Countering wildfire risk with AI-enabled sensor platforms

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Motivation

- **Climate change** is expected to **intensify wildfire risk**
- **Forestry machinery** cause **200–500 wildfires annually** in Sweden
- Existing **ignition risk maps** are too coarse and lack precision

The fire safety challenge in forestry

- **Sparks from stones and boulders** can ignite dry fuels
  - Especially on **clear-cuts**, during forwarding and site preparation
- **Fine-fuel moisture** is a critical factor for ignition risk
- **Operating bans in dry weather** protect against fire but create a **tension between safety and economic loss**

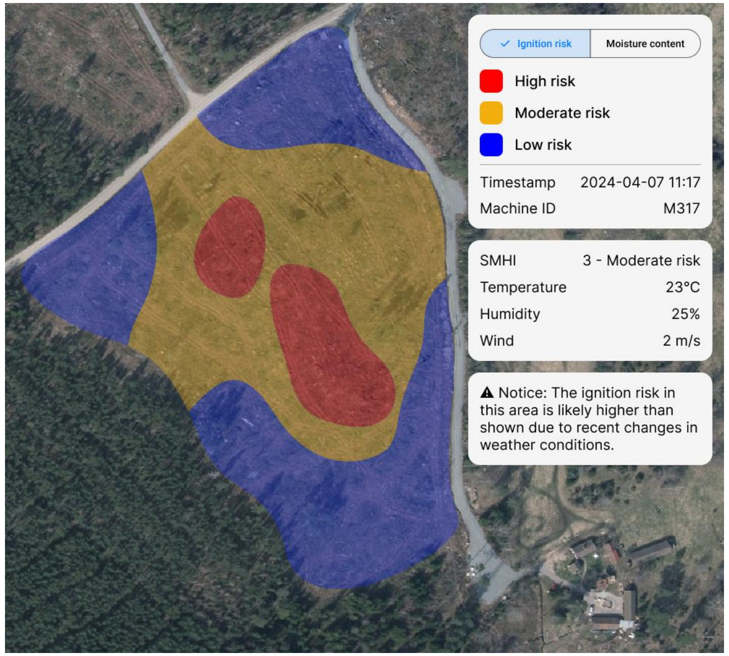
Opportunity – AI-enabled sensor platforms

Prevention → Preparedness → Response → Recovery

- **Onboard perception & risk assessment**
  - Forestry machines sense their environment and evaluate risk as they operate
- **Dynamic ignition risk maps**
  - Generated in real time, with high resolution
- **From bans to safe operations**
  - Shift from shutting down work in dry conditions to enabling informed, safe activity

