# DEM Super-Resolution with EfficientNetV2

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# Outline

- Introduction
- Related Work
- Approach
- Data
- Results

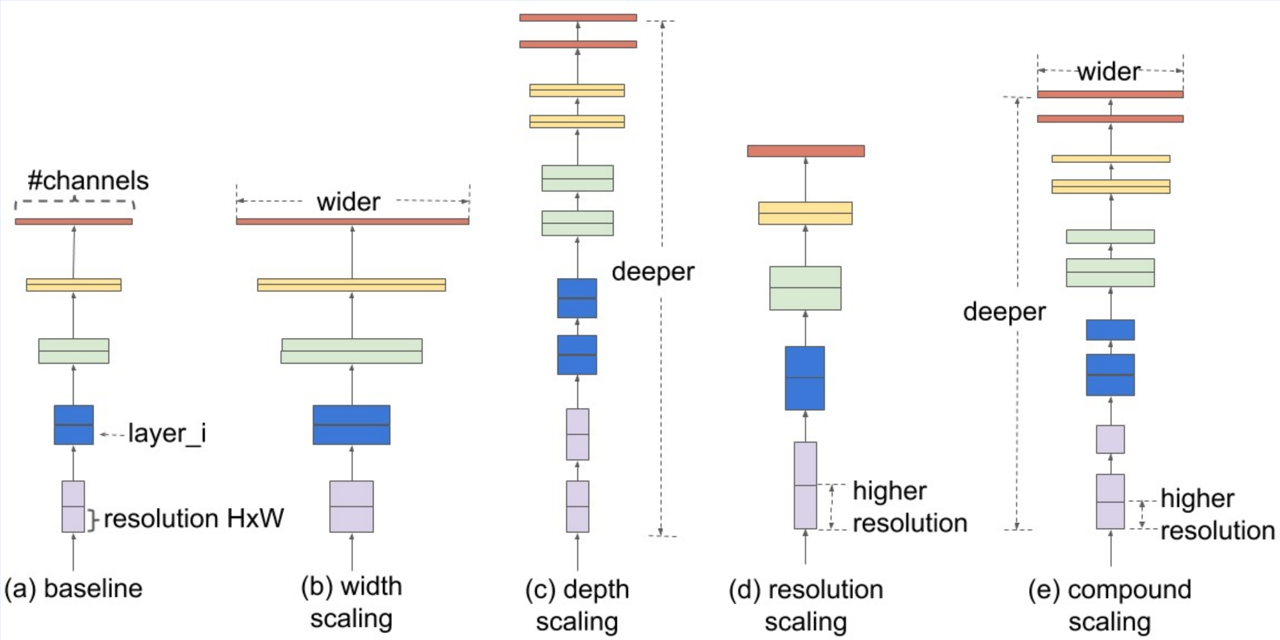
# Introduction

- The devastating impacts of natural disasters [1]
  - $210 billion worldwide
  - $95 billion in the US
- The effect of the climate change [2, 3]
- Introduction of DEM [4]
- Importance of high-resolution DEM [5, 6, 7]

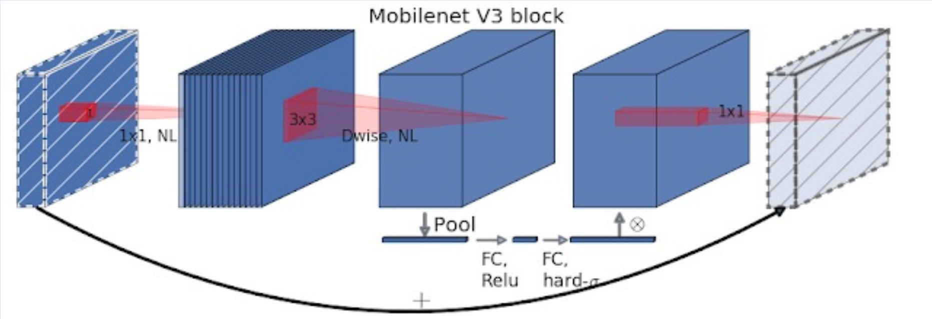
# Related Work

- Similarity between image and DEM [8, 9]
- Neural network based super-resolution methods [8, 9, 10]
  - D-SRCNN [8]
  - DPGN [9]
  - D-SRGAN [10]
- Effort of more efficient designs [11]
  - EfficientNets [12, 13]
  - MobileNets [14, 15]

