On the Defense Against Adversarial Examples Beyond the Visible Spectrum

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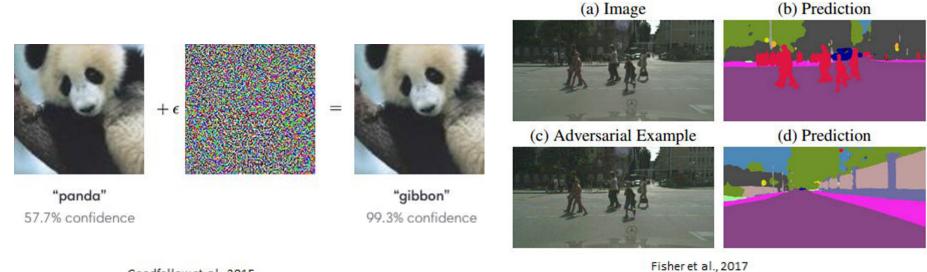
2 US Army Research Laboratory







Adversarial Examples on Natural Images



Goodfellowet al., 2015

Adversarial Examples Beyond the Visible Spectrum

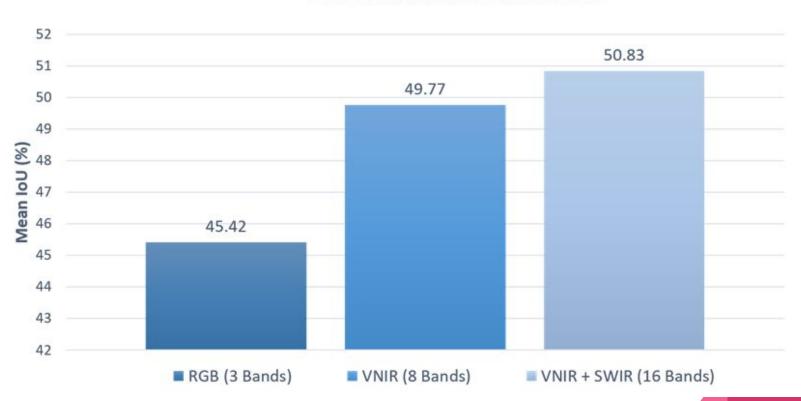
Experimantal Setup

- •DSTL Dataset:
- •1 km x 1 km Satellite Image
- Spatial resolution: 31 cm
- •3 channels RGB
- •8 Channels VNIR
- •8 Channels SWIR
- 10 Classes (Buildings, roads, track, trees, crops)
- DigitalGlobe's WorldView Satellite System
- Task: Semantic Segmentation
- Evaluation Metric: Mean IoU
- •Architecture:
- •Fully Convolutional Networks (FCN-8) with VGG-19 as backbone



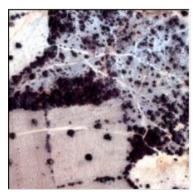
Performance Evaluation DSTL Dataset

Performance Baselines

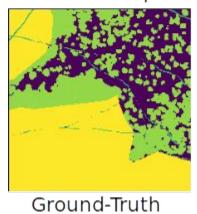


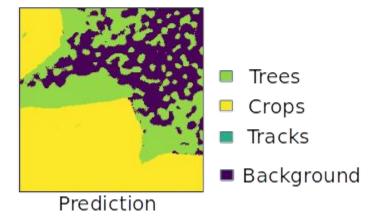
Adversarial Examples Beyond Visible Spectrum

