Flood Inundation Meets Image Super-Resolution

Xi Zhang[1], Akshay Aravamudan[1], Zimeena Rasheed[2], Kira E. Scarpignato[1], Witold F. Krajewski[3] , Efthymios I. Nikolopoulos[2], Georgios C. Anagnostopoulos[3]

[1]Florida Institute of Technology [2]Rutgers University [3]Iowa Flood Center, University of Iowa

Motivations: Flooding on farmlands

- Farms tend to be concentrated in river valleys because the soils are fertile and easily cultivated. Thus, many farms are vulnerable to floods.
- According to The Iowa Farm Bureau Federation, in 2019, the losses to farmers along the flooded Missouri River are around $1.6 billion[1].

Fig 1. Flooded Iowa soybean field.

Image credits to : https://crops.extension.iastate.edu/files/styles/large/public/icm/May2008FloodedSoybean.jpg?itok=jj64fbGe
[1] Source: https://www.desmoinesregister.com/story/money/agriculture/2019/04/03/iowa-flooding-nebraska-missouri-river-farm-losses-damage-2-billion-ag-group-bureau-crop-insurance/3351972002/

Motivations: Avoid flood-prone areas

- Flood mitigation measures, such as the use of drainage systems and flood-resistant crops, can help to reduce the impact of floods on agricultural land.
- BUT, in many cases, the best approach may be to avoid building in flood-prone areas altogether.
- Examines the riverine flood risk for cropland, as illustrated in Figure 2, is critical in understanding flood risks and make cost-effective decisions.

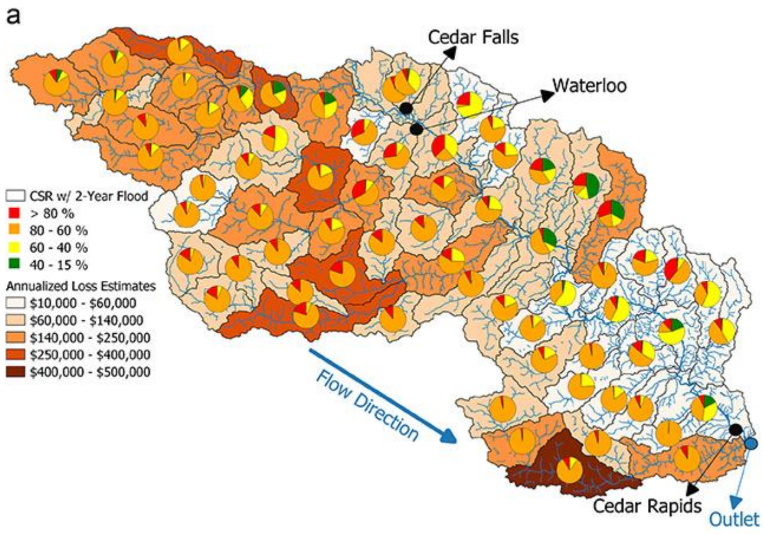


Figure 2. The flood risk, crop yield, and annual average losses for farmland under 2-year intervals in the Middle Cedar watershed, Iowa.

source and image credit to: https://now.uiowa.edu/2022/04/ui-researchers-create-map-showing-flood-risk-iowa-farmland

Motivations: what’s available (for free!)

Flood Inundation Maps (FIMs)

Produced from (NASA/USGS Landsat8) satellite images

- Maps show areas that are at risk of flooding during a specific flood event.
- **High image resolution** with 1 pixel indicates an area of 30*30 square meters.
- Low temporal frequency with 1 image in the area bi-weekly.

Water Fraction Maps (WFMs)

Produced from (NASA/NOAA VIIRS) satellite images

- Map show the distribution and extent of water in a given area.
- Low image resolution with 1 pixel indicates an area of 300*300 square meters.
- **High temporal frequency** with 1 image in the area daily.

