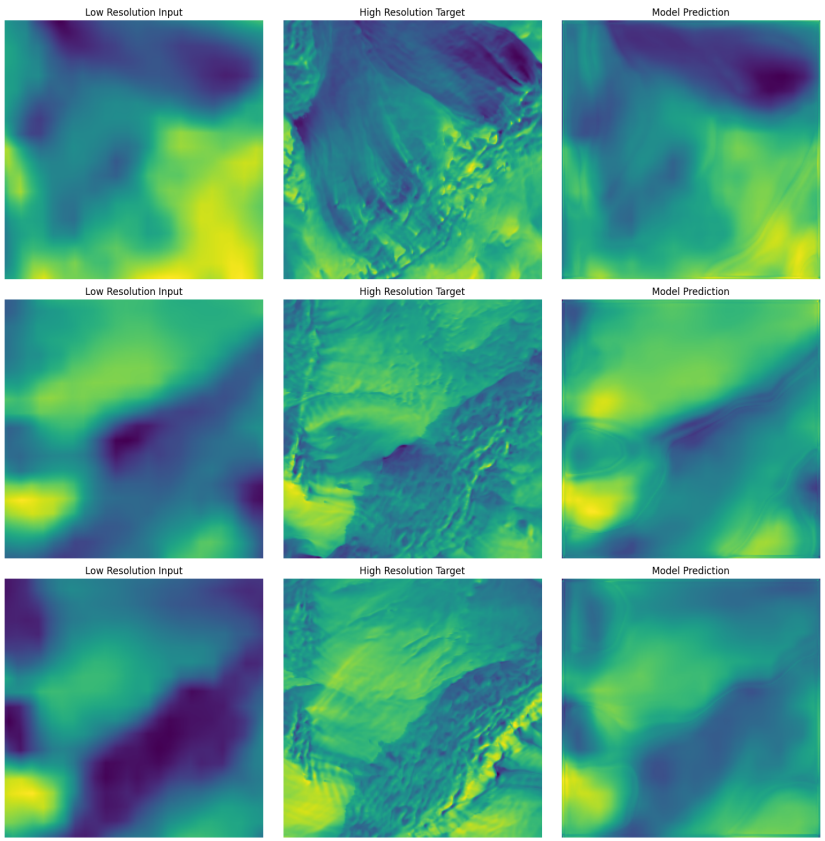
Table: Comparison of bilinear interpolation vs transposed convolution.

Model and hyperparameters - Loss

Even the best model couldn't get decent results with the suggested MSE loss, so we adopted a combined loss approach



L1 + SSIM loss. SSIM: 0.7556



MSE loss. SSIM: 0.7022

Model and hyperparameters - Loss

```
class L1SSIMLoss(nn.Module):
    def __init__(self, alpha=0.85, ssim_window_size
        =11, ssim_data_range=1.0, ssim_channel=1):
        super(L1SSIMLoss, self).__init__()
        self.alpha = alpha
        self.l1_loss = nn.L1Loss() # Mean Absolute
            Error
        self.ssim_loss_fn = SSIMLoss(window_size=
            ssim_window_size, data_range=
            ssim_data_range, channel=ssim_channel)

    def forward(self, y_pred, y_true):
        ssim_val_loss = self.ssim_loss_fn(y_pred,
            y_true)
        l1_val_loss = self.l1_loss(y_pred, y_true)

        combined_loss = self.alpha * ssim_val_loss +
            (1 - self.alpha) * l1_val_loss
        return combined_loss
```

