Deep learning and energy models for fine dead wood segmentation

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Maching Learning for Climate

UCSB - KITP

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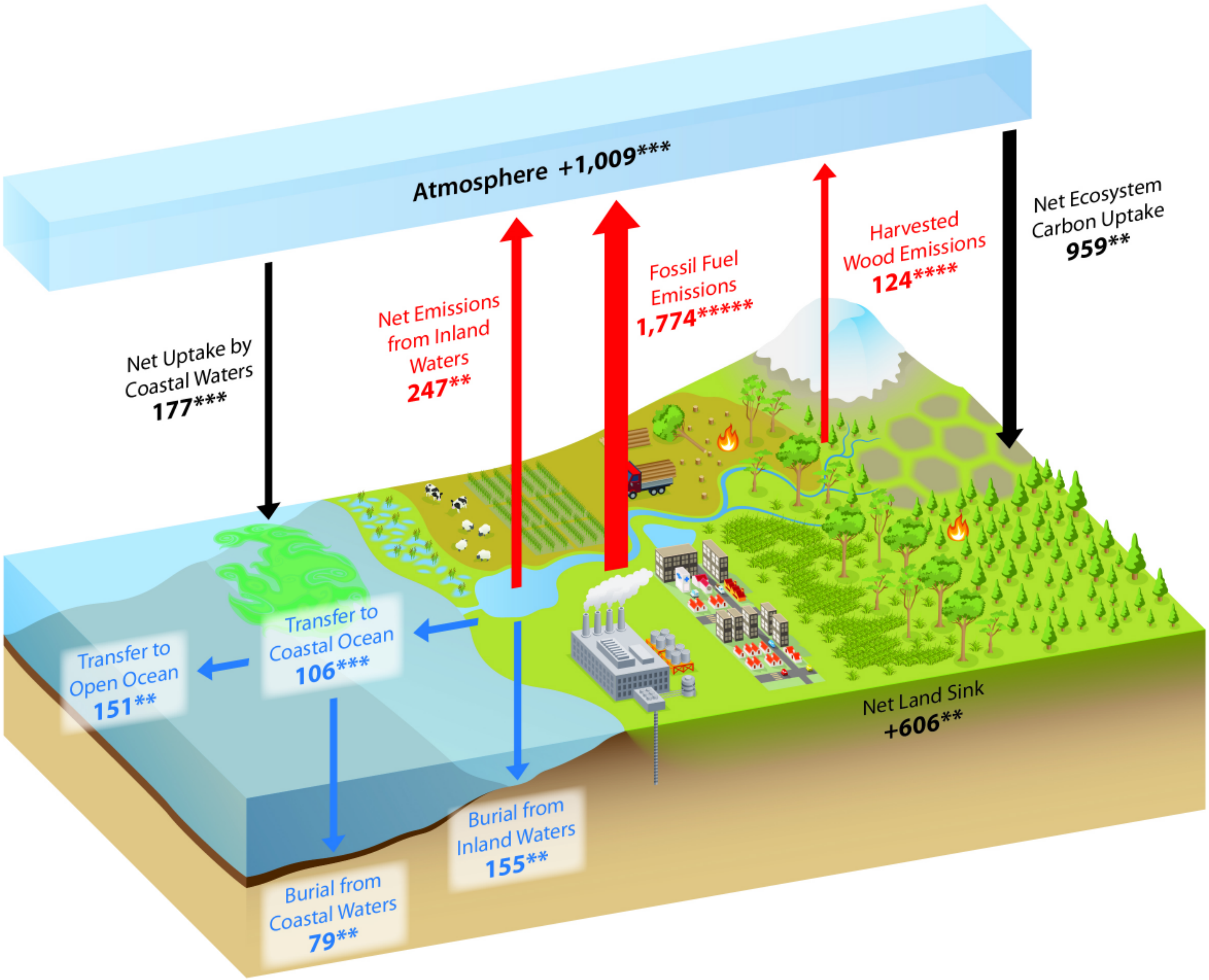
Introduction - The Carbon Cycle



Introduction - Motivation

Why dead trees?

- **Forests** are a key component in the **global carbon cycle** *and* the most **efficient** CO2 scrubbers
- **Dead wood** is an important part of **forest ecosystems**
  - **Sequesters** 8% of global forest carbon and 8.5% atmospheric carbon
  - **Provides habitat** for $\sim \frac{1}{3}$ of plant and animal species $\rightarrow$ imperative for **biodiversity**
- **Forest biodiversity** helps maintain forest health and shield against **climate change**

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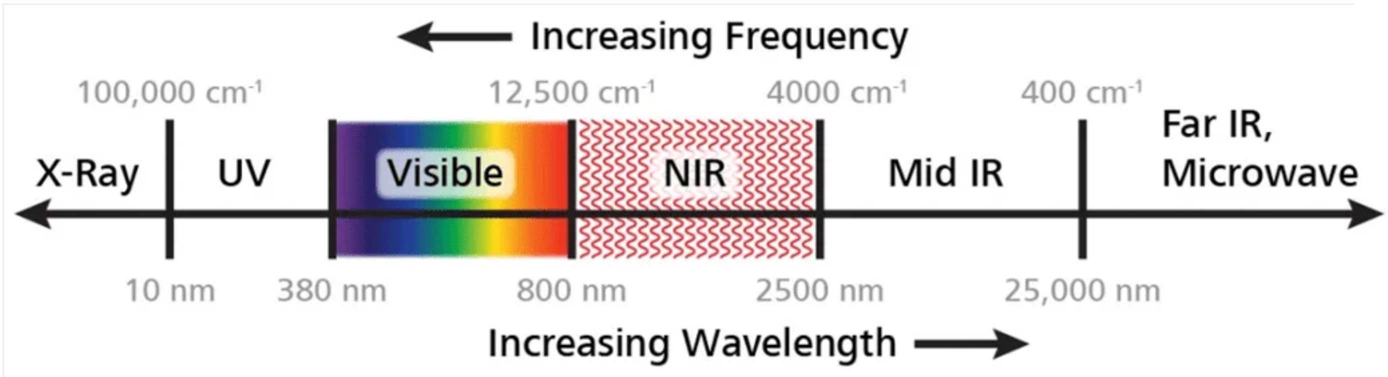
- **Forest biodiversity** helps maintain forest health and shield against **climate change**
- **Basically: indicator of overall forest health**...and beyond

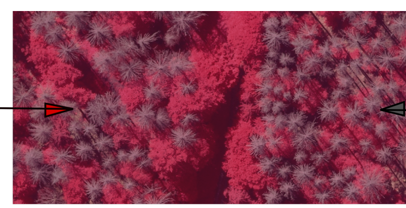
Now what?

- **Need** accurate ways to *measure* and *monitor* dead wood quantities and types...**Machine Learning!**

Data - Color infrared imagery (CIR)

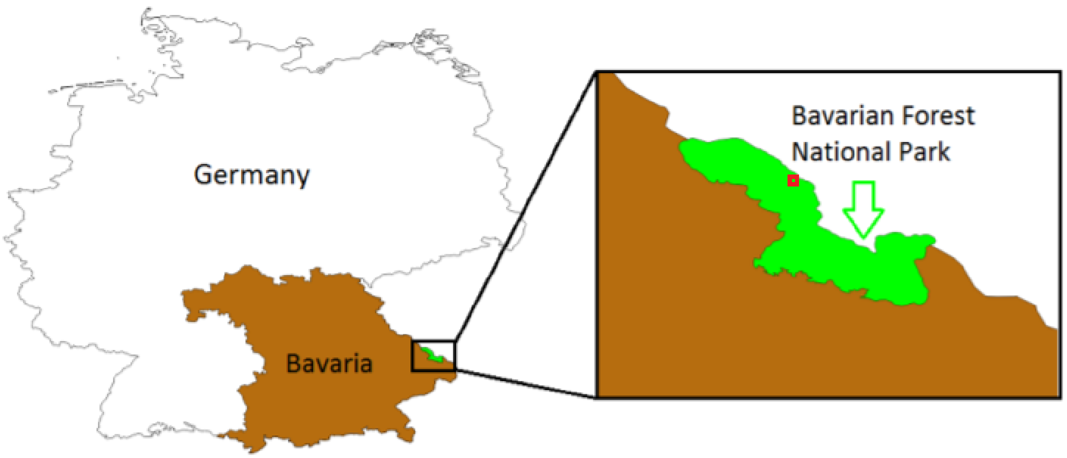


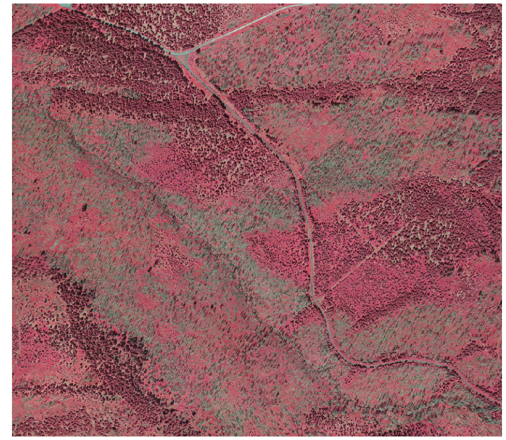
- Distinguish between live and dead vegetation
  $\rightarrow$ chlorophyll has high reflectance in the near-infrared (NIR) spectral band:



- Color infrared imagery (CIR): consists of the NIR, red, and green bands instead of the usual RGB