Motivations

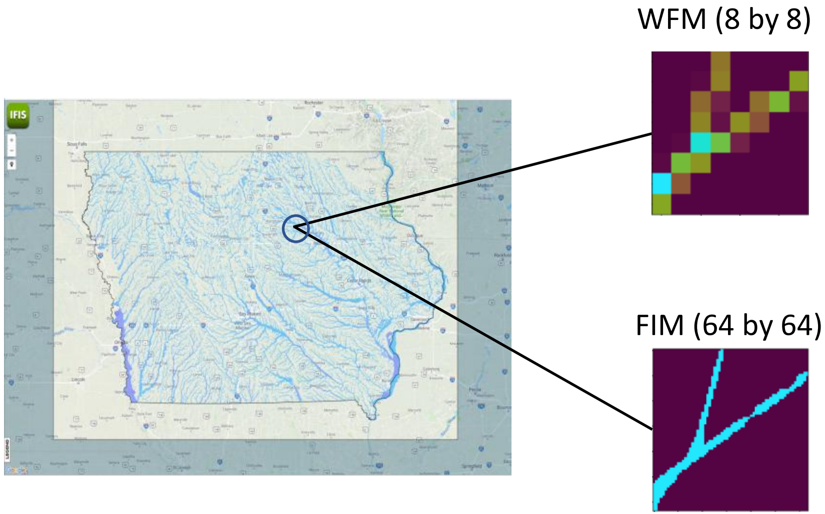


Figure 3. WFM and FIM in the given area in Iowa.

During a flood event in a given area

One image daily

A greyscale images whose pixel value indicates the fraction of flood inundation.

One image bi-weekly

Binary valued images indicate the presence of floods in the same region.

Propose

~~**Bi-weekly** available~~
~~**high** image resolution~~
~~FIMs from Satellite~~

Daily available
low image resolution
WFMs

Deep Super-Resolution Model

Daily available
high image resolution
FIMs

Datasets

- In this preliminary work:
  - The low resolution WFMs in our datasets are create from FIMs.
  - We adopt super-resolution of scale 8.

Too scarce, not enough for training deep models

- Real-world Iowa dataset:
  - 1487 high-resolution FIMs from Landsat8 from Cedar Creek river site and Des Moines river site within Iowa.
- Synthetic Iowa dataset:
  - ~46K simulated FIMs provided by the Iowa Flood Center via hydraulic simulations for the entire state of Iowa [8].
  - Adopt as a surrogate data source for training.

Deep SR Models

Residual Dense Networks (RDN)

- Zhang, Yulun, et al. "Residual dense network for image super-resolution." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2018. [5]
- The key is to make full use of both the local features and the global features with a series of residual dense blocks (RDBs), where RDB serves as the basic build module and is built by series of dense connected convolutional layers.

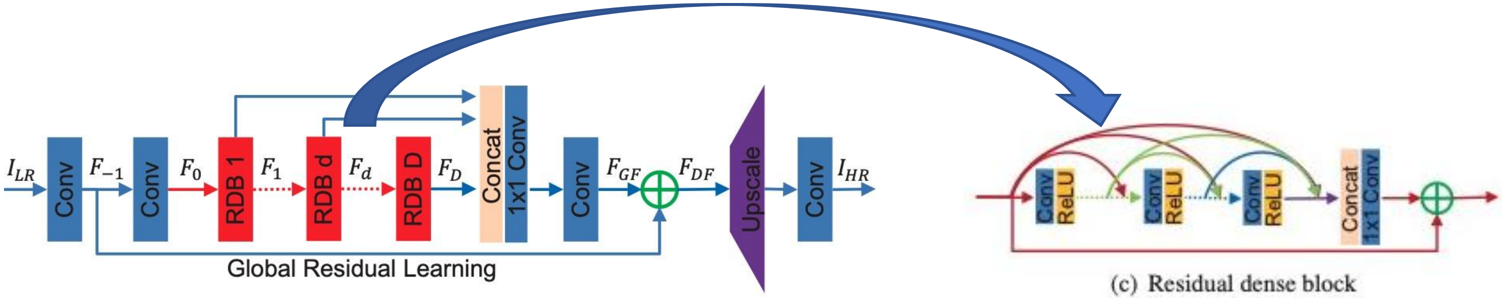


Figure 4. The architecture for the RDN. Image adapted from [5].

Residual Channel Attention Networks (RCAN)

- Zhang, Yulun, et al. "Image super-resolution using very deep residual channel attention networks." Proceedings of the European conference on computer vision (ECCV). 2018.
- The paper propose a residual in residual (RIR) structure to form very deep network, which consists of several residual groups with long skip connections. Each residual group contains some residual blocks with short skip connections.
- Furthermore, they propose a channel attention mechanism to adaptively rescale channel-wise features by considering interdependencies among channels.

