FLANDERS MAKE

DRIVING INNOVATION IN MANUFACTURING

Counting strawberry flowers on drone images with artificial intelligence

Webinar EUKA / Flanders Make

Rob Heylen, 14 Dec 2020

VLAIO Proeftuin “Drones in de bouw en landbouw”

AGENTSCHAP INNOVEREN & ONDERNEMEN

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KENNIS. INNOVATIE. TOEKOMST

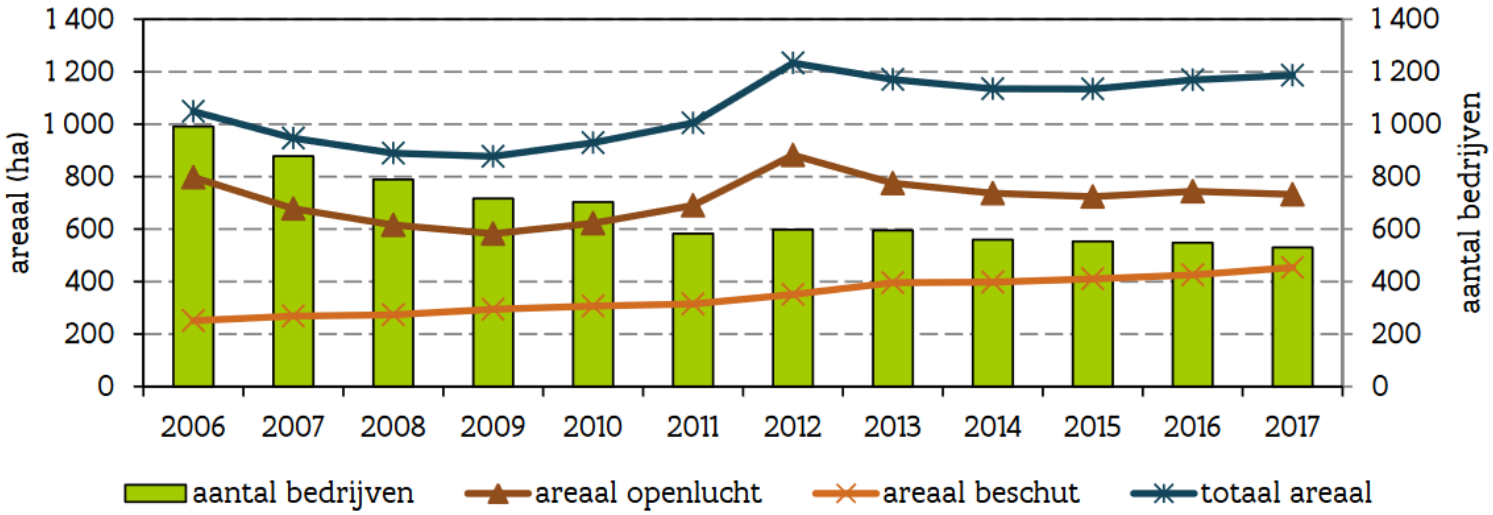
Strawberry cultivation in Flanders

Strawberry cultivation is an important economical activity in Flanders:

- 50.000 metric tons per year
- 150-million-euro revenue
- 530 companies
- 1180 hectare

DEPARTEMENT LANDBOUW & VISSERIJ

Figuur 1: areaal aardbeien en aantal bedrijven met aardbeienproductie in Vlaanderen.



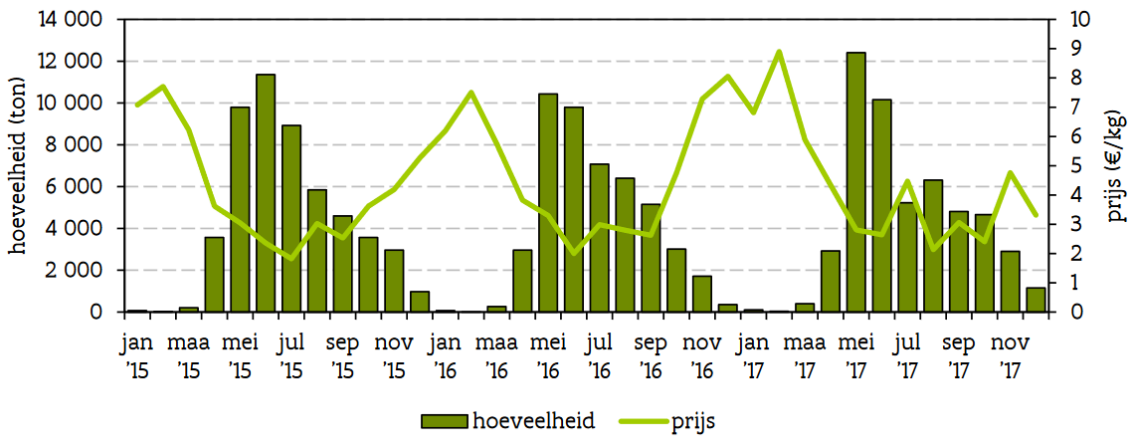
Bron: Statbel (Algemene Directie Statistiek - Statistics Belgium). De knik in 2012 kan verklaard worden door een verandering van databron door Statbel (Algemene Directie Statistiek – Statistics Belgium).