Sensor platform mounted on a forwarder for ignition risk detection

Opportunity – Site-specific risk maps and overlays

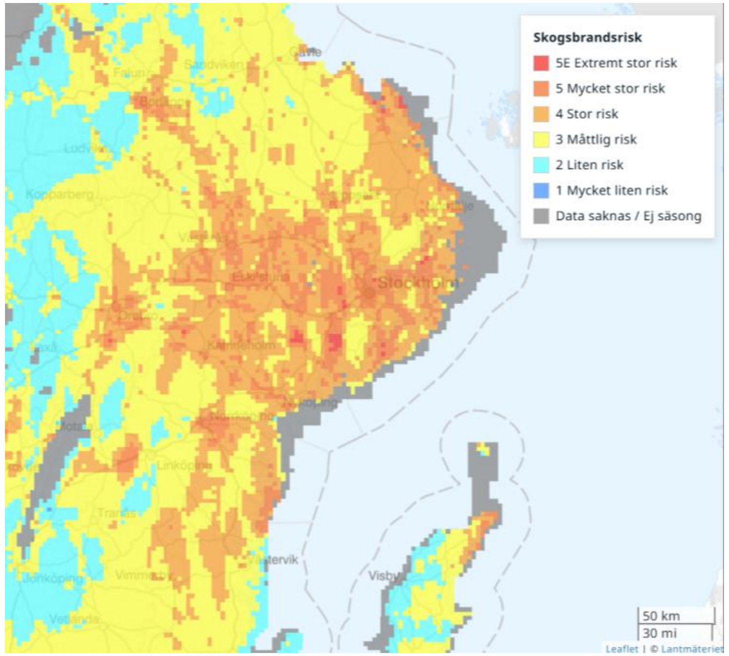


Site-specific risk map

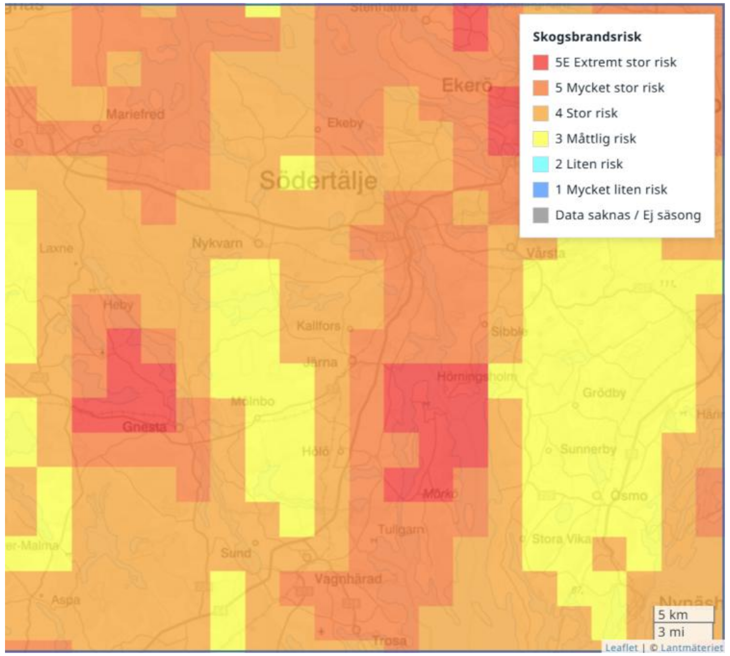
Overlay for machine operators

Overlay for machine operators

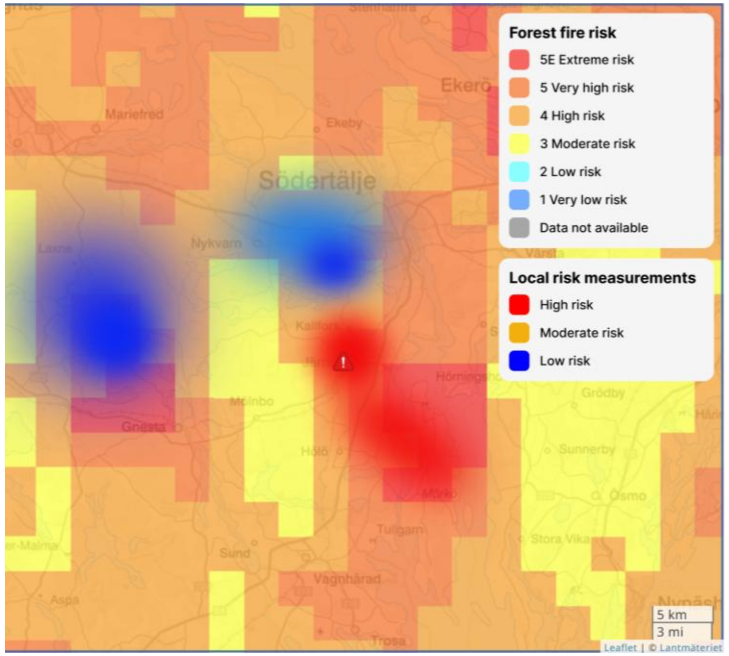
Opportunity – Integration with existing risk maps