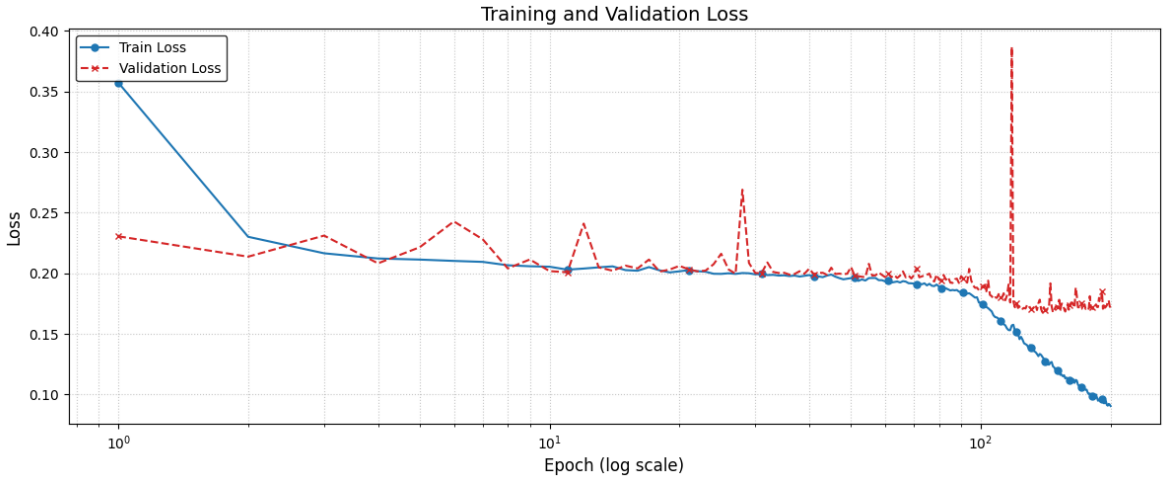
Model and hyperparameters - Hyperparameters

Channels	Epochs	Loss	Batch Size	LR	LR Scheduler	Weight Decay	Test Loss	Test SSIM
[32, 64, 128]	200	L1 + SSIM	8	1.00E-03	NO	1.00E-05	0.19090	0.71990
[16, 32, 64, 128]	200	L1 + SSIM	8	1.00E-03	NO	1.00E-05	0.17700	0.74170
[16, 32, 64, 128, 256]	300	L1 + SSIM	8	1.00E-03	NO	1.00E-05	**0.16768**	**0.75555**
[16, 32, 64, 128, 256]	300	MSE + SSIM	8	1.00E-03	NO	1.00E-05	<u>0.15464</u>	<u>0.75391</u>
[16, 32, 64, 128, 256]	300	MSE	8	1.00E-03	NO	1.00E-05	0.00327	0.70218
[16, 32, 64, 128, 256, 512]	300	L1 + SSIM	8	1.00E-03	NO	1.00E-05	0.19207	0.71774
[16, 32, 64, 128, 256, 512]	300	L1 + SSIM	8	1.00E-03	YES	1.00E-05	0.19207	0.71774

Table: Performance comparison of different network configurations. Best and runner-up models are highlighted in bold and underline, respectively.

Local Training - Loss and SSIM curves

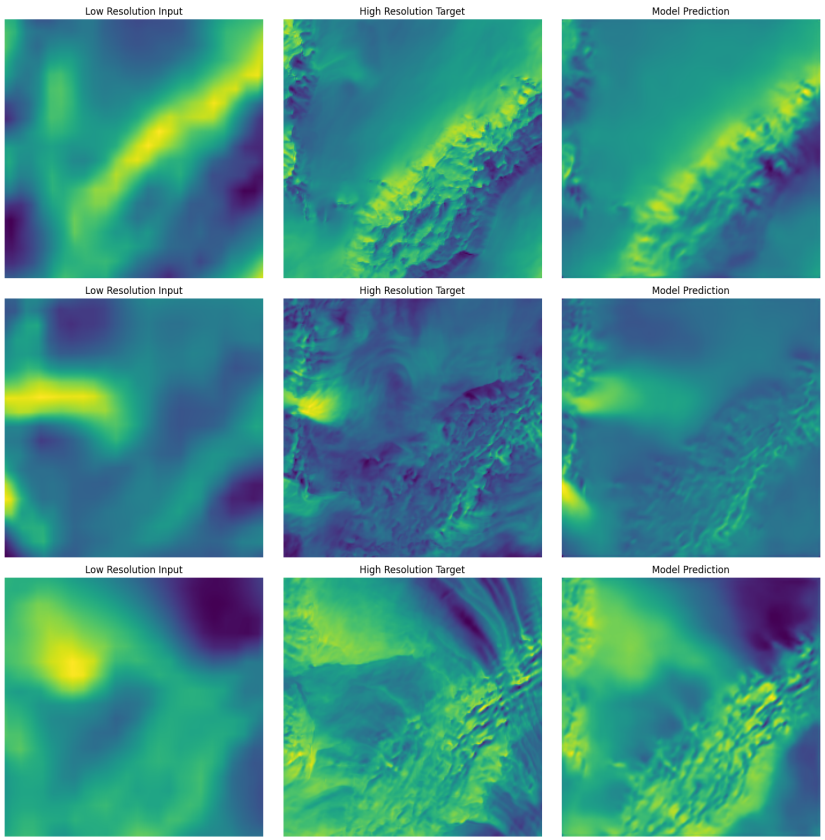
Training curves for the best model on local data (loss and SSIM):



