A hybrid convolutional neural network/active contour approach to segmenting dead trees in aerial imagery

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Tackling Climate Change with Machine Learning

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Climate Change AI

THE HONG KONG POLYTECHNIC UNIVERSITY 香港理工大學

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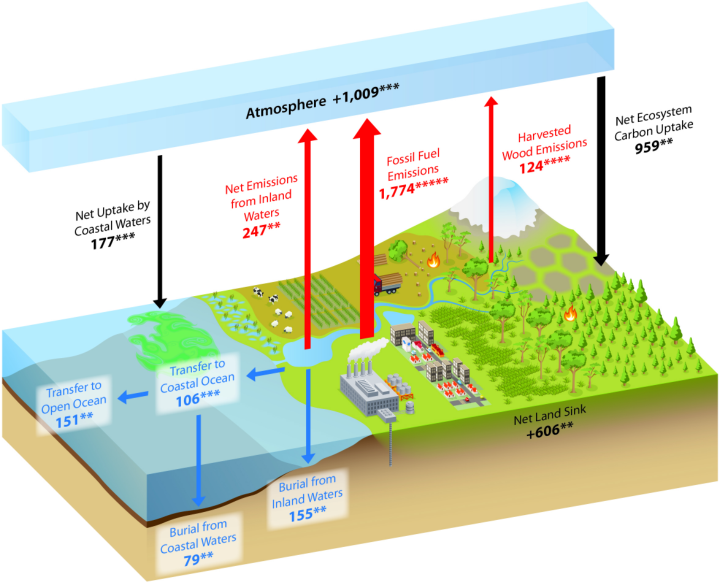
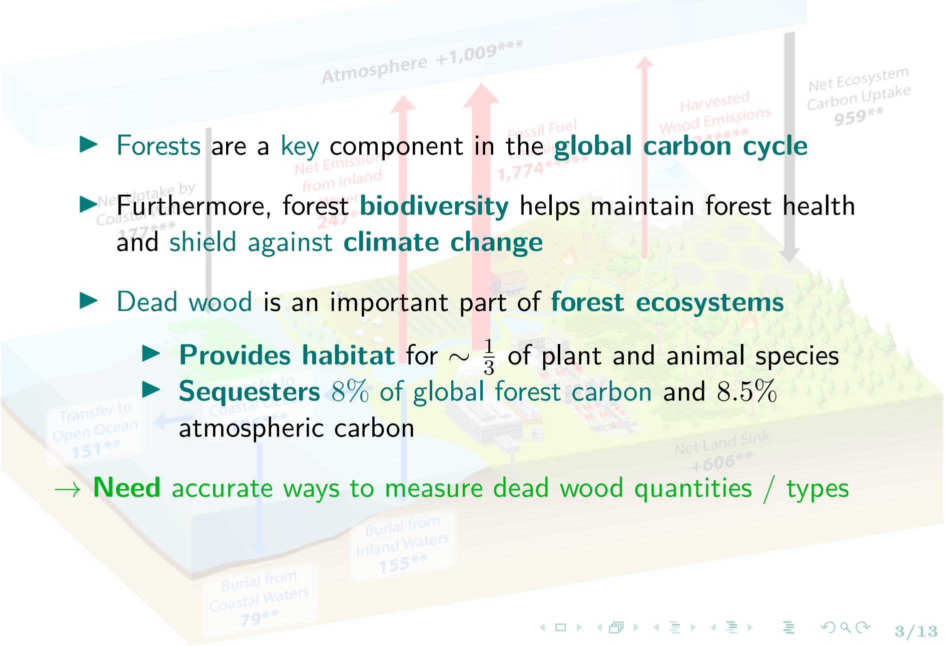
The Carbon Cycle



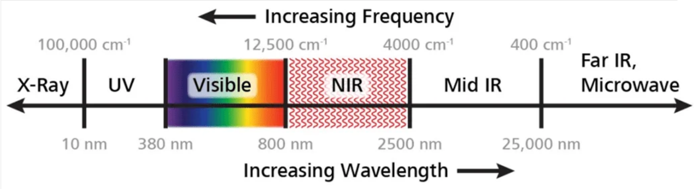
Why Dead Trees?



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

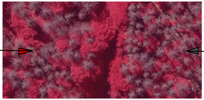
$\rightarrow$ **Need** accurate ways to measure dead wood quantities / types

Data - Color infrared imagery (CIR)



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

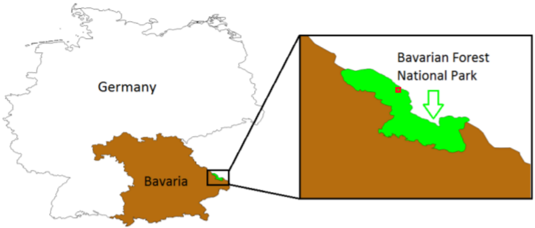
live

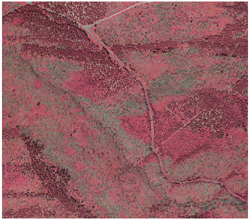


dead

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

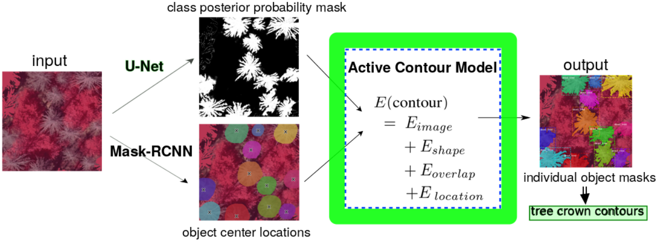
Data - Bavarian Forest National Park





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

Approach - Build an energy model!

