Resolving Super Fine-Resolution SIF via Coarsely-Supervised U-Net Regression

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Motivation: monitoring crop productivity

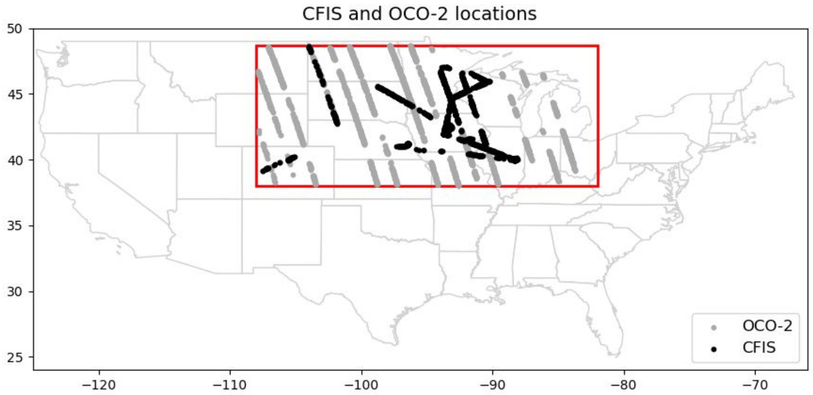
- Crop production is extremely sensitive to climate change
  - Anthropogenic climate change has slowed agricultural productivity growth by 21% since 1961 (Ortiz-Bobea et al, 2021)
- Heat and drought stress are particularly damaging
- Monitoring the effects of climate change on crop growth in real time is crucial, particularly for **food security** (He et al, 2020)

Solar-induced chlorophyll fluorescence (SIF)

- Satellites can inexpensively monitor crop growth from space
- A lot of work uses vegetation indices (VIs) such as NDVI
    - Simple combinations of a few spectral bands (“greenness”)
- By contrast: **Solar-Induced Chlorophyll Fluorescence (SIF)** has direct **mechanistic linkages to photosynthesis** (Magney et al, 2019)
    - Better at predicting crop yields than VIs (Peng et al, 2020)
    - Can detect crop response to heat stress (Song et al, 2018) and drought (Zhang et al, 2019)

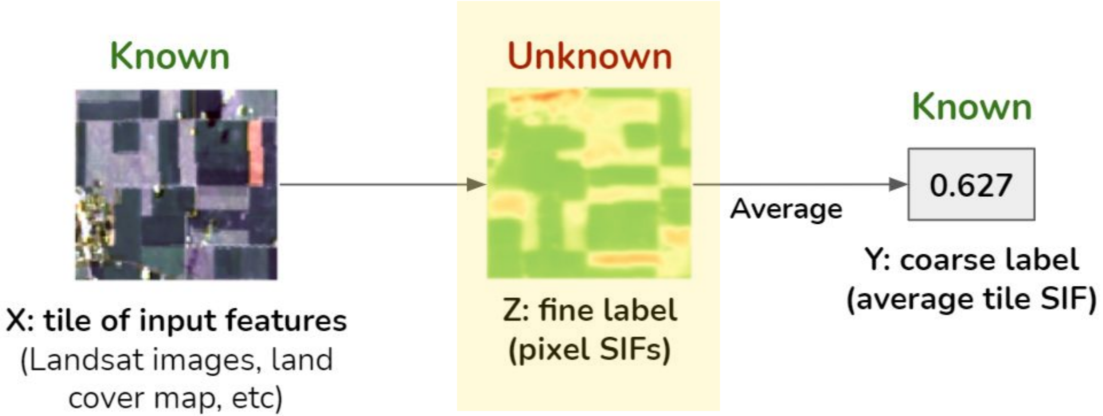
Problem: coarse resolution of SIF

- SIF is difficult to measure from space
- Existing satellites (such as OCO-2) can capture at most 3x3km resolution; coverage is limited
- Within a large area (many square km), SIF can vary dramatically between farms due to **crop type**, **management practices**, etc.
- Want to predict SIF at finer resolution (e.g. 30x30m)