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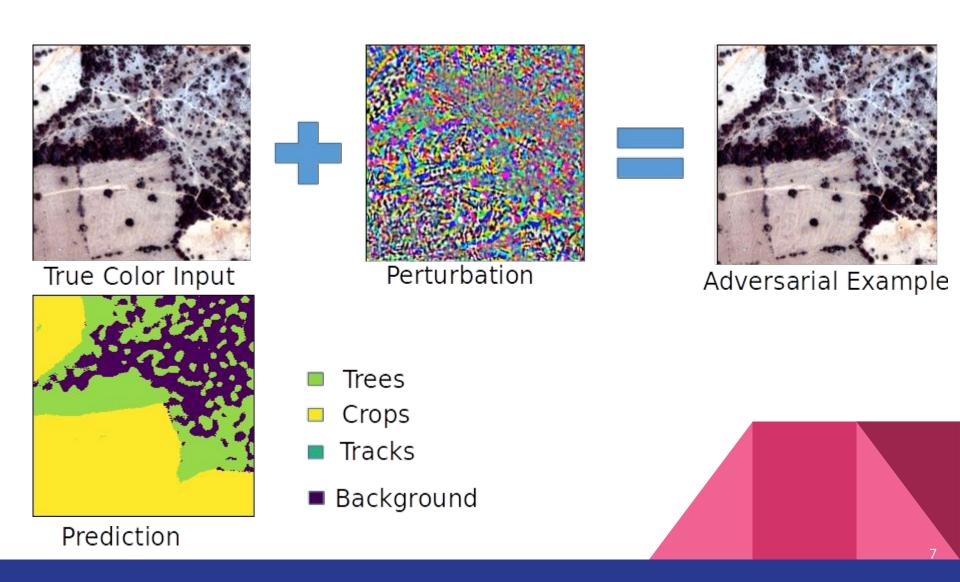


True Color Input

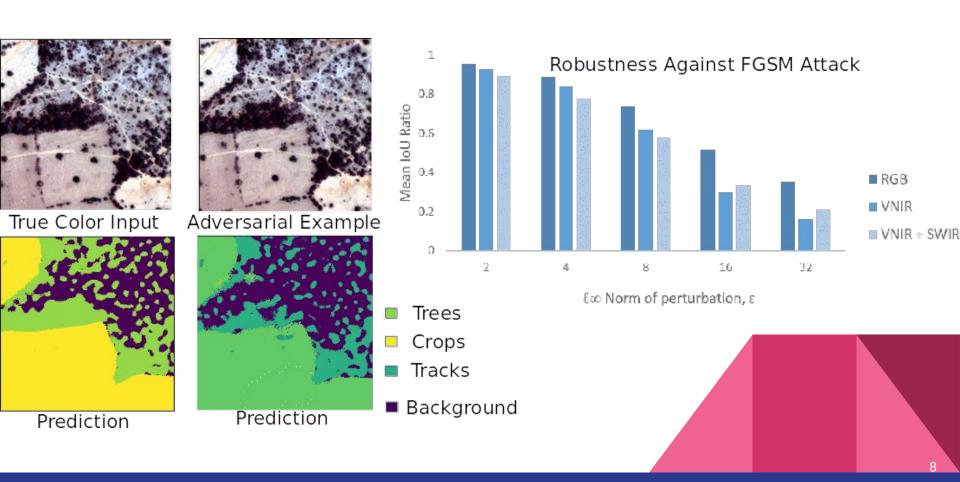




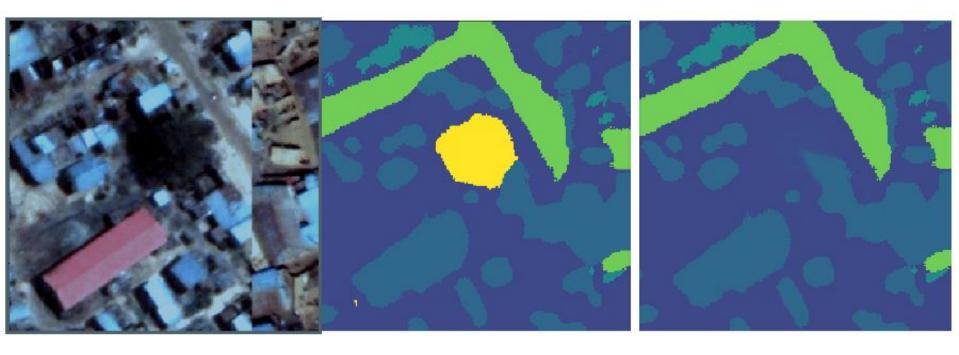
Adversarial Examples Beyond Visible Spectrum