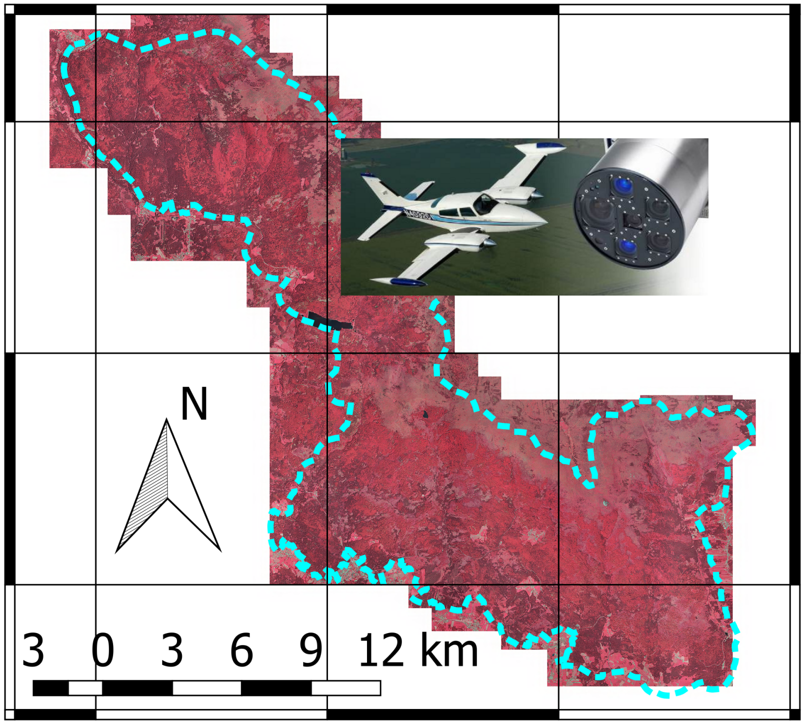
Data - Bavarian Forest National Park

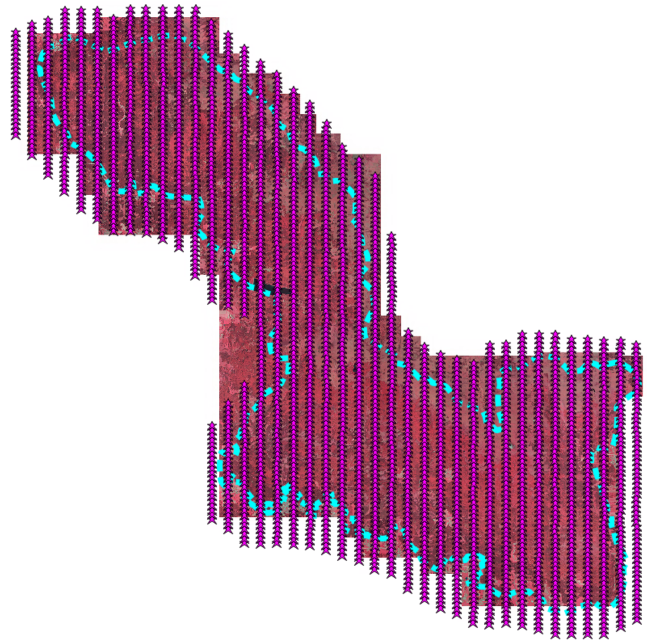




- Located in southeastern Germany, bordering the Czech Republic
- Consists of mostly Norway spruce (Picea abies) and European beech (Fagus sylvatica)
- Suffered bark beetle infestation (Ips typographus): between 1988-2010, total of $5,800$ hectors of the Norway spruce stands died
- Ideal for dead wood studies – decaying wood left undisturbed in forest for scientific purposes

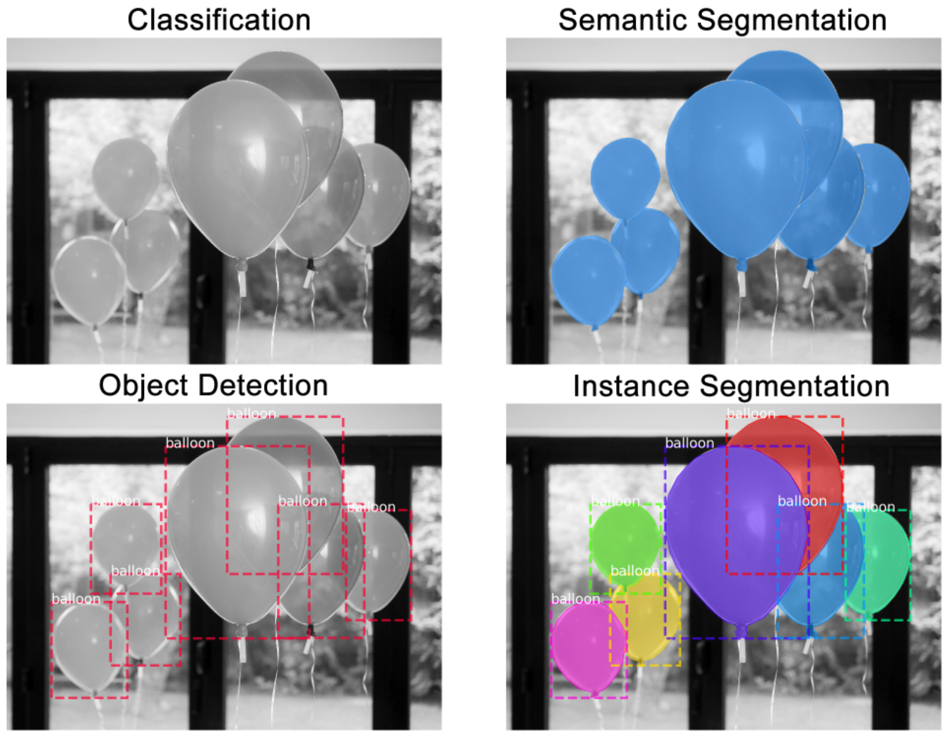
Data - Aerial imagery of Bavarian Forest National Park





- Flight campaign in June 2017 acquired $\sim 2,500$ images
- Mean flight altitude: $2879m$, resulting in a high resolution ground sampling distance of $10cm$ $\rightarrow$ each pixel $= 10 \times 10cm$
- Image resolution of aerial camera: 14592×25728 pixels, with each image covering $\sim 3.7km^2$

Approach – Review of classic segmentation tasks

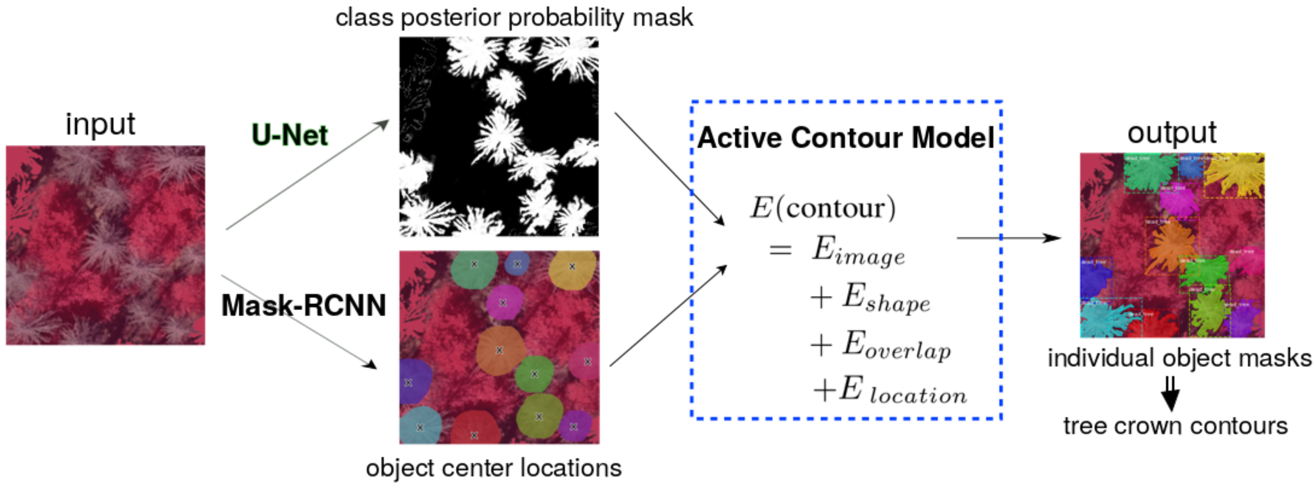


Source: "Splash of color" tutorial by Waleed Abdulla

- Classification: balloon is present in image (or not)
- Semantic Segmentation: find *all* the balloon pixels
- Object Detection: find balloon *quantity* and *location*, e.g. 7 balloons here
- **Instance Segmentation**: identify all pixels belonging to *each* of 7 balloons

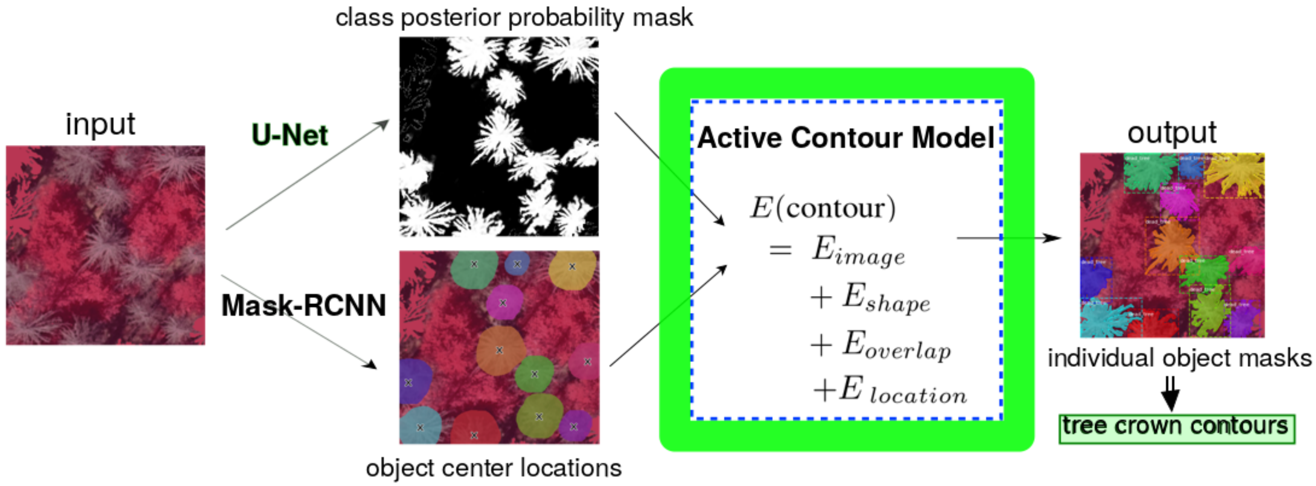
→ Note: **encountering objects that overlap** – our approach **MUST** account for this

Approach – How to attack this problem?