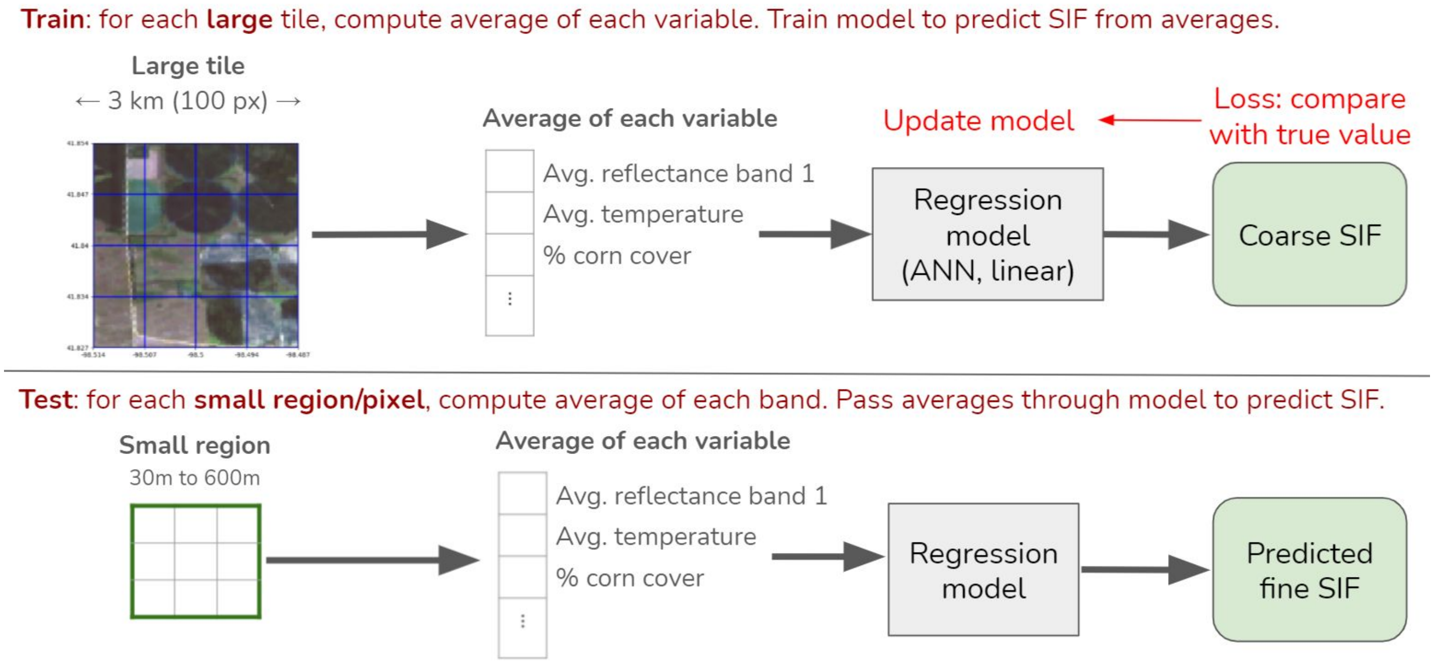
Task: coarsely supervised regression

- To predict SIF at a very fine resolution (30 meters), we can use 30m-resolution satellite imagery from Landsat, plus other features
- Goal is to learn mapping from (fine-resolution features) → (fine-resolution SIF)
- However, during training, we only have **coarse-resolution SIF labels** (3km resolution) for supervision (no fine-resolution labels). So supervised super-resolution methods don't work
- We call this type of problem **"coarsely-supervised regression"**
    - Problem is highly under-determined; need regularization and prior knowledge