Adversarial Examples Beyond Visible Spectrum



Dynamic Adversarial Perturbation Attack

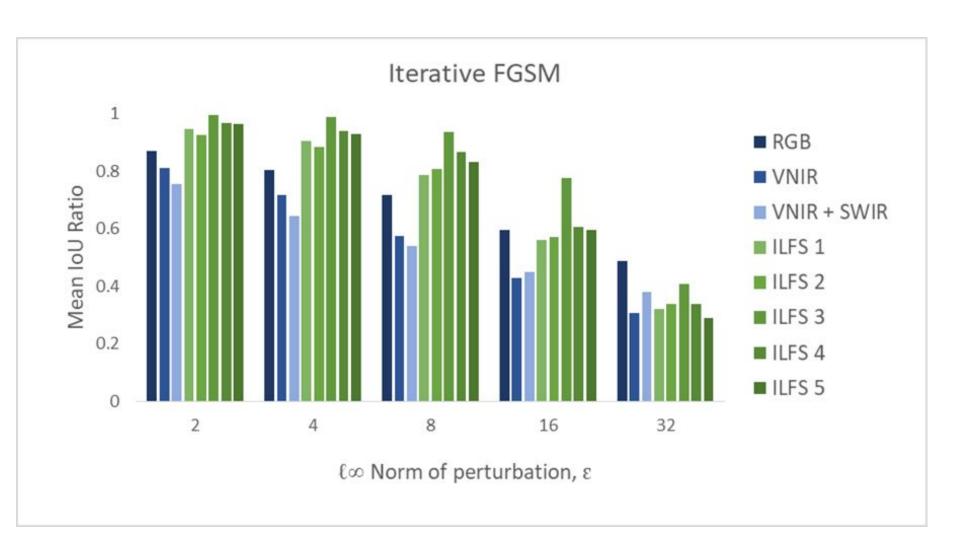


True Color Input

Prediction Clean

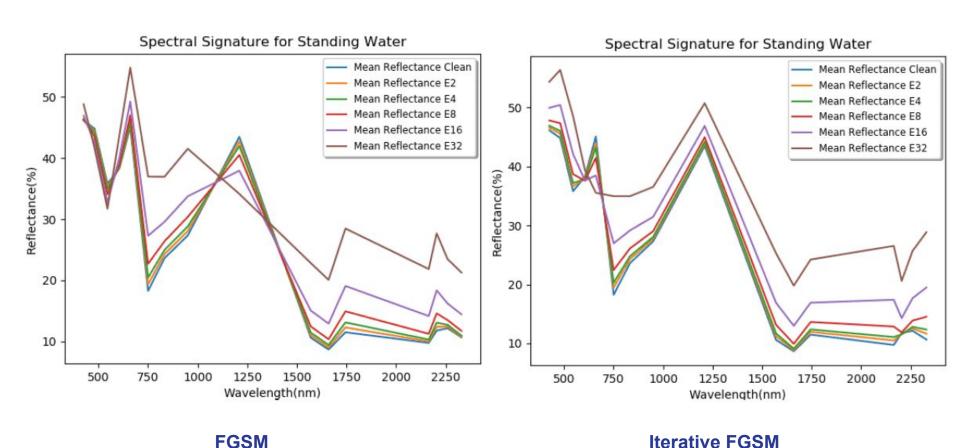
Prediction Adversarial

ILFS as a Defense Against Adversarial Examples



Detecting Adversarial Examples

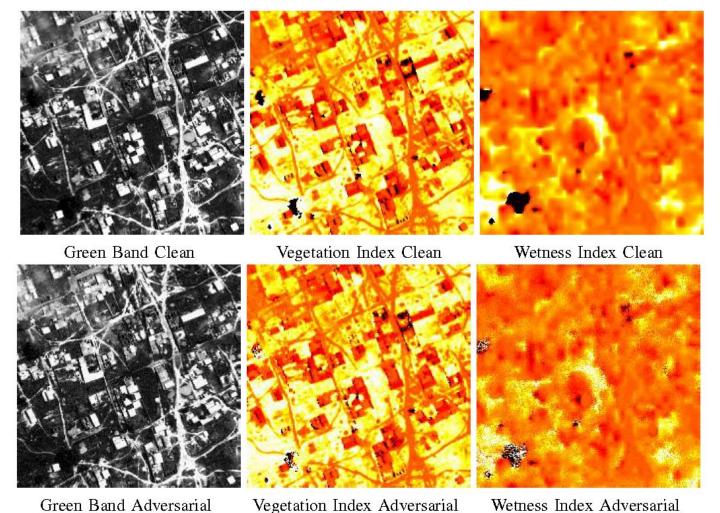
Spectral Signature Adversarial Examples



Wetness Index

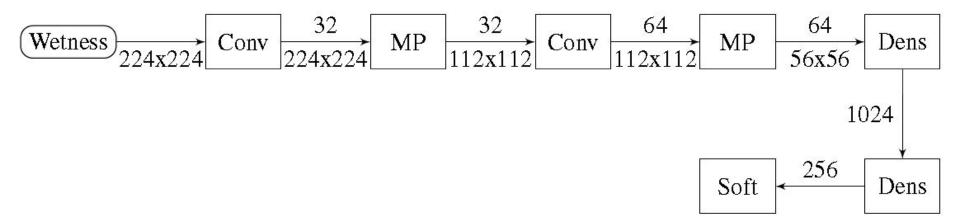
$$wetness = \frac{b_{swir2} - b_{swir4}}{b_{swir2} + b_{swir4}}$$

Band swir2:1550-1590nm Band swir4: 1710-1750nm



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Detector Network Architecture