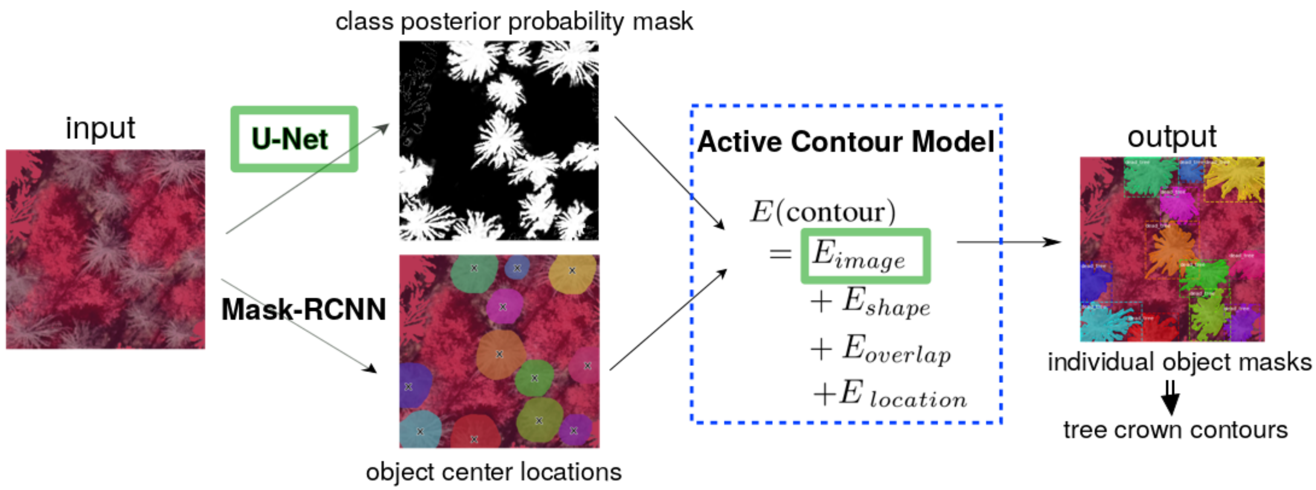
- First, let's break the problem down into basic components
- Next, recognize we can employ state-of-the-art deep learning methods to form the building blocks of our approach

Approach - Build an energy model!



- First, let's break the problem down into basic components
- Next, recognize we can employ state-of-the-art deep learning methods to form the building blocks of our approach
- Combine these methods to formulate a multi-term **energy model** for refined contour segmentation

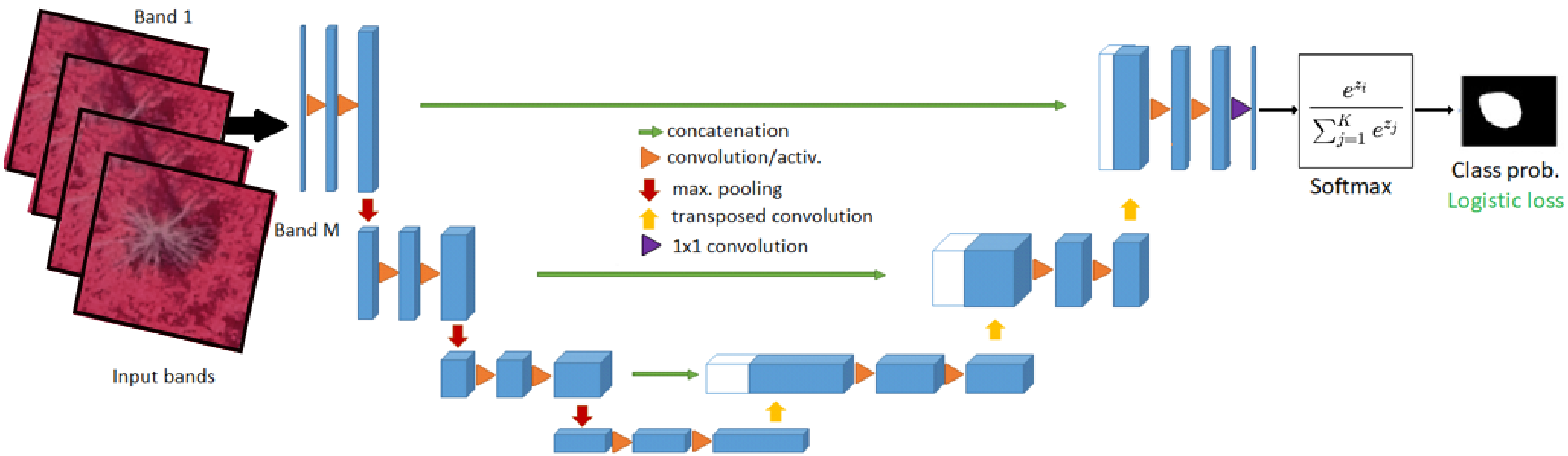
Approach – U-net: energy term for image



Build each energy term: $E_{\,image}(\text{contour})$:

- **U-net:** fully convolutional neural network (FCN) with an *encoder-decoder architecture*
  $\rightarrow$ get class probabilities aka dense ***semantic segmentation***
- Suited for this task: preserves contours, thus fine details of the tree crowns

Approach - U-net: energy term for image

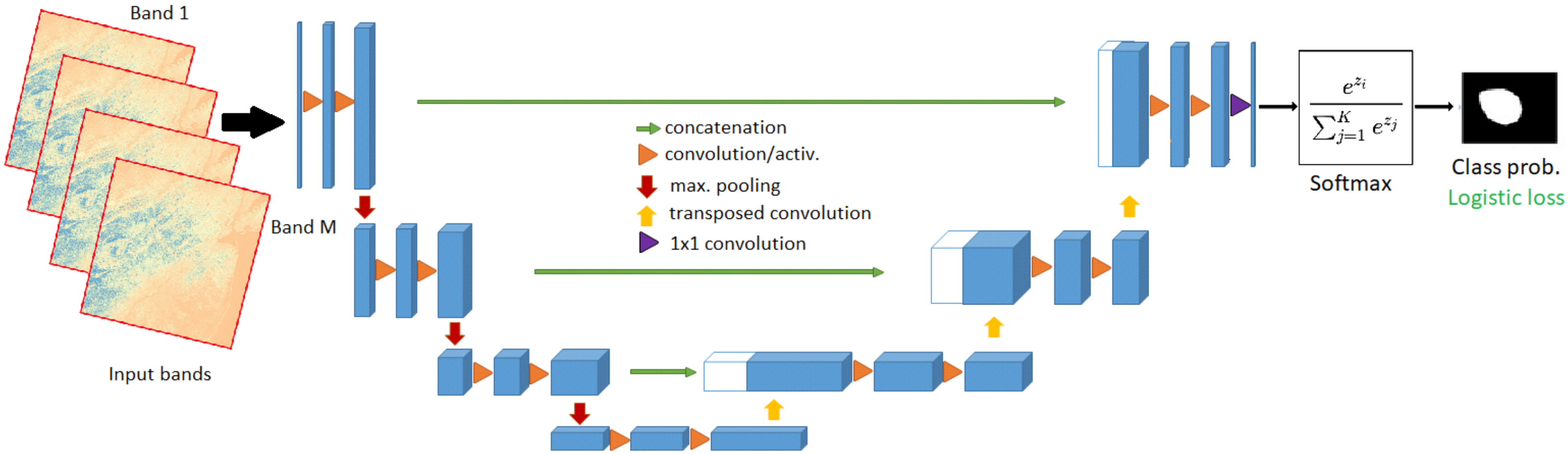


- **U-net:** FCN with encoder-decoder architecture
  - Encoding branch derives convolutional features at successively coarser scales
  - Decoding branch upsamples through transposed convolution

- Preserves detail with high-resolution original feature maps

$\rightarrow$ Additionally, U-nets can also be used for regression...

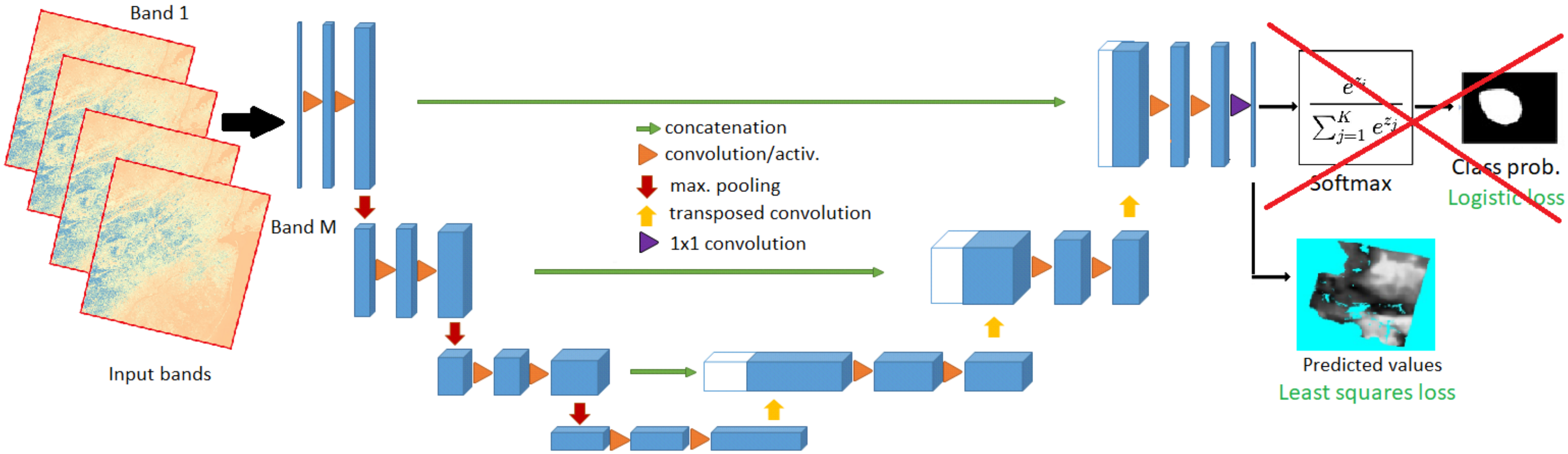
Approach - *Side-bar*: U-net for regression