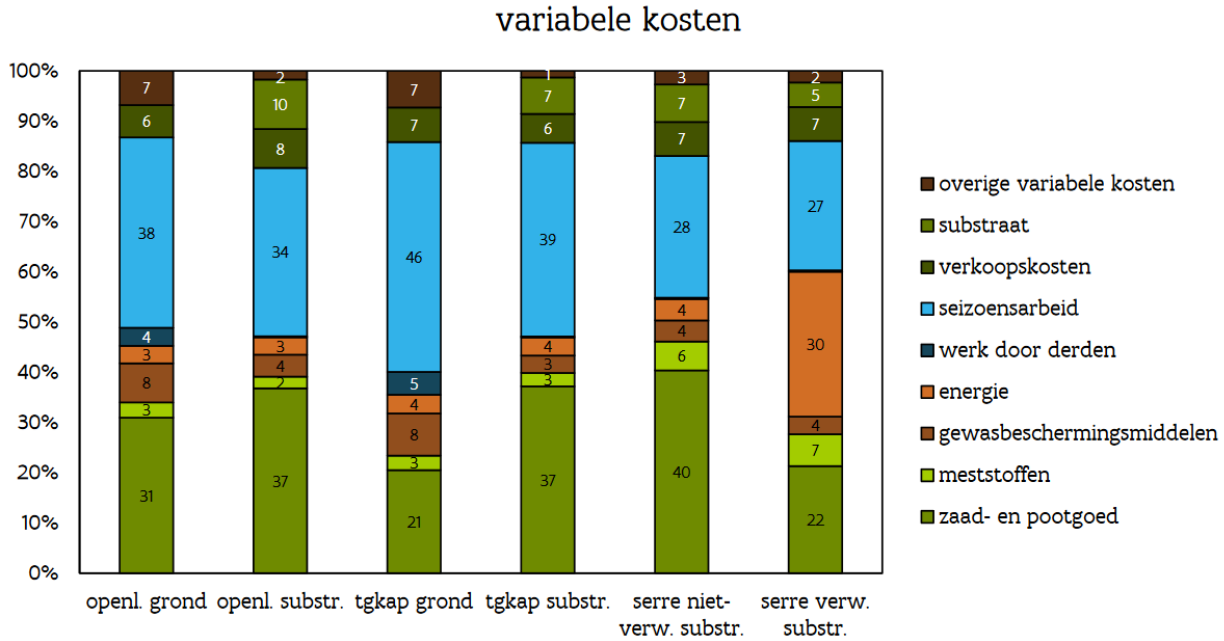
De Samber J. (2019) Aardbeienteelt in Vlaanderen. Resultaten uit het Landbouwmonitoringsnetwerk, Departement Landbouw en Visserij, Brussel.

Strawberry cultivation in Flanders

Strawberry cultivation is complex, diverse and intensive:

- Many strategies for cultivation and spreading of production in time
- Strong dependence on meteorological conditions, unpredictable yield that comes in waves
- Largest variable cost: Seasonal labor (up to 46% of total)
- Additional variable costs: logistics, storage, interests for risk spreading and investment.





De Samber J. (2019) Aardbeienteelt in Vlaanderen. Resultaten uit het Landbouwmonitoringsnetwerk, Departement Landbouw en Visserij, Brussel.