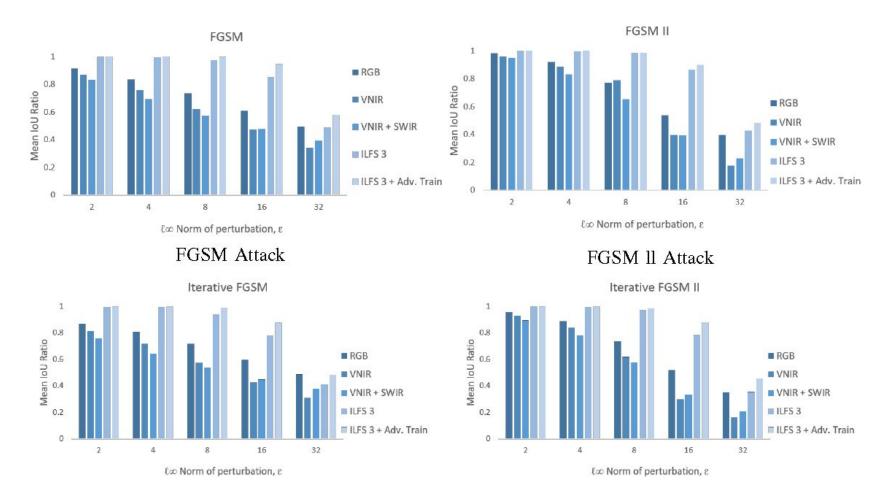


Detection Results

Wetness-based Detector Network Accuracy					
Attack	$\varepsilon = 2$	ε = 4	$\varepsilon = 8$	ε = 16	$\varepsilon = 32$
FGSM	0.84	0.99	1.00	1.00	1.00
FGSM ITER	0.94	0.99	1.00	1.00	1.00
FGSM 11	0.83	0.99	1.00	1.00	1.00
FGSM 11 ITER	0.95	0.99	1.00	1.00	1.00

Adversarial Training Helps

Adversarial Training Helps



Iterative FGSM Attack

Iterative FGSM ll Attack

Conclusions

- Multispectral and Hyperspectral Images are vulnerable to adversarial examples.
- With the right prior, adversarial examples can successfully be detected.
- Adversarial Training improve models robustness beyond RGB and generalize across attacks.

Thank you