Current coarse risk map

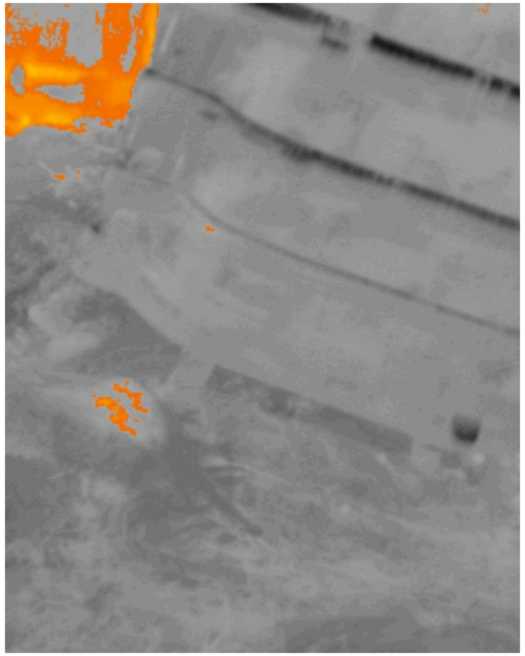


Current coarse risk map

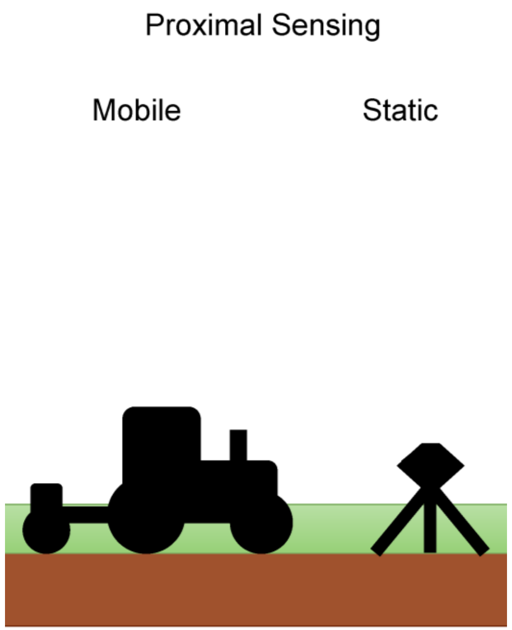


Current coarse risk map with local information overlay

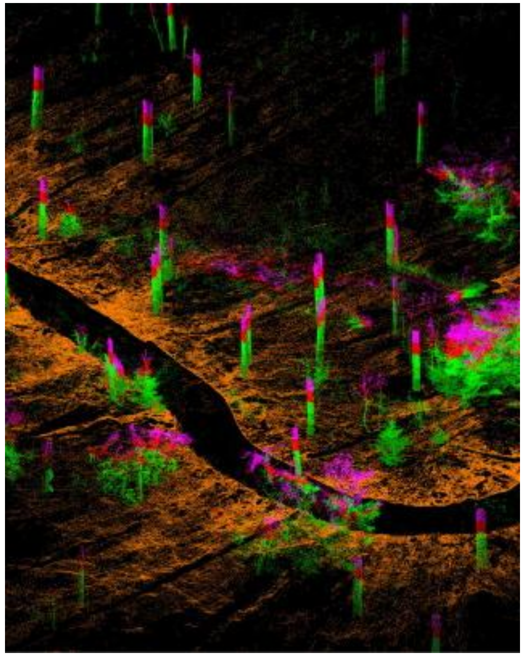
Challenges



How are sparks generated?



Proximal sensing



SLAM

Image segmentation

Understanding ignition risk in the field

Sparks and their behavior

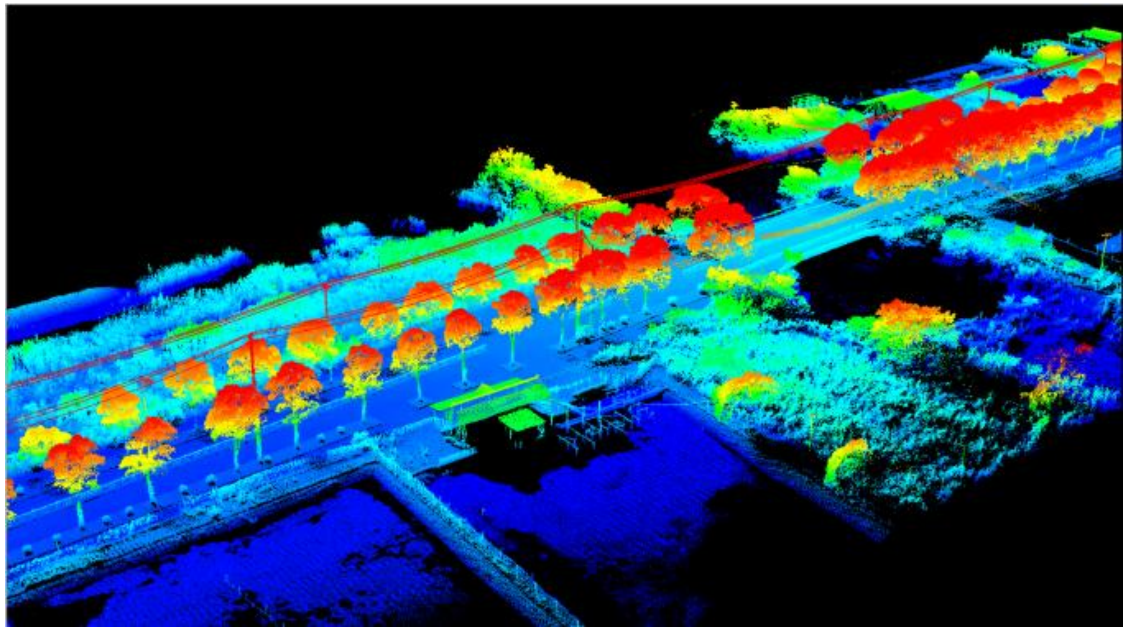
- How are sparks generated during forestry operations?
- How far can they travel before extinguishing or igniting fine fuels?
- How is spark generation affected by driving behavior?
- Largely unstudied, but central to real-world ignition risk