# Related Work

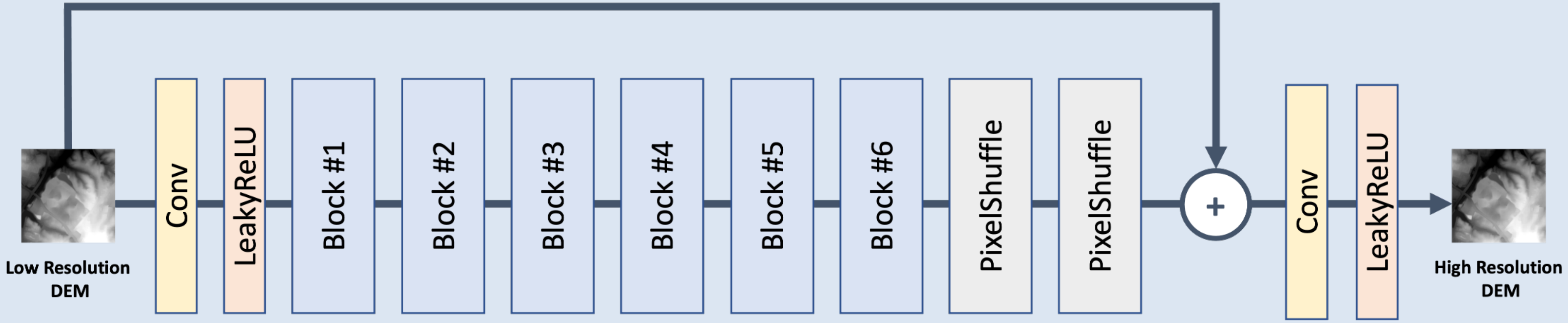



Unlike conventional scaling methods (b)-(d) that arbitrary scale a single dimension of the network, EfficientNet's compound scaling method uniformly scales up all dimensions in a principled way.




MobileNetV3 extends the MobileNetV2 inverted bottleneck structure by adding h-swish and mobile friendly squeeze-and-excitation as searchable options.