- **U-net** for regression: remove soft-max layer and logistic loss, which gave us the class probabilities

Shelton, J., Polewski, P., Yao, W., (2020). *U-Net For Learning And Inference Of Dense Representation Of Multiple Air Pollutants From Satellite Imagery. Climate Informatics, Virtual Worldwide (9 2020).*

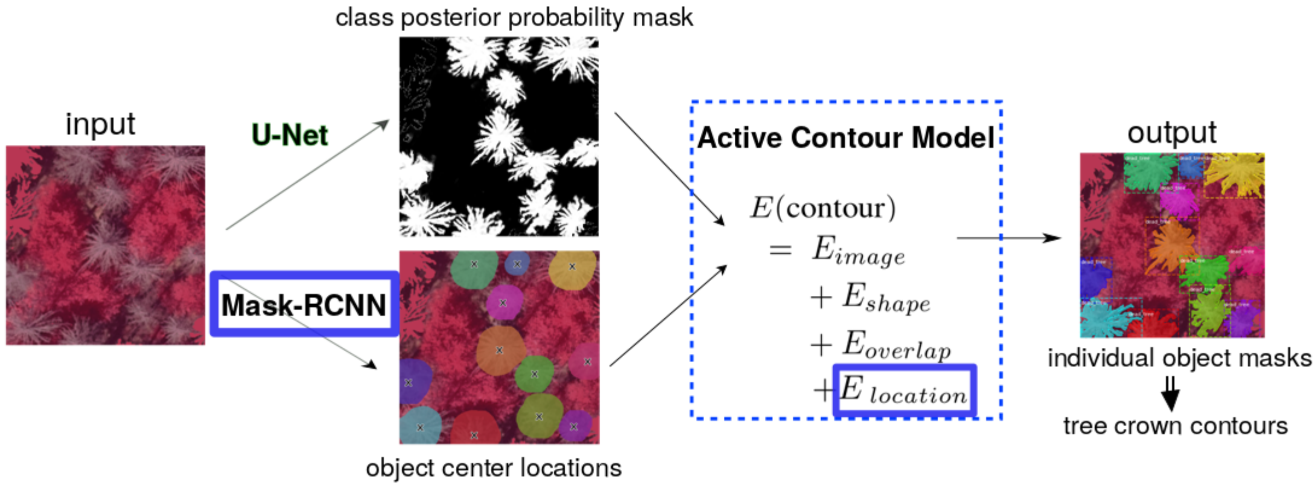
Approach – *Side-bar*: U-net for regression



- **U-net** for regression: remove softmax layer and logistic loss, which gave us the class probabilities
- Instead, train with least-squares loss directly on the 1×1 convolution output (final layer) for dense/pixel predictions
- Our previous work: using a U-net for regression we successfully predicted dense estimates of atmosphere pollutants (NO_3 , NH_4 , $PM_{2.5}$)

Shelton, J., Polewski, P., Yao, W., (2020). *U-Net For Learning And Inference Of Dense Representation Of Multiple Air Pollutants From Satellite Imagery*. *Climate Informatics, Virtual Worldwide (9 2020).*

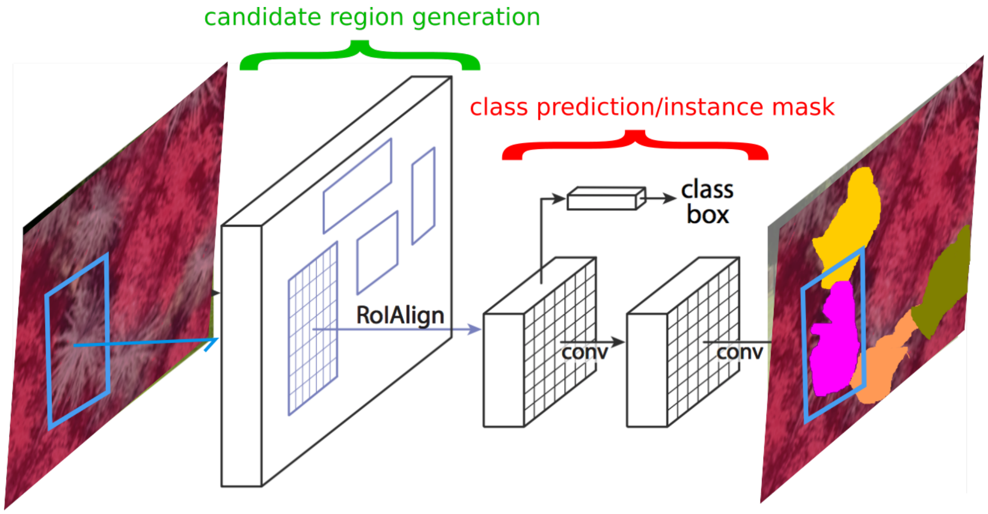
Approach – Mask R-CNN: energy term for location



Build next energy term: $E_{location}(\text{contour})$:

- **Mask R-CNN:** FCN for ***instance segmentation*** – get separate pixel masks for all object instances present in input image:
  (1) region proposal network: select regions of interest (RoI) likely to contain object instances
  (2) fine-grained detection component: evaluate candidate RoI, predict object class, bounding box, and pixel (instance) mask

Approach – Mask R-CNN: energy term for location



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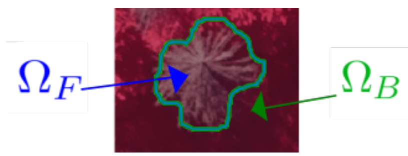
Approach - Formalize energy model

Begin building our energy model and its terms/potentials:

- Consider image plane $\Omega \subset \mathbb{R}^2$ and image $I : \Omega \mapsto \mathbb{R}^D$
- Segmentation of a **single** contour C:
  C: evolving shape contour, partitions image into
  foreground Ω_F, background Ω_B $(C \longleftrightarrow \Omega_F, \Omega_B)$



Note: problem **easier** with only **1 contour** and **no overlap**

Express contour model to optimize (probability or energy):

$$\mathcal{P}(\Omega_F, \Omega_B | I) \propto \mathcal{P}(I | \Omega_F, \Omega_B) P(\Omega_F, \Omega_B)$$

$$\Leftrightarrow \quad E(C) = \underbrace{-\log \mathcal{P}(I | \Omega_F, \Omega_B)}_{\text{image term}} \underbrace{-\log P(\Omega_F, \Omega_B)}_{\text{shape term}}$$

Approach - Formalizing energy model: image term

- Reminder: C uniquely identifies Ω_F, Ω_B ($C \longleftrightarrow \Omega_F, \Omega_B$)

$$E(C) = \underbrace{-\log \mathcal{P}(I|\Omega_F, \Omega_B)}_{\text{image term: } E_{img}} \underbrace{-\log \mathcal{P}(\Omega_F, \Omega_B)}_{\text{shape term}}$$

Simplifying assumption:

- Labelings of foreground and background regions are independent: $\mathcal{P}(I|\Omega_F, \Omega_B) = \mathcal{P}(I|\Omega_F)\mathcal{P}(I|\Omega_B)$
- Let $\mathbb{1}_X$ denote the indicator function for $\omega \in X$

$$E_{img}(C) = -\int_{\omega\in\Omega} [\overbrace{\mathbb{1}_{\Omega_F}}^{[\![\omega\in\Omega_F]\!]} \log \mathcal{P}(I(\omega)|\Omega_F) + \overbrace{\mathbb{1}_{\Omega_B}}^{[\![\omega\in\Omega_B]\!]} \log \mathcal{P}(I(\omega)|\Omega_B)]d\omega$$

$$= -\int_{\omega\in\Omega} [\mathbb{1}_{\Omega_F} \log \mathcal{P}(I(\omega)|\Omega_F) + \underbrace{(1 - \mathbb{1}_{\Omega_F})}_{\text{indicator for } \omega\in\Omega_B} \log \mathcal{P}(I(\omega)|\Omega_B)]d\omega$$

Approach – Formalizing energy model: image term

$$E_{img}(C) = -\int_{\omega\in\Omega} [\mathbb{1}_{\Omega_F} \log \mathcal{P}(I(\omega)|\Omega_F) + \underbrace{(1-\mathbb{1}_{\Omega_F})}_{\text{indicator for } \omega\in\Omega_B} \log \mathcal{P}(I(\omega)|\Omega_B)] d\omega$$

$$= -\int_{\omega\in\Omega} [\mathbb{1}_{\Omega_F} [\log \frac{\mathcal{P}(I(\omega)|\Omega_F)}{\mathcal{P}(I(\omega)|\Omega_B)}] d\omega + \text{constant}$$

Simplifying assumption:

- Prior probability of observing foreground/background is equal: $P(\Omega_F) = P(\Omega_B)$

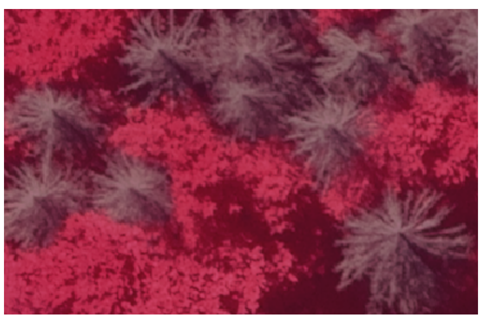
$$\frac{\mathcal{P}(I(\omega)|\Omega_F)}{\mathcal{P}(I(\omega)|\Omega_B)} = \frac{\mathcal{P}(\Omega_F|I(\omega))\mathcal{P}(I(\omega))}{\mathcal{P}(\Omega_B|I(\omega))\mathcal{P}(I(\omega))} \times \frac{\mathcal{P}(\Omega_B)}{\mathcal{P}(\Omega_F)} \text{(Bayes rule)}$$

$$E_{img}(C) = -\int_{\omega\in\Omega} \mathbb{1}_{\Omega_F} \log \frac{\mathcal{P}(\Omega_F|I(\omega))}{\mathcal{P}(\Omega_B|I(\omega))} \frac{\mathcal{P}(\Omega_B)}{\mathcal{P}(\Omega_F)} d\omega + \text{constant}$$