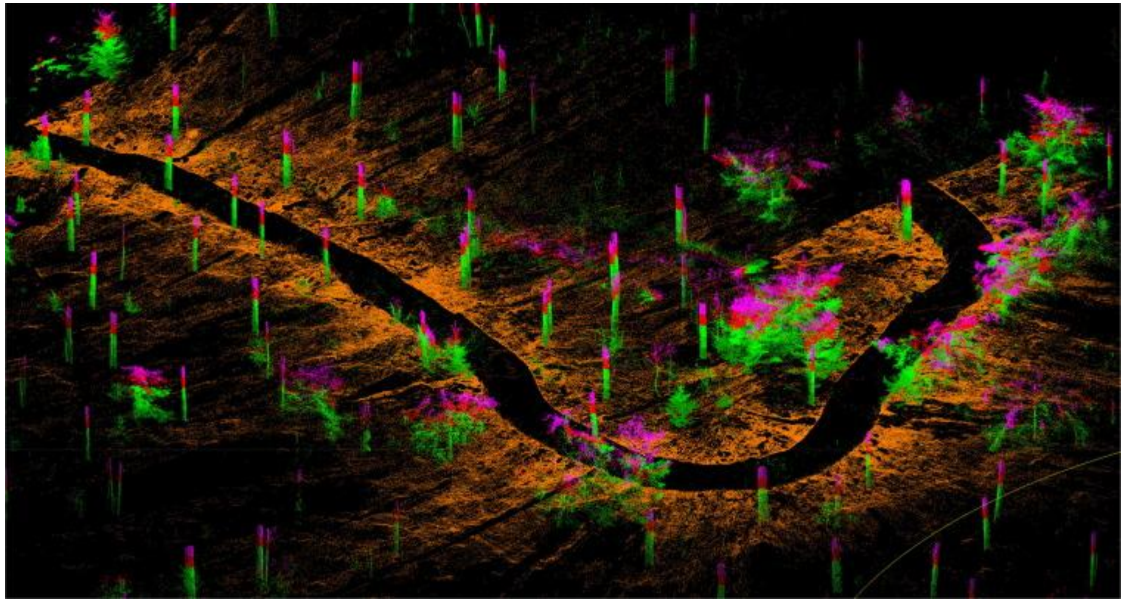
Moisture in fine fuels

- Fine-fuel moisture drives ignition probability
- Local variation often missed in coarse-resolution weather/fire maps
- Need reliable proximal sensing approaches
  - LiDAR and/or RADAR are typically used for proximal sensing of moisture content in other fields

SLAM – state-of-the-art

- **Urban & structured environments**
  - Most SLAM advances target cars/robots in cities or indoors
- **Main challenge: dynamic objects**
  - Cars, pedestrians → filtering moving agents from point clouds
- **Use of additional odometry sensors**
  - Wheels, IMUs, GNSS → help stabilize pose estimation
  - Less effective in forestry (wheel slip, articulated steering)
- **Different algorithmic approaches**
  - Direct point-based (e.g., ICP variants)
  - **Feature-based** (e.g., LOAM, MULLS)
  - Learning-based (e.g., CAE-LO, TransLO)