# Approach




Architecture of Proposed Method

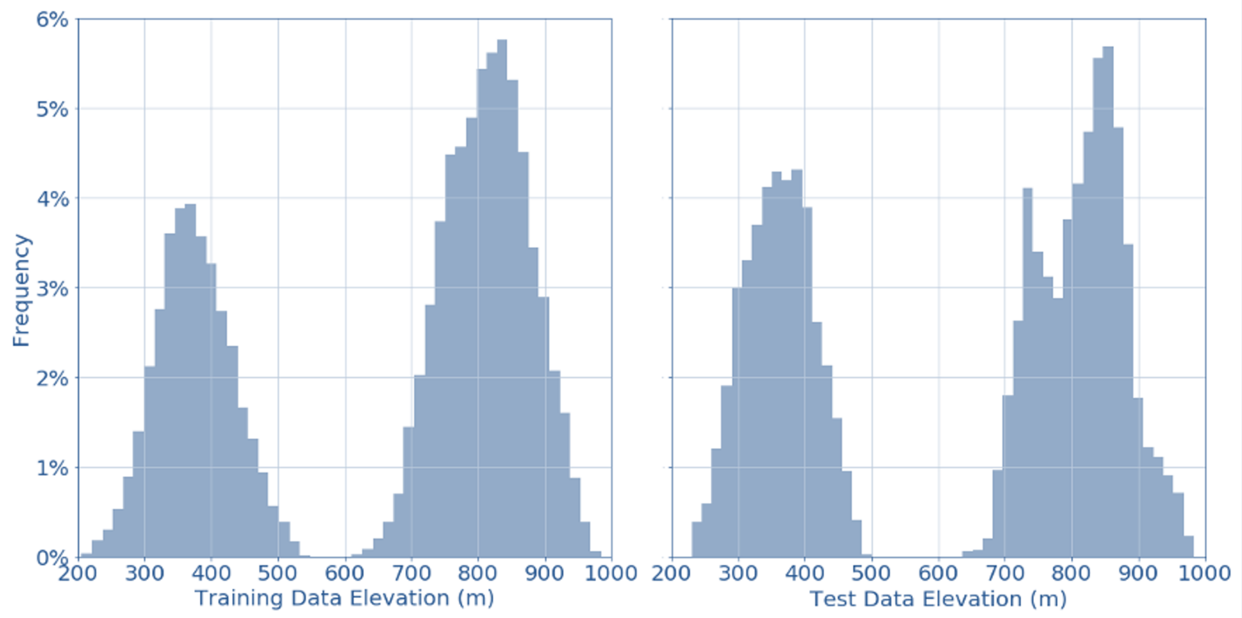
| | Block#1 | Block#2 | Block#3 | Block#4 | Block#5 | Block#6 |
|---|---|---|---|---|---|---|
| # of Channels | 24 | 48 | 64 | 128 | 160 | 256 |
| Expansion ratio | 1 | 4 | 4 | 4 | 6 | 6 |
| #ofLayers | 2 | 4 | 6 | 6 | 9 | 15 |

MobileNet blocks in our model

# Data

- Collected from Wake and Guilford, North Carolina
  - approximately 2 points per square meter
  - 3 feet => high-resolution
  - 5 feet => low-resolution
- Total area of 732 $km^2$
  - Training => 590 $km^2$
  - Test => 142 $km^2$

| | Avg. Elevation (m) | Min. Elevation (m) | Max. Elevation (m) |
|---|---|---|---|
| Training | 653.1 | 205.7 | 984.9 |
| Test | 621.7 | 230.0 | 982.7 |