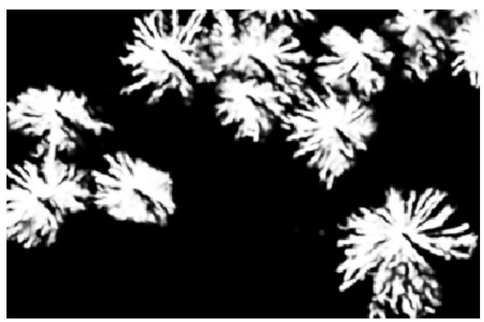
Approach - Formalizing energy model: image term

$$E_{img}(C) = -\int_{\omega\in\Omega} \mathbb{1}_{\Omega_F} \log \frac{\mathcal{P}(\Omega_F|I(\omega))}{\underbrace{\mathcal{P}(\Omega_B|I(\omega))}_{\text{two classes: } 1-\mathcal{P}(\Omega_F|I(\omega))}} d\omega + \text{constant}$$

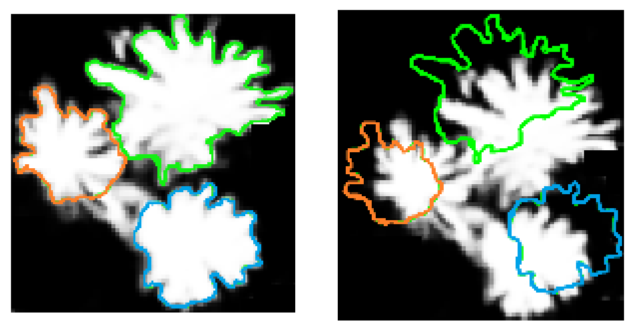
$$= -\int_{\omega\in\Omega} \mathbb{1}_{\Omega_F} \log \frac{\mathcal{P}(\Omega_F|I(\omega))}{1-\underbrace{\mathcal{P}(\Omega_F|I(\omega))}_{\text{arbitrary model of class probs}}} d\omega + \text{constant}$$



Sample CIR image



Posterior probability map



contour positions with:
low energy high energy

Approach – Formalizing energy model: shape term

Denote an approximation of foreground region indicator:

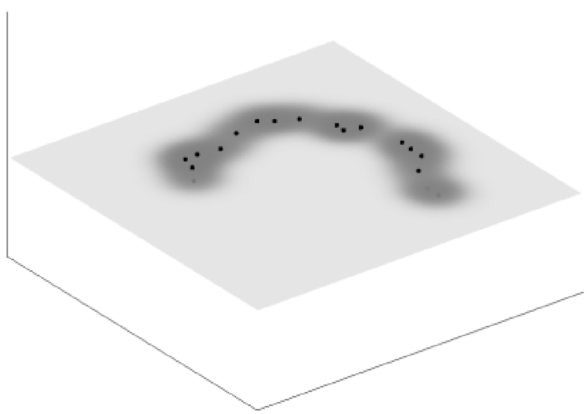
- $\mathbb{1}_{\Omega_F} \approx G(\alpha, x, y)$, where $G(\dots)$ is parameterized by a shape coefficient vector $\alpha \in \mathbb{R}^m$ and center position (x, y)

$$E(C) = E(\alpha, x, y) = \underbrace{-\log \mathcal{P}(I|\alpha, x, y)}_{\text{image term}} \underbrace{-\log \mathcal{P}(\alpha)}_{\text{shape term: } E_{shp}}$$

- $G(\dots)$ instantiates a shape given by coefficients α centered at (x, y) in the image
- Shape term E_{shp} is dependent *only* on the shape coefficients, *not* the position (x, y)
- Standard model: all positions are deemed equally likely – no prior knowledge available/used

- $\mathcal{P}(\alpha)$ can be modeled in a non-parametric fashion in terms of training shape coefficients
- Let $T = \alpha_1, \ldots, \alpha_N$ be a database of training shape coefficients and $K(x, y)$ denote a kernel function quantifying similarity between two vectors $x, y \in \mathbb{R}^m$
- The probability of a shape coefficient vector α is given by:

$$\mathcal{P}(\alpha) \propto \frac{1}{N} \sum_{i=1}^{N} K(\alpha, \alpha_i)$$



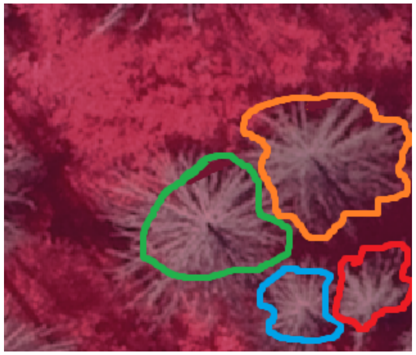
Source: Cremers and Rousson, 2007

$\rightarrow$ bulk of probability mass concentrated in regions of shape coefficient space with training vectors (black dots), regions far away allocated minimal probability

Approach – Multi-contour segmentation

But we **really** want to model **multiple** contours:

- $C_1, \ldots, C_K$: simultaneously evolving shape contours representing different object instances
- Contour C_i is parameterized by shape coefficient vector α_i and position (x_i, y_i)



$$\mathcal{P}(C_1, \ldots, C_K | I) \propto \mathcal{P}(I | C_1, \ldots, C_K) P(C_1, \ldots, C_K)$$

$$\Leftrightarrow E(C_1, \ldots, C_K) = \underbrace{-\log \mathcal{P}(I | C_1, \ldots, C_K)}_{\text{image term}} \underbrace{-\log P(C_1, \ldots, C_K)}_{\text{shape term}}$$

Approach – Multi-contour shape term

$$E(C_1,\dots,C_K) = \underbrace{-\log \mathcal{P}(I|\dots)}_{\text{image term}} \underbrace{-\log \mathcal{P}(C_1,\dots,C_K)}_{\text{shape term}}$$

- The contours are not independent: penalize overlap
- Include location information from Mask R-CNN
- Consider each contour's shape independent of position

$\Rightarrow$ Shape term as an undirected graphical model:

$$\mathcal{P}(C_1,\dots,C_K) = \frac{1}{Z}\prod_{\lambda\in\Lambda}\Psi_\lambda(C_\lambda)$$

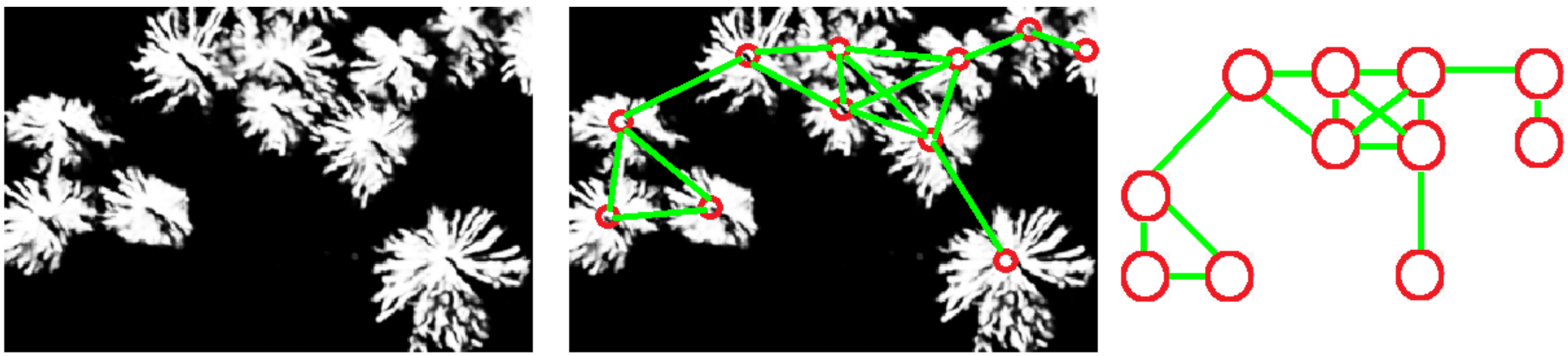
$\lambda \in \Lambda$: cliques of the graph $\mathcal{H}$ induced by object/tree crown centroids from Mask R-CNN and
Ψ_λ: are potential functions defined on subsets of contours

Approach – Shape term as a Graphical model

⇒ Remember:

$$\mathcal{P}(C_1, \ldots, C_K) = \frac{1}{Z} \prod_{\lambda \in \Lambda} \Psi_\lambda(C_\lambda)$$

$\Rightarrow \lambda \in \Lambda$ are cliques of the graph $\mathcal{H} = (\mathcal{V}, \mathcal{E})$ induced by Mask R-CNN found centroids



- Left: class probability map of dead tree scene
- Center: red circles = object centroids detected by Mask R-CNN and green lines connect centroids within d_{thr}
- Right: graph induced by the connections/edges and centroids/nodes

Approach – Graphical model potentials

$$\mathcal{P}(C_1, \ldots, C_K) = \tfrac{1}{Z} \prod_{\lambda \in \Lambda} \Psi_\lambda(C_\lambda)$$

$\Rightarrow$ Our model includes unary and pairwise potentials Ψ:

$$E_C(C_1, \ldots, C_K) = -\log \mathcal{P}(C_1, \ldots, C_K) + \text{constant} =$$