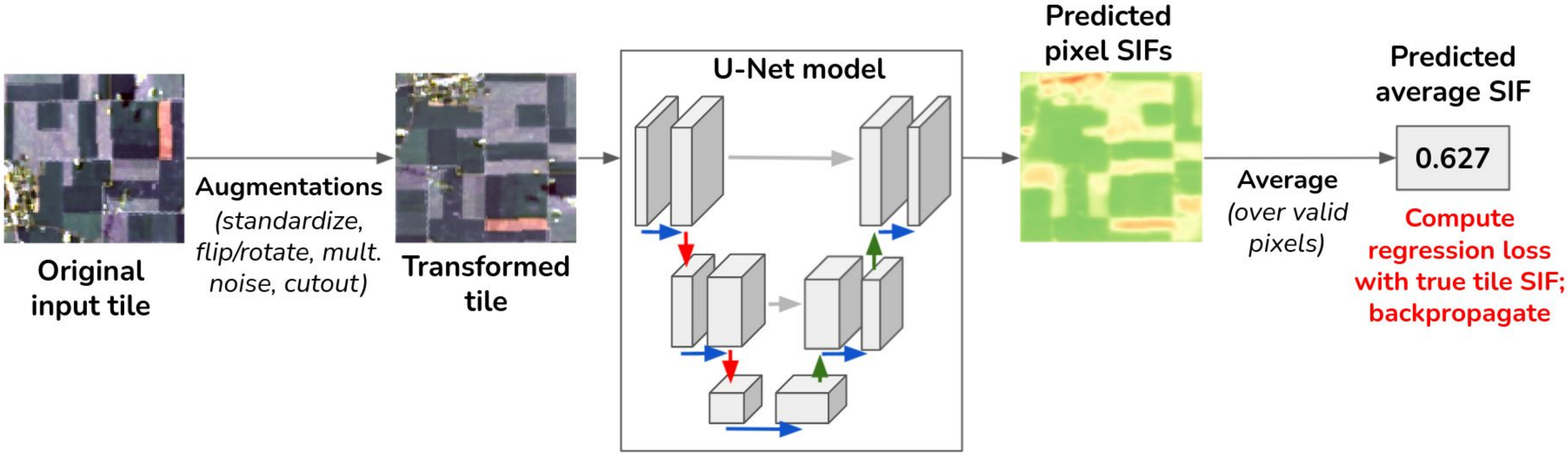


Existing baselines: averaging-based

- Existing baselines train by taking average of each feature across large tile.
- Spatial variation lost during training

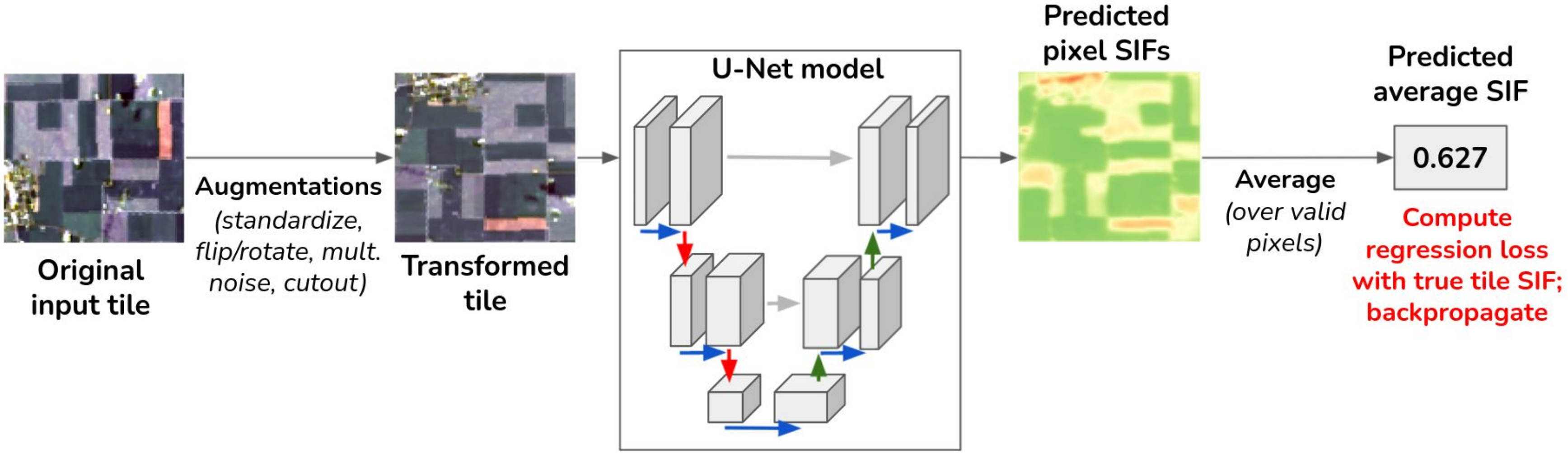


Our approach: Coarsely Supervised Regression U-Net (CSR-U-Net)



1. Apply augmentations to input tile
2. Pass transformed tile through U-Net to obtain predicted pixel SIFs
3. Take average SIF across valid pixels in tile
4. Compare predicted average SIF with true (coarse) average SIF; compute loss (error)
5. Backpropagate to adjust model parameters

Our approach: CSR-U-Net



NOTE - model does not look at fine-resolution SIF labels during training!