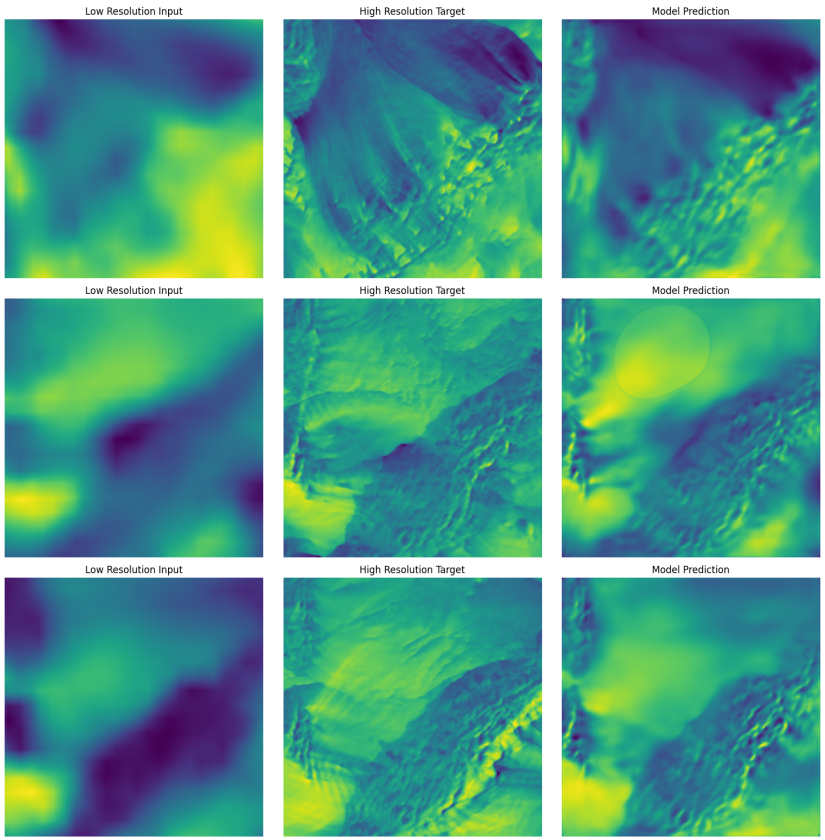
Loss curve

SSIM curve

Colab Training - Difference with Local data



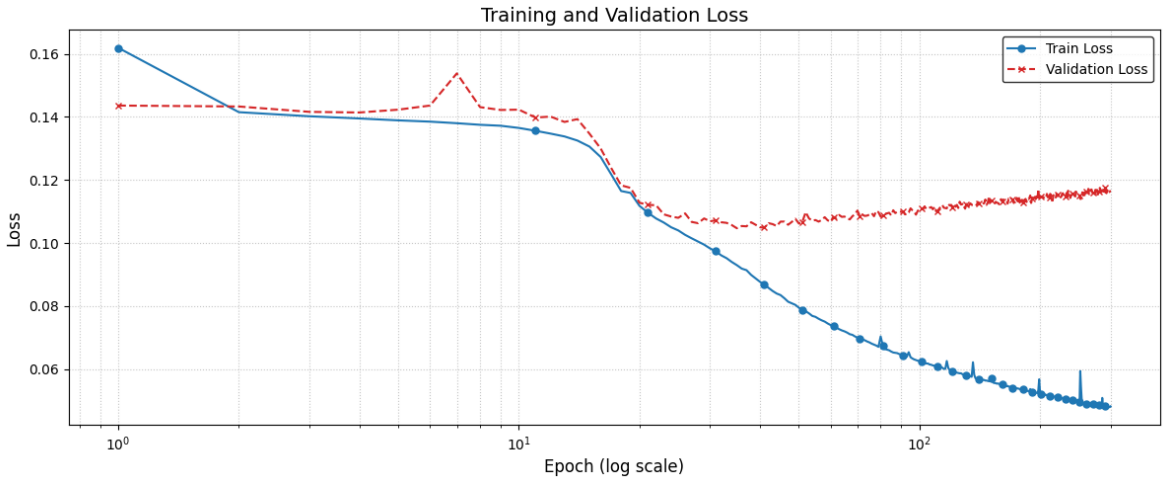
Colab data. SSIM: 0.84483