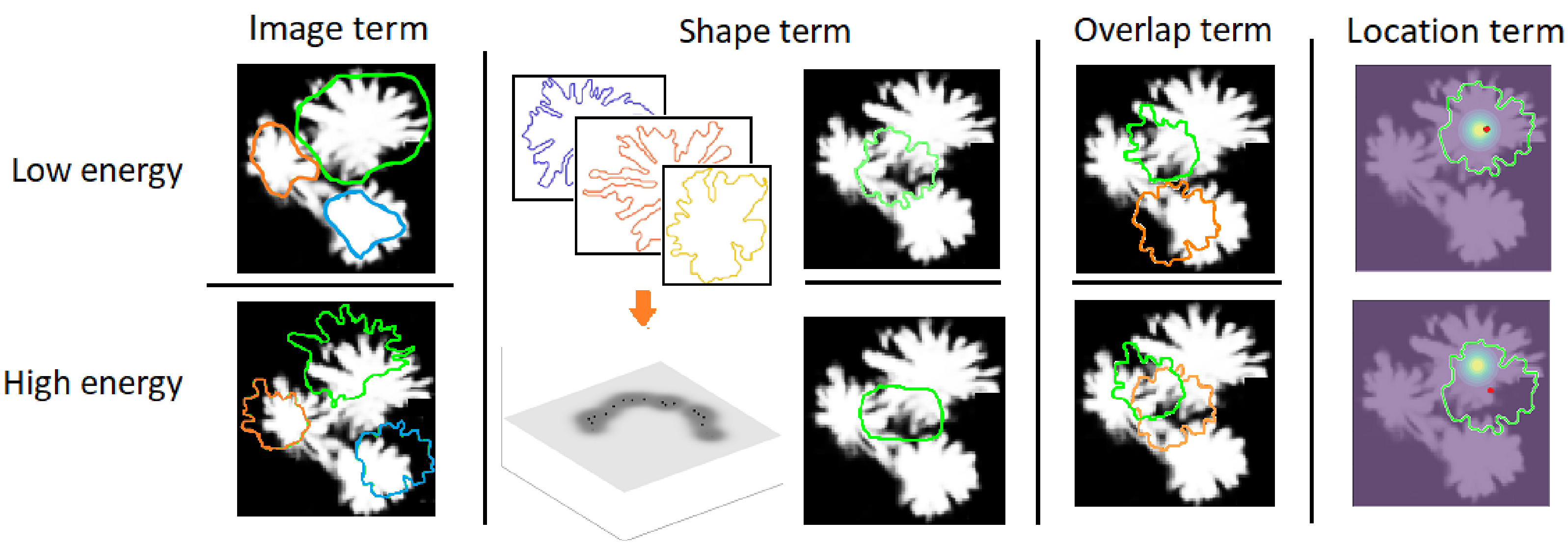
$$-\sum_{k=1}^{K} \log \Psi^{shp}(\alpha_k) - \sum_{k=1}^{K} \log \Psi_k^{loc}(x_k, y_k) - \sum_{(k,l) \in \mathcal{E}} \log \Psi_{ovp}(C_k, C_l)$$

- Shape potential: $\Psi^{shp}(\alpha_k) = \mathcal{P}(\alpha_k)$ - global KDE model
- Location potential: Gaussian centered on k-th centroid μ_k: $\Psi_k^{loc}(z) \propto \exp(-\frac{1}{2}(z - \mu_k)^T \Sigma^{-1} (z - \mu_k))$
- Overlap potential: overlap area between contours C_k, C_l: $\log \Psi_{ovp}(C_k, C_l) =$ $-\int_\omega G(\alpha_k, x_k, y_k)[\omega] \cdot G(\alpha_l, x_l, y_l)[\omega] d\omega$

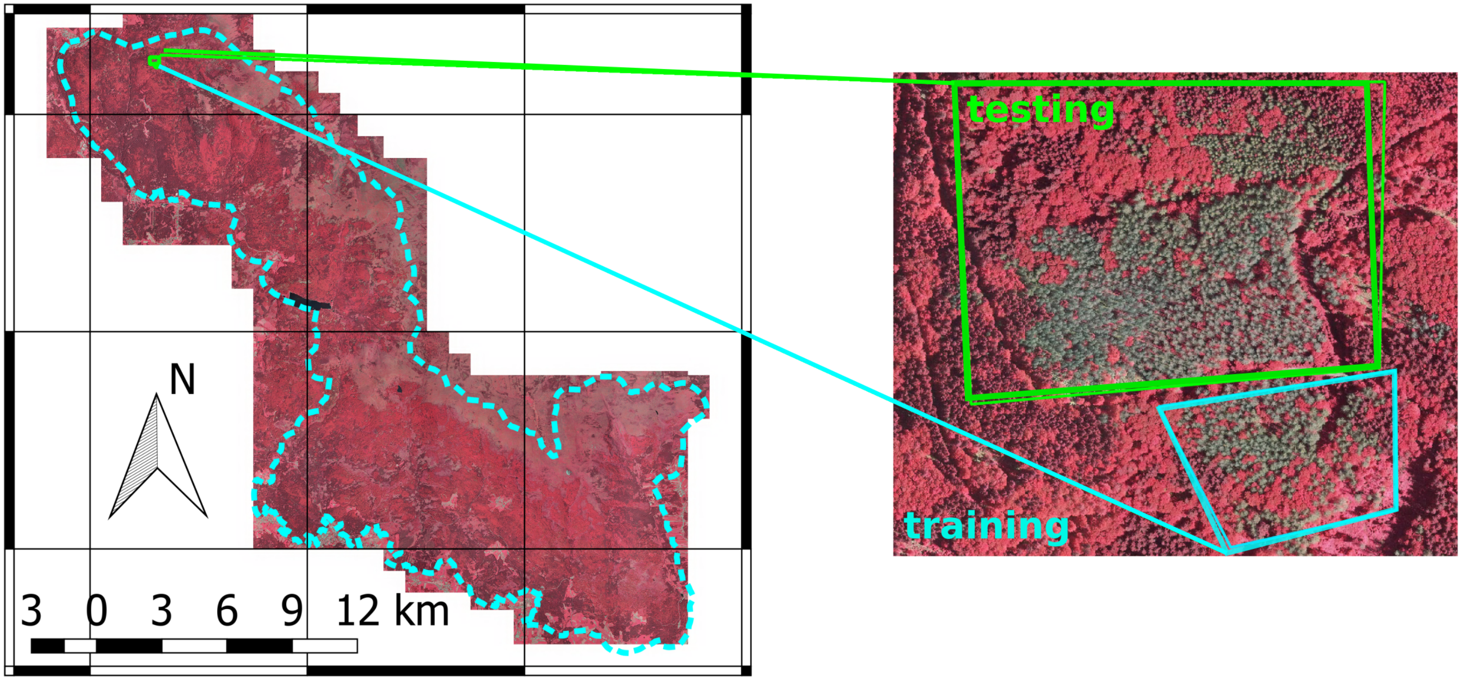
Approach – Put all the pieces together

$$E_{\text{total}}(C_1,\dots,C_K) = \underbrace{-\log \mathcal{P}(I|C_1,\dots,C_K)}_{\text{image term}} \underbrace{- \sum_{k=1}^{K} \log \Psi^{shp}(\alpha_k)}_{\text{shape term}}$$

$$\underbrace{- \sum_{(k,l)\in\mathcal{E}} \log \Psi^{ovp}(C_k, C_l)}_{\text{overlap term}} \underbrace{- \sum_{k=1}^{K} \log \Psi_k^{loc}(x_k, y_k)}_{\text{location term}}$$



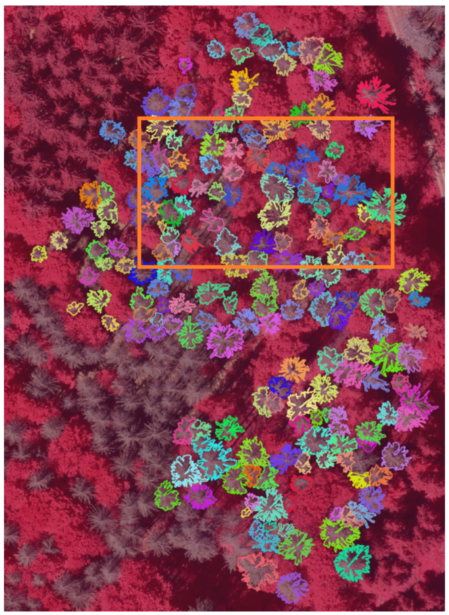
Experiments - Data: train and test areas

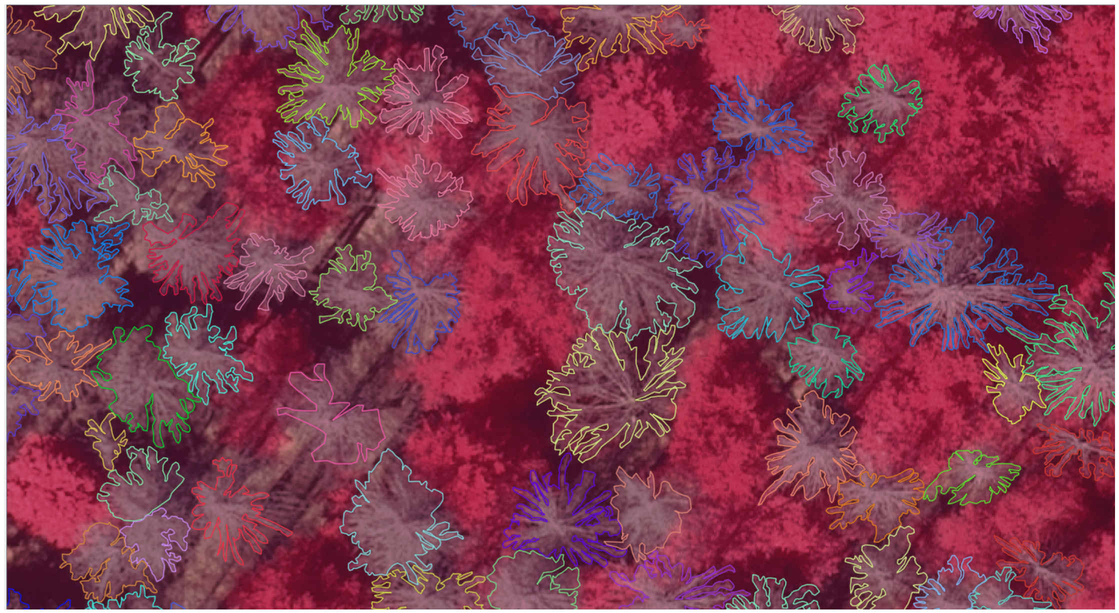


- We labeled tree crown polygons in forest areas for datasets:

$$\text{training} = 201 \text{ and } \text{testing} = 750$$

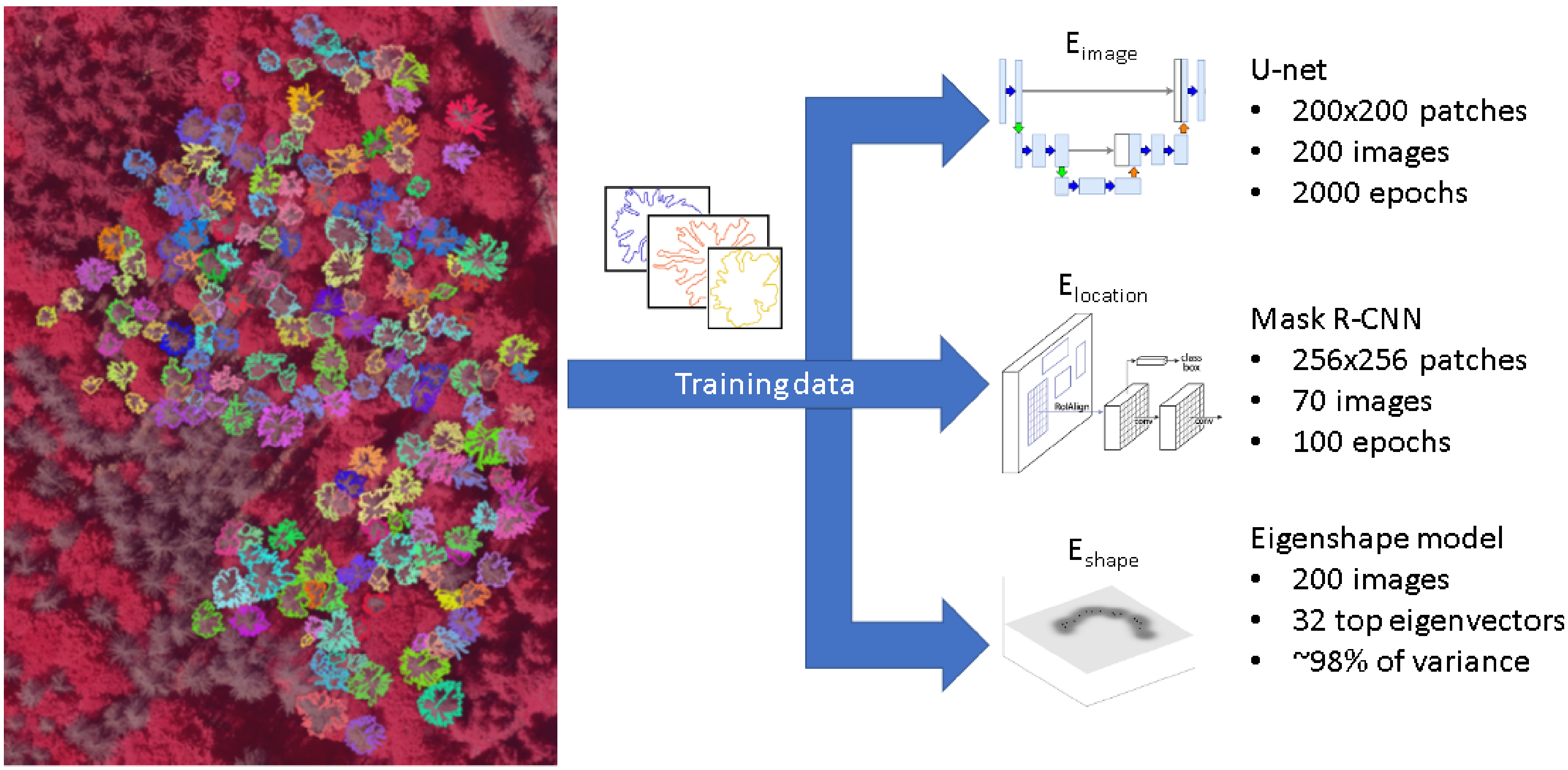
Experiments - Data: labels for training data





- Labeled 201 individual tree crown polygons for training area

Experiments - Training of the models



Experiments - Setting and evaluation metrics

Setting

- Data: $N = 750$ contours from test area in Bavarian National Forest
- Goal: experiment to compare polygons learned by **(1) Mask R-CNN** against contours refined by our active **(2) multi-contour model**
- Evaluation: both pixel level and object level of detected vs. reference polygons

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Setting

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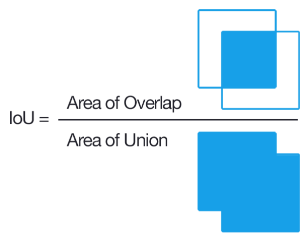
Metrics

- Pixel level:

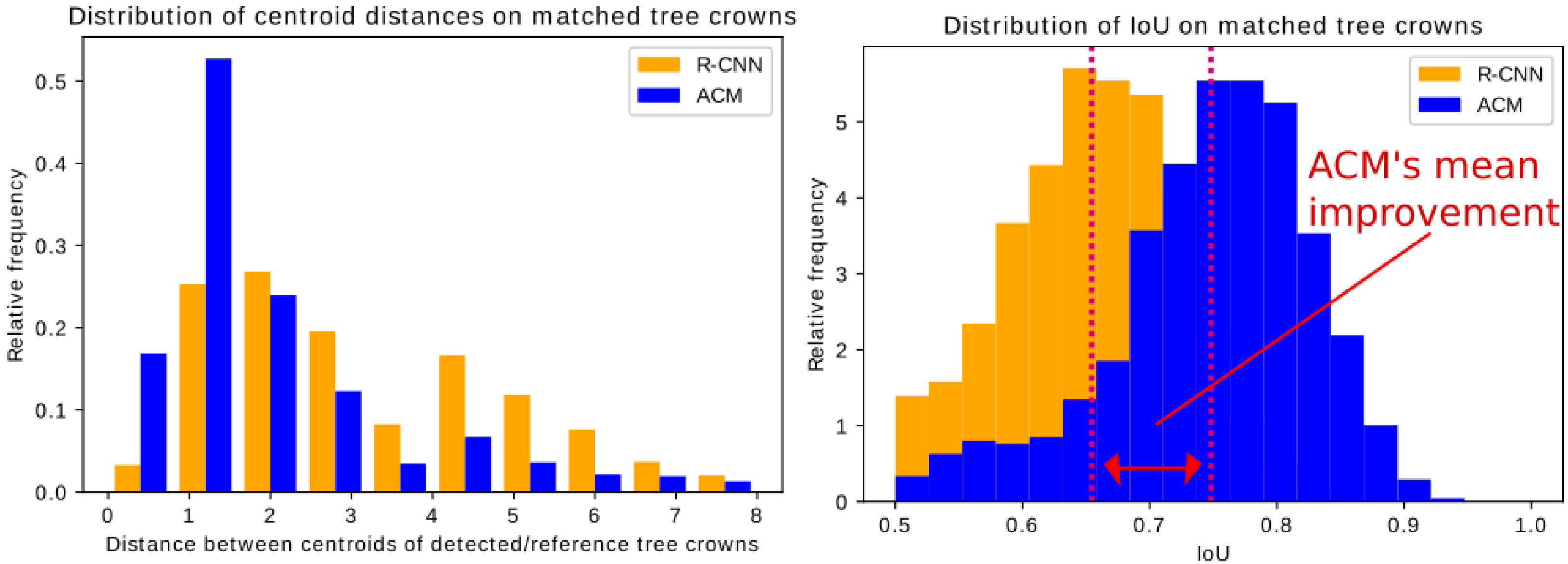


$\rightarrow$ intersection over union (IoU):
ratio intersection area to union area of compared shapes:
$IoU(A, B) = \frac{|A \cap B|}{|A \cup B|}$

- Object level:
  - mean distance between centroids of reference & detected polygons at $IoU \geq 0.5$
  - precision and recall at $IoU \geq 0.5$:

$$\text{precision} = \frac{\#\text{matched polygons}}{\#\text{detected polygons}} \qquad \text{recall} = \frac{\#\text{matched polygons}}{\#\text{reference polygons}}$$

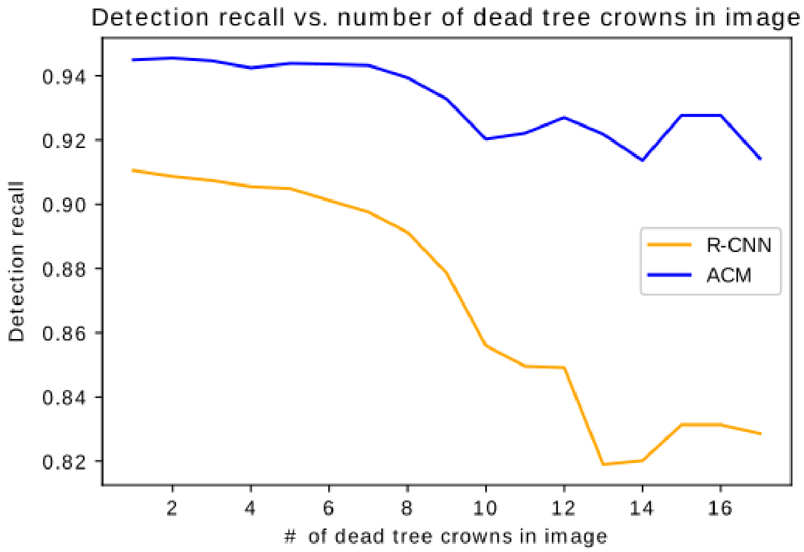
Experiments - Results: centroid distance and IoU

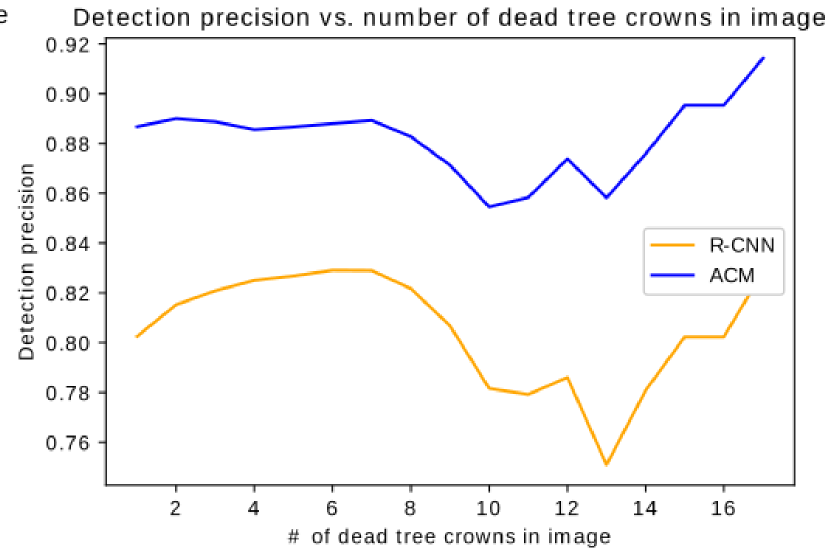


Shown: our active contour model (ACM) outperforms Mask R-CNN both in terms of identifying tree crown centers and discerning overlapping tree crowns