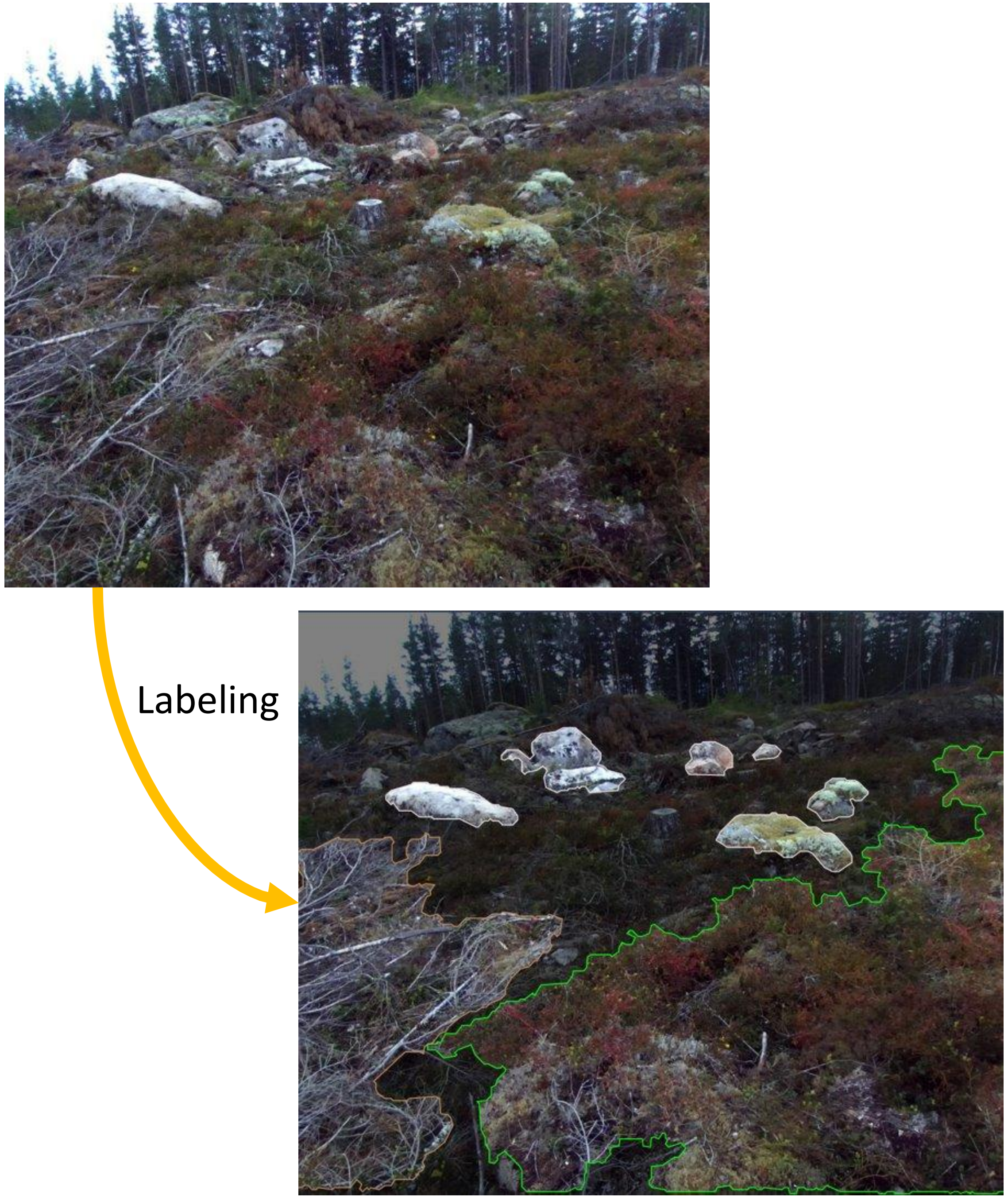


SLAM – Limitations in forestry

- **Unstructured & cluttered terrain**
  - Few stable features, vegetation clutter
- **Poor sensor reliability**
  - Wheel odometry, IMUs unreliable in forestry due to slip, articulated steering, vibrations, etc.
- **Limited benchmarks**
  - No datasets from clear-cuts to enable fair comparison
- **Different algorithmic approaches**
  - **Direct point-based** (e.g., ICP variants)
  - Feature-based (e.g., LOAM, MULLS)
  - Learning-based (e.g., CAE-LO, TransLO)