Regularization techniques: augmentations, multiplicative noise, early stopping

- Augmentations: flip/rotate, jigsaw, random subset
- **Multiplicative noise** - multiply all channels of entire image by a single random constant
  - Inspired by prior knowledge from vegetation indices, that the **ratio** between spectral bands can be more important than the absolute values
- Early stopping, based on fine-resolution validation set
  - Ensures similar farms have similar predictions. If we didn't do this, model can overfit (see below)

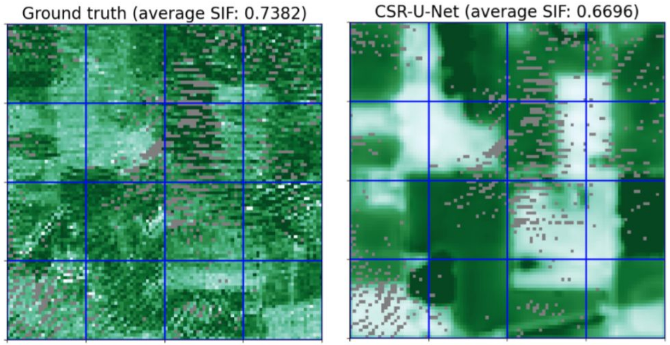


Figure 5: Example of overfitting. **Left:** ground-truth SIF map. **Right:** prediction by a U-Net that is over-trained. Note that the average tile SIFs are not too different, but the model tends to output extremely low and high values that do not reflect reality.

Datasets

Input features: Each input tile is of shape [24 features x 100 height x 100 width].

- Landsat reflectance bands
- FLDAS land data (temperature, rainfall, surface radiation)
- Land cover masks (corn, soybean, deciduous forest, grassland, etc)

Output SIF labels:

- During training, we use coarse SIF labels (gridded to 3km) from OCO-2 and CFIS
- During model selection and evaluation, we use a limited validation set of fine-resolution (30m) labels from CFIS to test accuracy of model's fine-resolution predictions