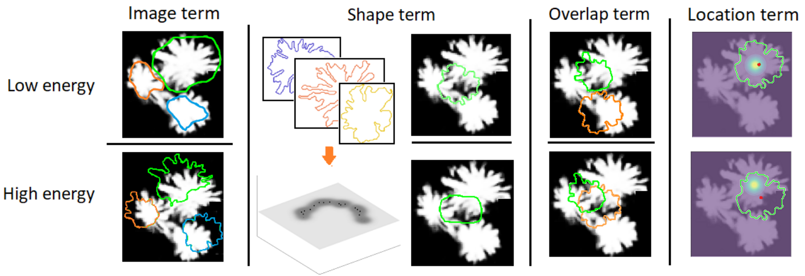


- First, let's break the problem down into basic components
- Next, recognize we can employ state-of-the-art deep learning methods to form the building blocks of our approach
- Combine these methods to formulate a multi-term **energy model** for refined contour segmentation

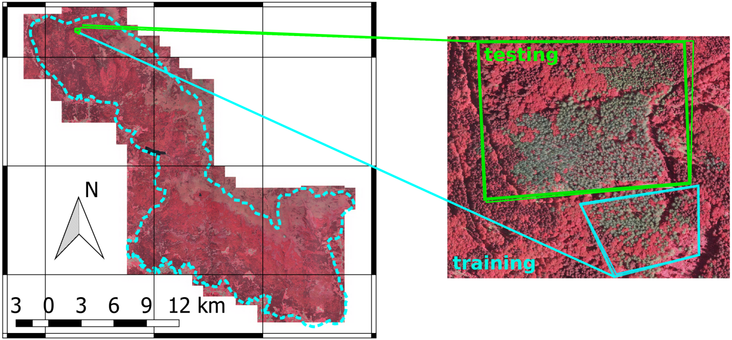
Approach – Put all the pieces together

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

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



Experiments - Data: train and test areas



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

training $= 201$ and testing $= 750$

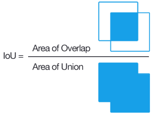
Experiments – Setting and evaluation metrics

Computational experiment

- $N = 750$ contours from the test area in the Bavarian National Forest used as the basis
- Comparison: the polygons discovered by **Mask R-CNN** against contours refined by our active **multi-contour model** (ACM henceforth)
- Evaluation: both pixel level and object level of detected vs. reference polygons

Metrics for comparison

- Pixel level:



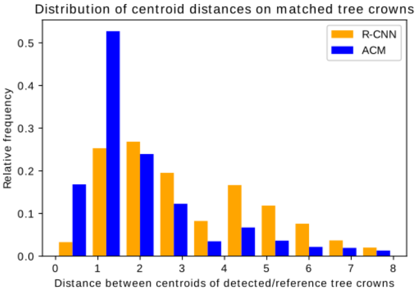
$\rightarrow$ intersection over union (IoU):
ratio intersection area to union area of compared shapes:

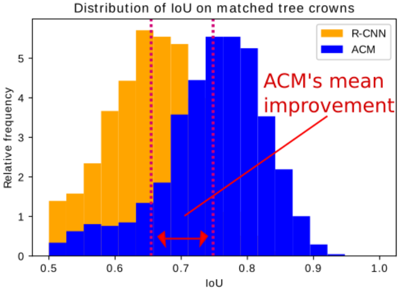
$$IoU(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

- 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

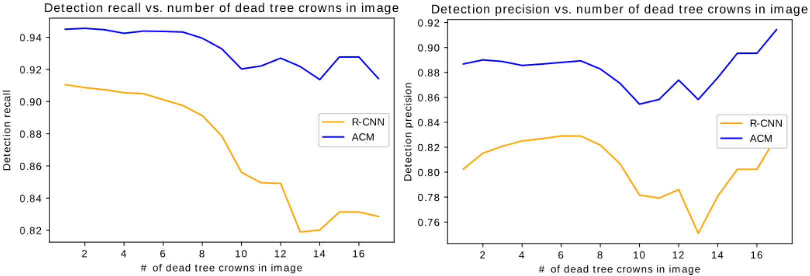




Shown: our active contour model (ACM) outperforms Mask R-CNN both in terms of identifying tree crown centers and discerning overlapping tree crowns

→ 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

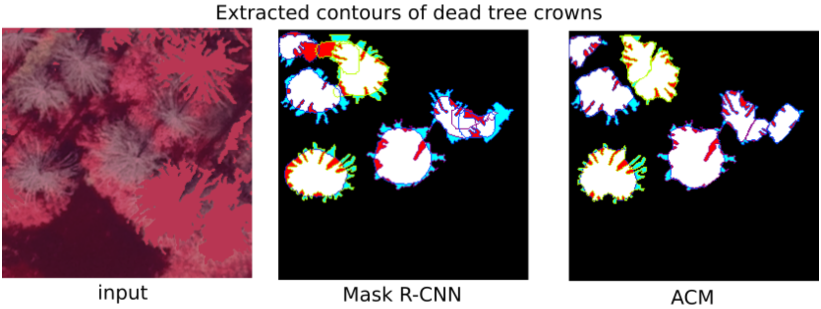


Shown: our active contour model (ACM) outperforms Mask R-CNN when shown *any* # of tree crowns

→ 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 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

Summary

To **summer**-ize...

- Dead wood comprises 8% of global forest carbon but better wood models necessary/lacking
- Our approach: combines neural networks and instance segmentation
  - Leverages prior knowledge of crown shape and appearance to construct comprehensive energy functional
  $\rightarrow$ **Discovers improved and refined contours of dead trees**
- Goals: efficient, robust, scalable ML methods, critical to:
  - Exploit modern remote sensing data – cheaper, higher quality, larger quantity, freely available
  - Better understand biodiversity and the role of dead wood and impacts of the climate