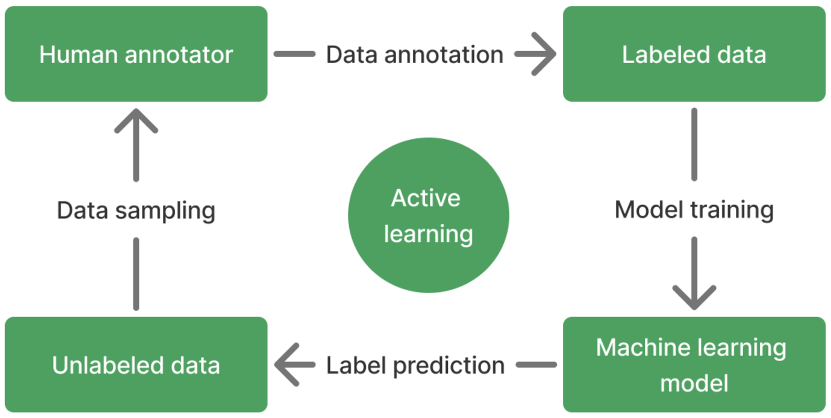
The labeling bottleneck

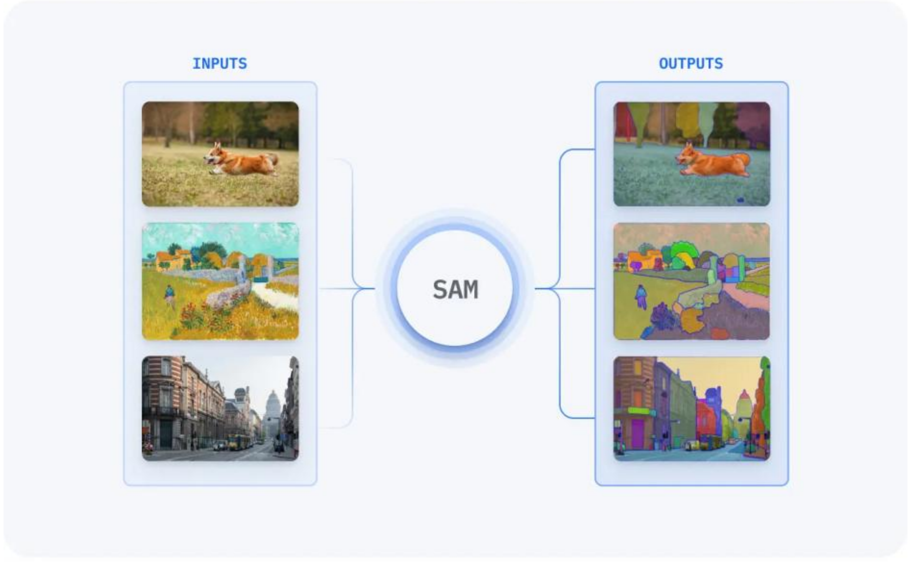
- Modern vision models (YOLO, ViTs) need **large labeled datasets** (COCO, KITTI, Cityscapes)
- Labels are mostly **manual/crowdsourced** → feasible in **well-funded** domains (e.g., autonomous driving)
- But this process is **expensive & slow** → smaller markets (e.g., forestry) left behind