Total of 2,102 training tiles

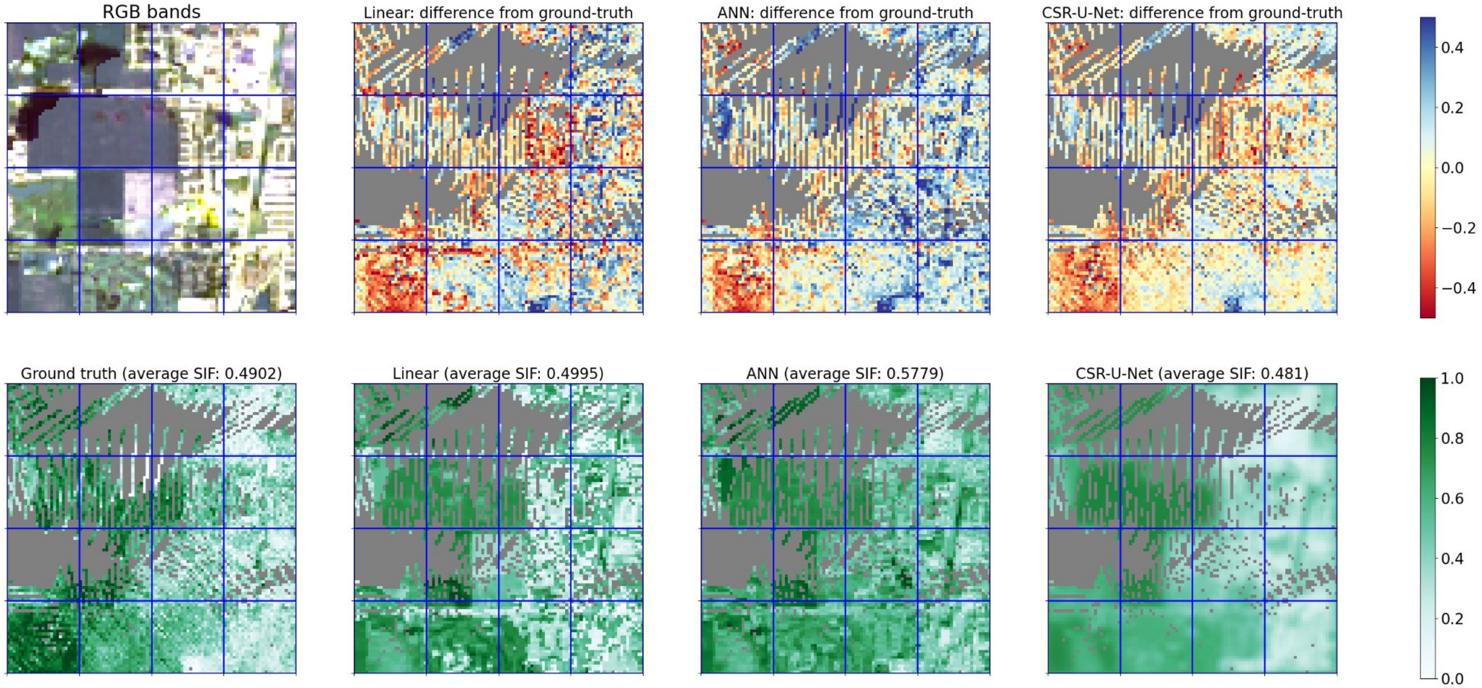
Results

Results on predicting SIF for 30m pixels (in train tiles - coarse-resolution SIF was seen during training, but not fine-resolution SIF)

Method	**NRMSE** (lower better)	R^2 (higher better)
Predict coarse	*0.248*	*0.373*
Ridge Regression	0.213	0.537
Gradient Boosting	0.225	0.486
ANN	0.244 ± 0.006	0.396 ± 0.027
CSR-U-Net	$\mathbf{0.196} \pm 0.002$	$\mathbf{0.609} \pm 0.007$

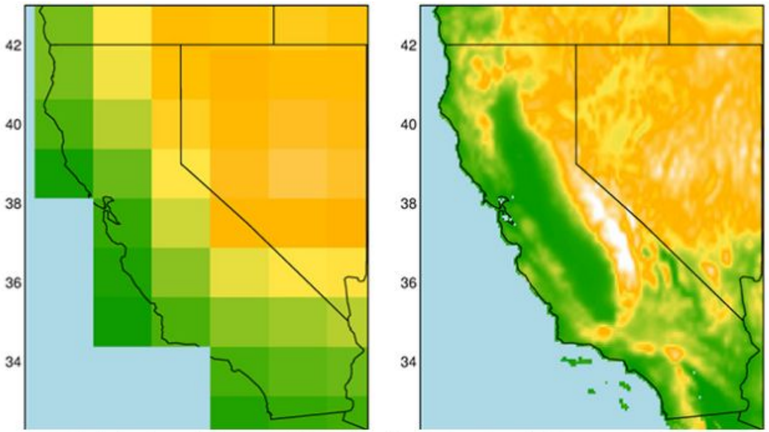
Our method outperforms baselines (reducing NRMSE by 8% and increasing R^2 by 13%).
Also true for completely unseen tiles, and across resolutions/crop types

Example output



Connection to "statistical downscaling" of climate models

- This task (inferring a fine-resolution map of a variable, given only coarse-resolution observations and other auxiliary data) is not exclusive to SIF
- Many related problems in climate science, including **downscaling climate models / climate variables**
  - Example: most global circulation models (GCMs) have a very coarse resolution.
  - Predicting at a finer resolution could enable more accurate understanding of climate impacts
- AI community should study this more!



Global climate model representation of California elevations (left) compared to LOCA

Image credit: USGS (public domain)

Conclusions

- We developed **Coarsely-Supervised Regression U-Net (CSR-U-Net)**, which can predict SIF at a super fine resolution (30m), even when only coarse-resolution (3km) SIF measurements are available
- Due to its localization properties, CSR-U-Net can figure out which farms within a large tile had higher and lower SIF.
- CSR-U-Net can avoid overfitting, thanks to techniques informed by prior knowledge, such as multiplicative noise and early stopping.
- Fine-resolution SIF estimates can facilitate improvements in crop yield prediction and monitoring.
- CSR-U-Net could be generalized to other related problems, such as predicting climate model variables (including precipitation, soil moisture, and evapotranspiration) at finer resolutions

References

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