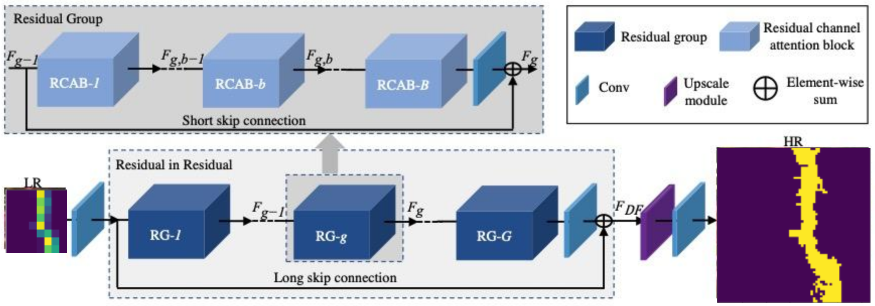


Figure 5: The architecture for the RCAN. Image adapted from [6].

Efficient Super-Resolution Transformers (ESRT)

- Lu, Zhisheng, et al. "Transformer for single image super-resolution." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2022.
- ESRT consists of a Lightweight CNN Backbone (LCB) and a Lightweight Transformer Backbone (LTB).
  - LCB can dynamically adjust the size of the feature map to extract deep features with a low computational costs by adopting High Preserving Block (HPB).
  - LTB is composed of a series of Efficient Transformers (ET) and is used to model the long-term dependence between similar local regions in an image.

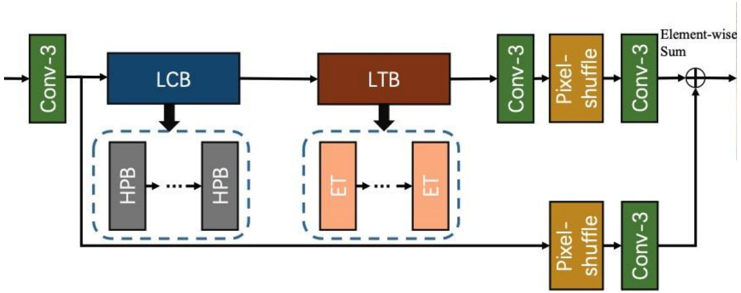


Figure 6: High level architecture for the ESRT. Image adapted from [9].

Loss Function

- Overall loss

$$L(X,Y,\hat{Y}) = L_{bce}(Y,\hat{Y}) + L_{sc}(X,Y,\hat{Y})$$

- Pixel-wise binary cross-entropy

$$L_{bce}(Y,\hat{Y}) = \frac{1}{H^2} \sum_{\forall (i,j) \in Y_{index}} (\log \hat{Y}_{i,j} Y_{i,j} + (1 - Y_{i,j})) \log (1 - \hat{Y}_{i,j})$$

- Soft constraint to ensure water fraction is obeyed.

$$L_{sc}(X,Y,\hat{Y}) = \eta \sum_{\forall (i,j) \in X_{index}} ||X_{i,j} - \frac{1}{f^2} \sum_{k,l \in \{1,2,\ldots,f\}} \hat{Y}_{f \times i+k, f \times j+l}||_2^2$$

Where,

- X is the WFM of size 8x8 with $X_{i,j} \in [0,1]$.
- Y is the ground truth FIM with $Y_{i,j} \in \{0,1\}$.
- $\hat{Y}$ is the predicted FIM with $\widehat{Y}_{i,j} \in \{0,1\}$.
- f is the scaling factor -> 8
- H is the length (height) of the output image -> 64.
- η is a hyperparameter associated with the soft constraint

Topological Features

Topological Features

- Topographic features derived from Digital Elevation Maps (DEMs)
  - Vertical Distance to Nearest Drainage (VDND) or Height Above Nearest Drainage.
  - Horizontal Distance to Nearest Drainage (HDND)
  - We normalize all the distances based on 95th quantile of values.