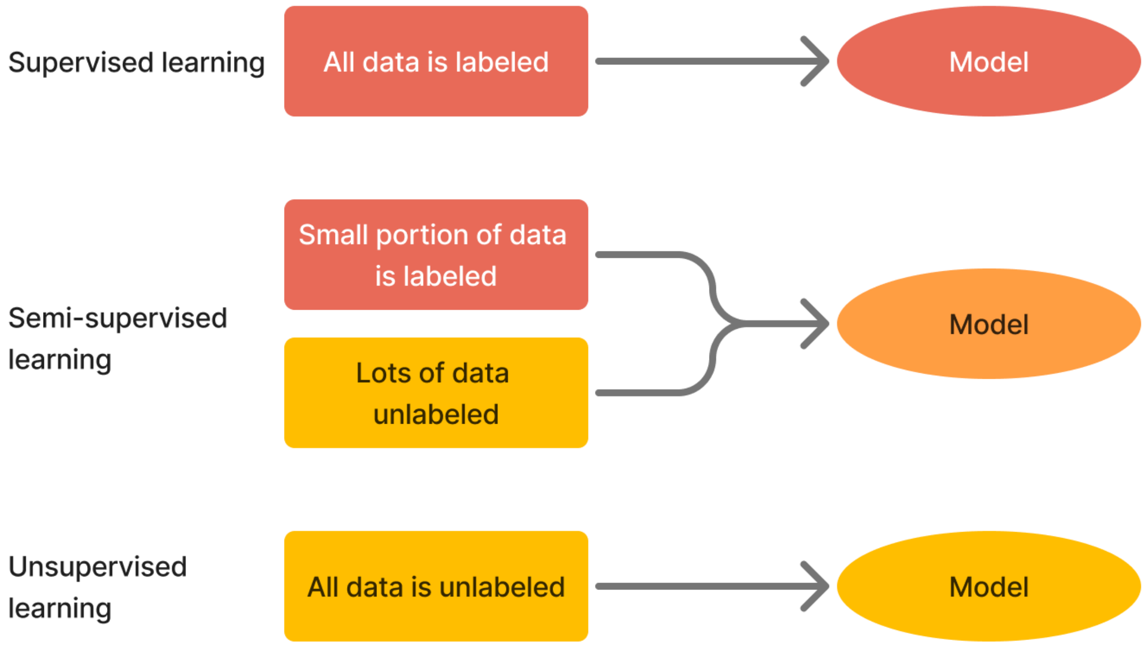


Current ways to reduce labeling cost

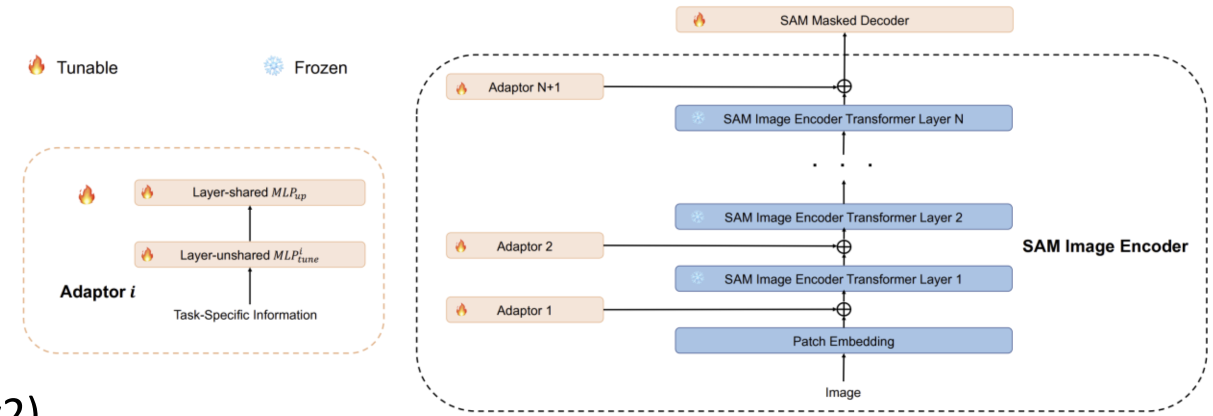
- Crowdsourcing
- Active learning
- Synthetic data generation
- Semi-supervised learning
- Foundational models (e.g., SAM)
    - Can these be exploited further?







Proposed labeling pipeline



- **Leverage large foundational models**
  - Use pre-trained vision models (e.g., SAM, CLIP, DINOv2)
- **Task-specific adaptation**
  - Train small **adapters** on a small set of labeled examples
  - Foundation model → domain alignment
  - Apply to forestry images → generate candidate segmentations
- **Efficient dataset labeling**
  - Cluster the auto-segmentations into consistent categories (stones, vegetation, soil)
  - Human input only for **cluster naming / verification**
- **Deployment strategy**
  - Foundation models used **only in training pipeline**
  - Final real-time system based on lightweight models trained on the generated labeled dataset

Summary: A smarter approach to wildfire prevention

- **The Problem:** Forestry machinery ignites 200-500 wildfires yearly in Sweden, but existing risk maps are too coarse for effective prevention
- **Our Solution:** Onboard AI-enabled sensor platforms create dynamic, high-resolution fire risk maps in real time
- **Methodology:** Our work tackles four central challenges for this domain:
  - Understanding ignition
  - Proximal sensing of fine-fuel moisture
  - SLAM on clear-cuts areas
  - Data labeling bottleneck

From perception to prevention

Prevention | Preparedness | Response | Recovery

- **Today:** We largely have the components in place needed to create a risk assessment system
- **Next steps:** Integrate robust perception, SLAM, and real-time risk assessment into a single, trustworthy system for forestry operations
- **Long-term goal:** Shift the industry from reactive operating bans to proactive, safe operations based on real-time, site-specific data

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