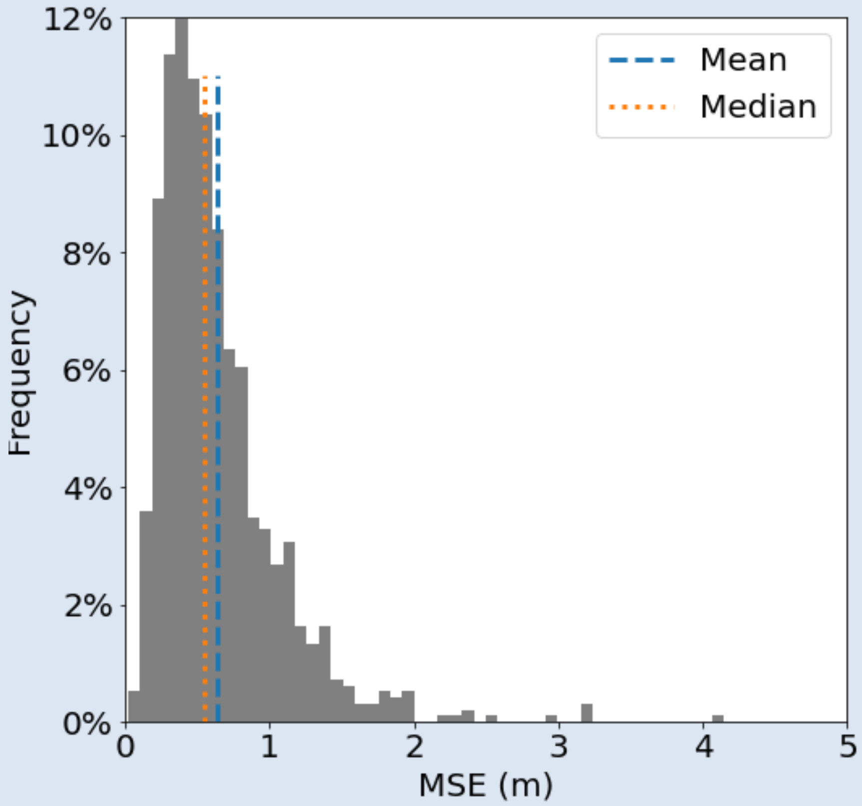



Statistical Summary of Dataset

# Results

| | Bicubic | Bilinear | D-SRCNN[8] | DPGN[9] | D-SRGAN[10] | EfficientNetV2-DEM |
|---|---|---|---|---|---|---|
| Training | 0.968 | 1.141 | 0.900 | 0.758 | 0.766 | 0.625 |
| Test | 0.946 | 1.124 | 0.872 | 0.803 | 0.753 | 0.640 |

The Performance Comparison of Different Methods as MSE in meters



Thank you

Any questions?

# References

1. Munich Re. Record hurricane season and major wildfires the natural disaster figures for 2020. https://www.munichre. com/en/company/media-relations/media-information-and-corporate-news/ media-information/2021/ 2020-natural-disasters-balance.html, 2020. [Online; accessed 30-May-2021].
2. Tabari, H. Climate change impact on flood and extreme precipitation increases with water availability. Scientific reports, 10(1):1–10, 2020.
3. The National Centers for Environmental Information. Us billion-dollar weather and climate disasters. https:// www.ncdc.noaa.gov/billions/, 2021. [Online; accessed 30-May-2021].
4. Florinsky I. Digital terrain analysis in soil science and geology. Cambridge: Academic Press; 2016.
5. D.-E. Kim, P. Gourbesville, and S.-Y. Liong, "Overcoming data scarcity in flood hazard assessment using remote sensing and artificial neural network," Smart Water, vol. 4, no. 1, pp. 1–15, 2019.
6. M. Sit, B. Demiray, and I. Demir, "Short-term hourly streamflow prediction with graph convolu- tional gru networks," arXiv preprint arXiv:2107.07039, 2021.
7. J. Vaze, J. Teng, and G. Spencer, "Impact of dem accuracy and resolution on topographic indices," Environmental Modelling & Software, vol. 25, no. 10, pp. 1086–1098, 2010.

# References

8. Z. Chen, X. Wang, Z. Xu et al., “Convolutional neural network based dem super resolution.” International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences, vol. 41, 2016.
9. Z. Xu, Z. Chen, W. Yi, Q. Gui, W. Hou, and M. Ding, “Deep gradient prior network for dem super-resolution: Transfer learning from image to dem,” ISPRS Journal of Photogrammetry and Remote Sensing, vol. 150, pp. 80–90, 2019.
10. B. Z. Demiray, M. Sit, and I. Demir, “D-srgan: Dem super-resolution with generative adversarial networks,” SN Computer Science, vol. 2, no. 1, pp. 1–11, 2021.
11. Z. Wang, J. Chen, and S. C. Hoi, “Deep learning for image super-resolution: A survey,” IEEE transactions on pattern analysis and machine intelligence, 2020.
12. M. Tan and Q. Le, “Efficientnet: Rethinking model scaling for convolutional neural networks,” in International Conference on Machine Learning. PMLR, 2019, pp. 6105–6114.
13. M. Tan and Q. V. Le, “Efficientnetv2: Smaller models and faster training,” arXiv preprint arXiv:2104.00298, 2021.
14. M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, “Mobilenetv2: Inverted residuals and linear bottlenecks,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2018, pp. 4510–4520.
15. A. Howard, M. Sandler, G. Chu, L.-C. Chen, B. Chen, M. Tan, W. Wang, Y. Zhu, R. Pang, V. Vasudevan et al., “Searching for mobilenetv3,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 1314–1324.