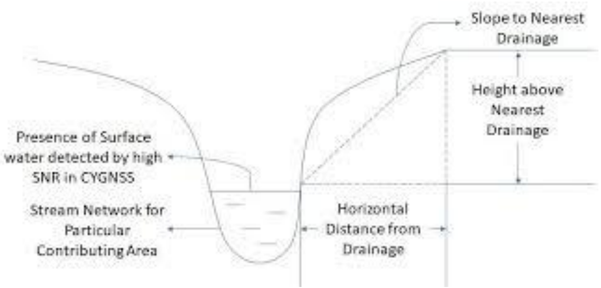


Figure 7: Illustration of VDND and HDND

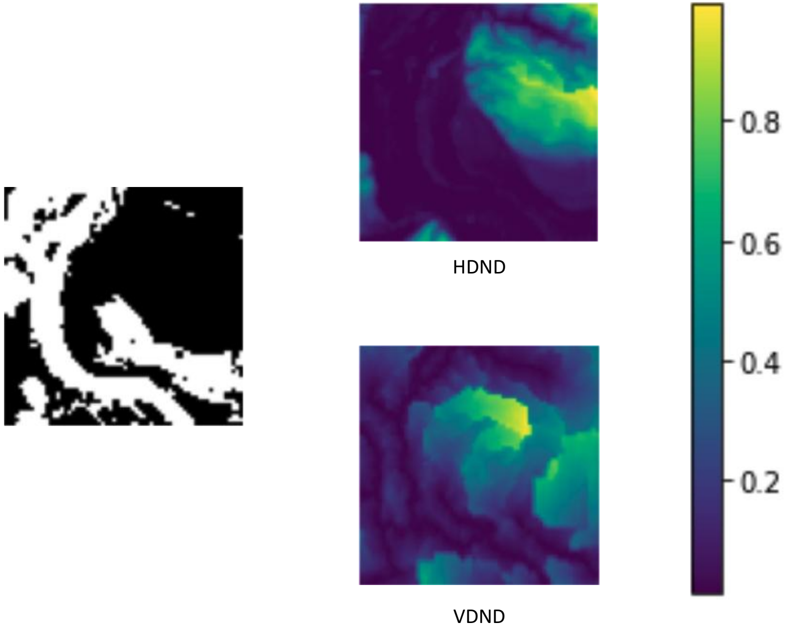


Figure 8: Example of VDND and HDND for a FIM.

Figure 7 Image credits to :https://encrypted-tbn0.gstatic.com/images?q=tbn:ANd9GcR0DOrWca8UC5U6zEJLc-Y4uKRhoY2W_juwRhERg6wCcA&usqp=CAU&ec=48600112

Deep Learning Architecture: Topographic Features

- In all the architectures, we incorporate topographic features by passing them through a series of convolutional + Relu layers.
- These features are then concatenated to the outputs from the architectures and passed through a series of convolutional layers to function as feature extractors.

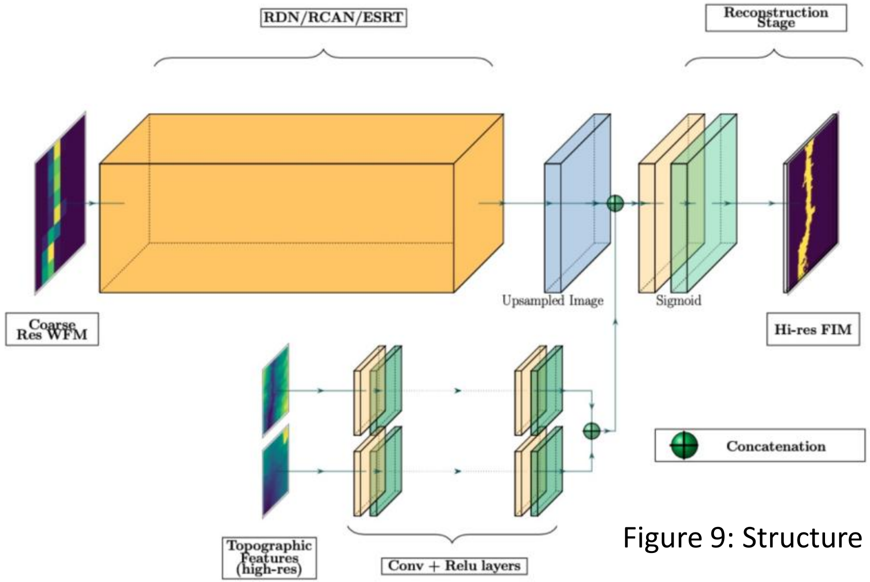


Figure 9: Structure of adopting Topographic features.

Experimental Results

Baselines

- Bicubic Interpolation
- Geomorphological Features-based Downscaling (GFD)
  - This model fills out flood inundations in the high-resolution output by utilizing the topographic information directly.
  - We rank the pixels by $\ell 1$ and $\ell 2$ distances of the topographic features and fill out the pixels until the water fraction is satisfied.