→ increased mean reference and detected centroid distance from 3.4 to 2.4 pixels (left)
→ increased mean matched IoU from 0.66 to 0.75 (right)

Experiments - Results: object-level precision and recall



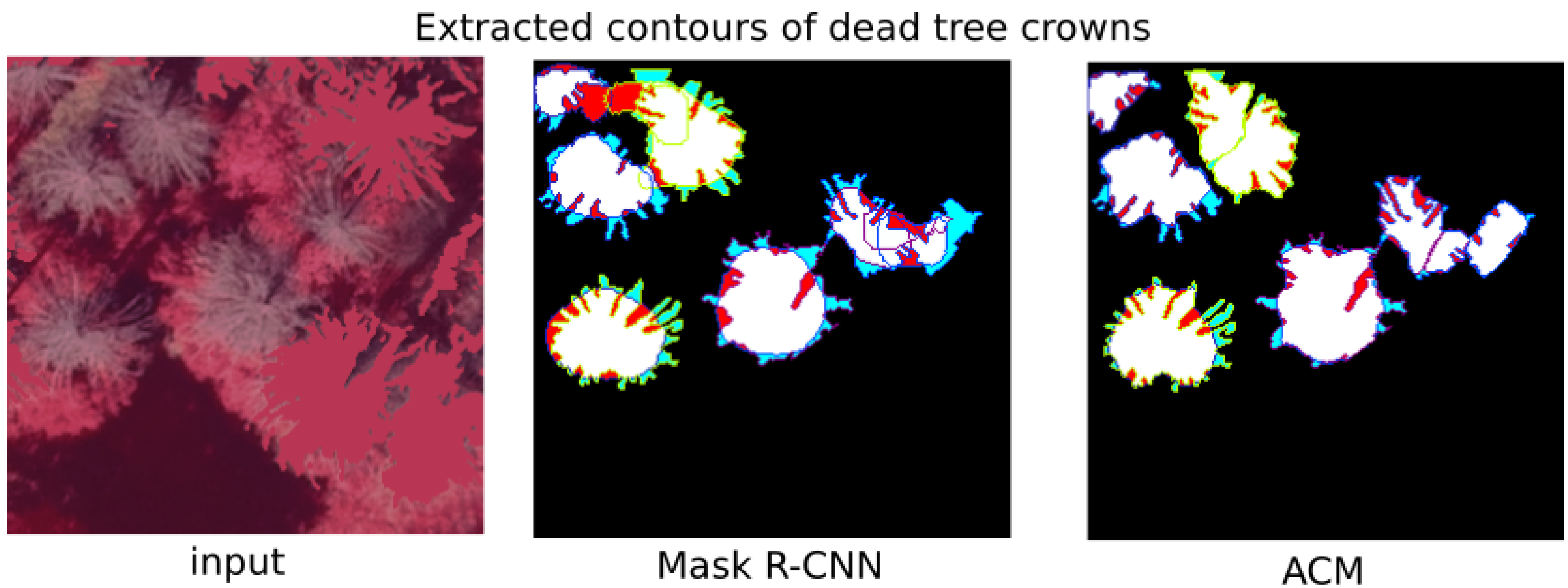


Shown: our active contour model (ACM) outperforms Mask R-CNN when shown *any* # of tree crowns

→ increased recall by 3.5 perentage points (left)
→ inreased precision by 8 percentage points (right)

Note: in images with **many** adjacent tree crowns → active contour model (ACM) can handle complex overlapping objects **far better** than Mask R-CNN

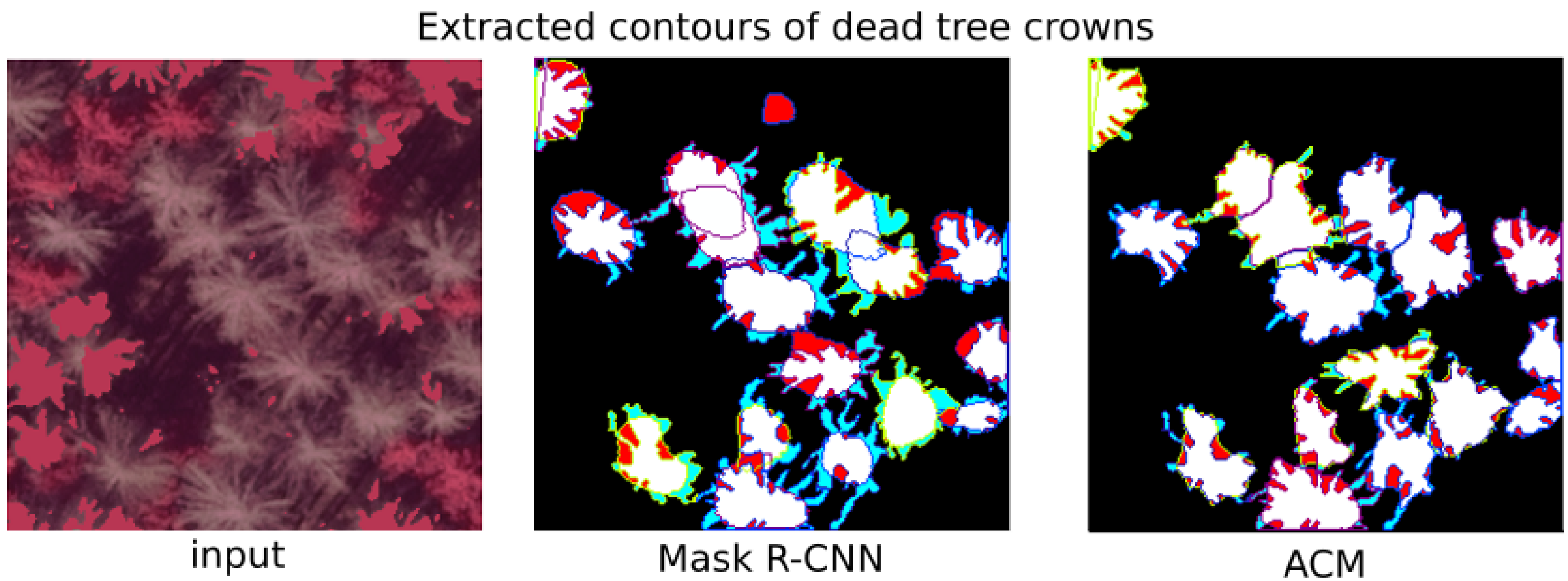
Experiments - Results: extracted contours



Shown: tree contours extracted from a CIR input image by our active contour model (ACM) are more refined and visually match the true contours than Mask R-CNN

→ Correctly identified tree crown pixels are shown in white
→ False positives are shown in red
→ False negatives are shown in cyan

Experiments - Results: extracted contours



Shown: tree contours extracted from a CIR input image by our active contour model (ACM) are more refined and visually match the true contours than Mask R-CNN

→ Correctly identified tree crown pixels are shown in white
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To **summer**-ize...

- Dead wood sequesters 8% of global forest carbon, houses $\frac{1}{3}$ of forests biodiversity, and is a **key indicator of overall forest health** ... but good wood models necessary/lacking

- This work:
  - Combines deep learning and instance segmentation
  - Leverages prior knowledge of crown shape and appearance
  - Constructs comprehensive energy functional for **multiple, overlapping contours**

$\rightarrow$ **Our approach discovers improved, localized and refined contours of dead trees**

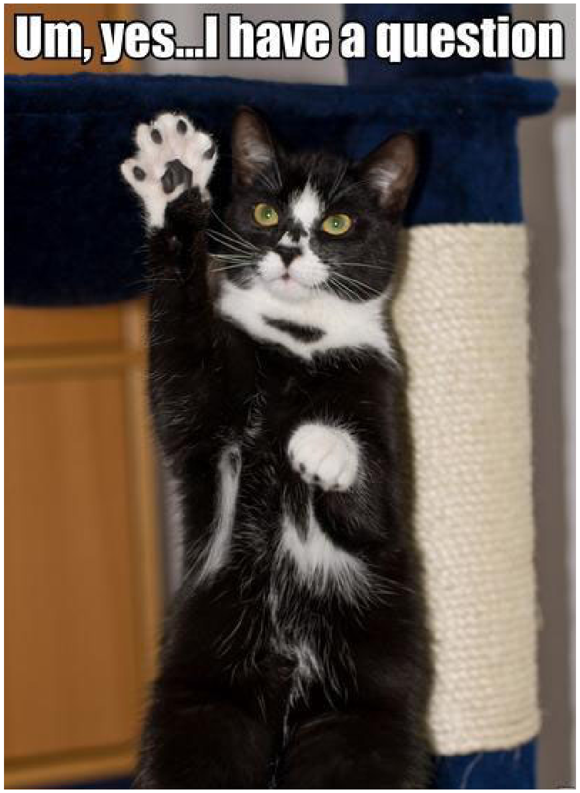
Outlook

Future/current work:

- **Goals (always):** efficient, robust, scalable ML methods, critical to:
  $\rightarrow$ Exploit modern remote sensing data – cheaper, higher quality, larger quantity, freely available
  $\rightarrow$ Better understand biodiversity and the role of dead wood, and impacts of climate
- **Change detection:** high quality contour delineation improves estimates of dead wood
  $\rightarrow$ Model of decay dynamics, tree type and tree counts
- **Advanced priors:** replace vanilla eigenshape prior with GAN generated shapes
  $\Rightarrow$ **preliminary results show contour improvements**
- **Sparsity and approximations:** GANs to develop contours using only pixels on the outline $\rightarrow$ save computational resources

Thanks for your attention!

Questions, feedback, suggestions, cats, ideas, musings?
Very eager for all of the above!



Obligitory morbid satire...

Where is Wiley going!?

"We have built a civilization based on a world that doesn't exist anymore."

– Katharine Hayhoe, climate scientist at Texas Tech University and chief scientist at the Nature Conservancy

Appendix - References

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