Local data. SSIM: 0.7556

Colab Training - Loss and SSIM curves

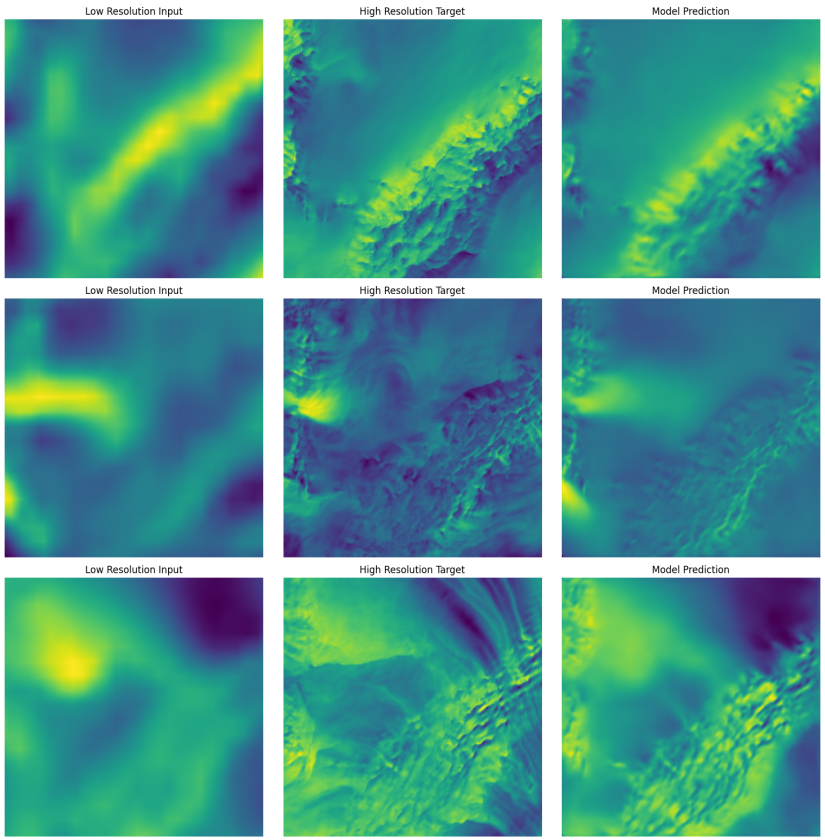
Training curves for the best model on colab data (loss and SSIM):