Evaluation Metrics

- Accuracy

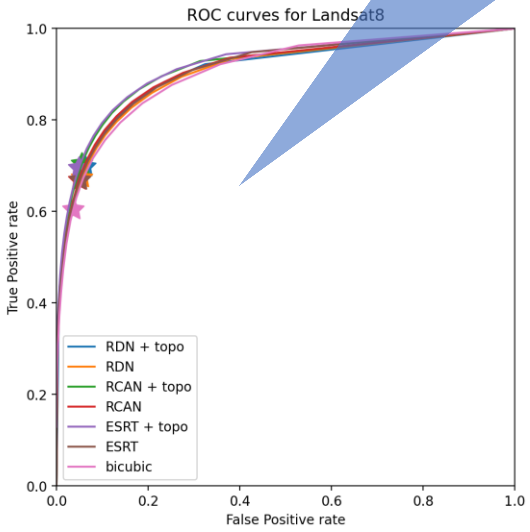
- Matthew's Correlation Coefficient:
    - The coefficient is generally regarded as a balanced measure which can be used even if the classes are of very different sizes.

- RoC curves:
    - a graph showing the performance of a classification model at all classification thresholds

Model Performances

Model	Accuracy (%)	MCC
Bicubic	87.69	0.64
GFD – $\ell 1$	84.23	0.57
GFD – $\ell 2$	83.87	0.56
RDN	87.91	0.65
RCAN	88.26	0.66
ESRT	88.1	0.66
RDN + topo	87.98	0.66
RCAN + topo	88.65	0.68
ESRT + topo	**88.91**	**0.68**

Star in the ROC curve indicates performance when the threshold = 0.5.



- All model comparisons are shown to be statistically significant via Holm Bonferroni method for multiple comparison test.
- A 1% difference in accuracy corresponds to an area of 19.55 km^2

Conclusion

- Our experimental results reveal that data-driven approaches exhibit superior reconstruction accuracy, when compared to classic interpolation alternatives.
- Our results affirm the viability of employing high-quality synthetic data as a surrogate data source for training such models in lieu of an abundance of real-world data.
- The performance gains from including topographic features in the real-world dataset are minimal, encouraging exploring alternative ways to incorporate these features.

References

1. W. Daniel, “Floods and droughts could cost the global economy $5.6 trillion by 2050, report says,” Fortune, 2022. [Online]. Available: https://fortune.com/2022/08/29/climate-change-costs-floods-droughts-could-cost-global-economy-5-trillion-by-2050/
2. Yulun Zhang, Yapeng Tian, Yu Kong, Bineng Zhong, and Yun Fu. Residual dense network for image super-resolution. CoRR, abs/1802.08797, 2018. URL https://openaccess.thecvf.com/content_cvpr_2018/html/Zhang_Residual_Dense_Network_CVPR_2018_paper.html.
3. Yulun Zhang, Kunpeng Li, Kai Li, Lichen Wang, Bineng Zhong, and Yun Fu. Image super-resolution using very deep residual channel attention networks. CoRR, abs/1807.02758, 2018a. URL https://openaccess.thecvf.com/content_ECCV_2018/html/Yulun_Zhang_Image_Super-Resolution_Using_ECCV_2018_paper.html.
4. Z. Lu, et al., "Transformer for Single Image Super-Resolution," in 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), New Orleans, LA, USA, 2022 pp. 456-465. https://doi.org/10.1109/CVPRW56347.2022.00061
5. Zheng, X., Tarboton, D.G., Maidment, D.R., Liu, Y.Y., and Passalacqua, P.. 2018. “ River Channel Geometry and Rating Curve Estimation Using Height above the Nearest Drainage.” *Journal of the American Water Resources Association* 54(4): 785– 806. https://doi.org/10.1111/1752-1688.12661.
6. Dasallas, Lea, Yeonsu Kim, and Hyunuk An. 2019. "Case Study of HEC-RAS 1D–2D Coupling Simulation: 2002 Baeksan Flood Event in Korea" *Water* 11, no. 10: 2048. https://doi.org/10.3390/w11102048

Thanks for listening!

For more information contact

Xi Zhang

zhang2012@my.fit.edu

Visit our website for out up to date research

SCAN ME