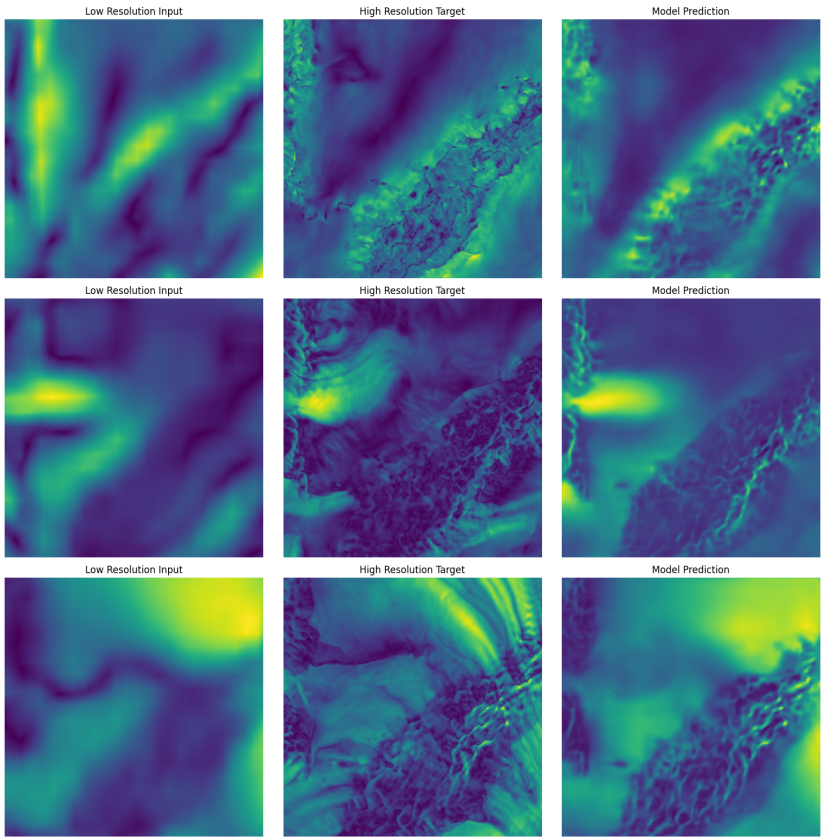
Loss curve

SSIM curve

Colab Training - Vectorial data vs Directional data



Vector data. SSIM: 0.84483



Direction data. SSIM: 0.48154

Alternative Datasets and Loss Function Experiments

Dataset	Loss	Observation	Test Loss	SSIM
Local direction	L1 + SSIM	Poor reconstruction performance	0.4912	0.3896
Local direction	MSE	Slight improvement, but low SSIM	0.0480	0.3563
Colab vectors	L1 + SSIM	Best overall performance	**0.1052**	**0.8445**
Local vectors	MSE + SSIM	Balanced compromise	0.1546	0.7539
Local vectors	MSE	Suboptimal results	0.3949	0.5229

- **Insight:** Directional data underperformed vs. vector-based representations.
- Combined losses (e.g., L1 + SSIM) improved perceptual quality.

Final Considerations

Societal Impact

More accurate high-resolution forecasts support *agricultural management*, *climate disaster preparedness* and *the coastal/tourist community*.

Next steps

- Check whether the *L1 + SSIM* loss still favors accurate reconstruction in complex areas with clear structures, compared to flatter regions where features are harder to predict.
- If not, consider analyzing the alpha weight in the loss function to see if the balance between L1 and SSIM is skewed, causing the network to rely too heavily on one component.

References

[1] Fabio Merizzi, Andrea Asperti, and Stefano Colamonaco. "Wind speed super-resolution and validation: from ERA5 to CERRA via diffusion models". In: *Neural Computing and Applications* 36.34 (2024), pp. 21899–21921.

[2] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation". In: *Medical image computing and computer-assisted intervention–MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18*. Springer. 2015, pp. 234–241.

[3] Robbie A Watt and Laura A Mansfield. "Generative diffusion-based downscaling for climate". In: *arXiv preprint arXiv:2404.17752* (2024).