Yield prediction

Yield prediction is an important aspect in strawberry cultivation

Many factors can be considered for yield prediction: Ongoing research at **Proefcentrum Fruitteelt**

One good predictor: **the number of strawberry flowers**

- A strawberry flower will become a ripe fruit 3 weeks later
- Simple predictor, just requires counting flowers
- But also, some issues:
  - **Counting flowers is also labor intensive**
  - **Hard to extrapolate a count on a small plot to a large field**

Idea: Let's use **drones** and **image processing** to automate strawberry flower counting!

Yield prediction

Why drones?

- Fast
- Large areas at once (high altitude or many stitched images)
- Can be flown autonomously

Why image processing?

- Fast
- Accurate
- Automatic

EUKA
Vlaamse Drone Federatie

Approach

1. **Acquire** images. Optionally stitch images.
2. **Annotate** images to generate ground truth
3. **Train** a neural network to count flowers.
4. **Tune** for optimal results.

The trained network can then be used in practice.

Strawberry flower data acquisition

Data collection at pcfruit PROEFCENTRUM FRUITTEELT VZW by DIDEX DRONE IMAGERY & DATA EXPERT under different conditions:

Cloudy day

Open greenhouse

Sunny day

Strawberry flower data acquisition

Low-altitude images are stitched into large orthographic photos by provider

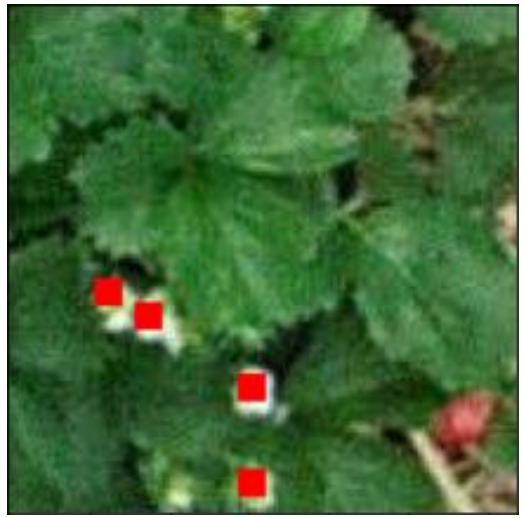
Rectified and stitched data set created with a DJI Mavic 2 pro drone flying at 10m altitude. Image is 3600 x 22500 pixels and contains 741 flowers.

Data annotation

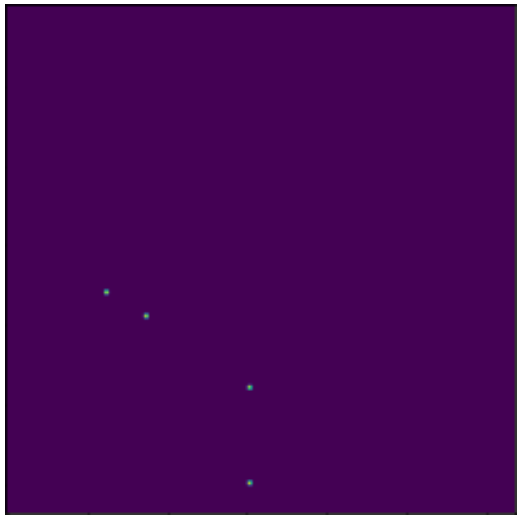
- AI learns from examples: We need to know where the flowers are in order to train it
- Go through the image and click on every flower: Point annotation
- Hundreds of annotated flowers in a full orthophoto
- Point annotations are not exact. Gaussian blur to turn points into density images

Part of the image

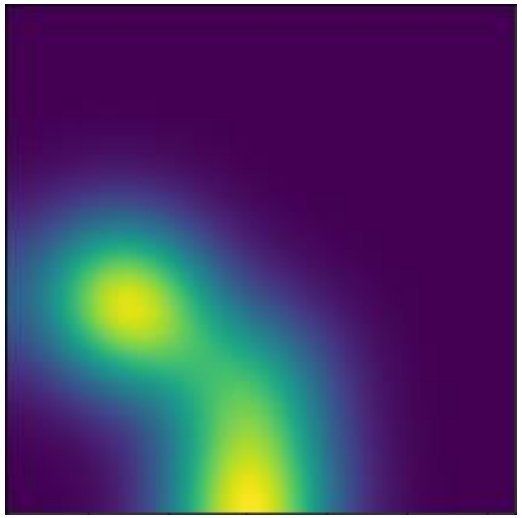
Annotated flowers



Logical image



Density image via Gaussian

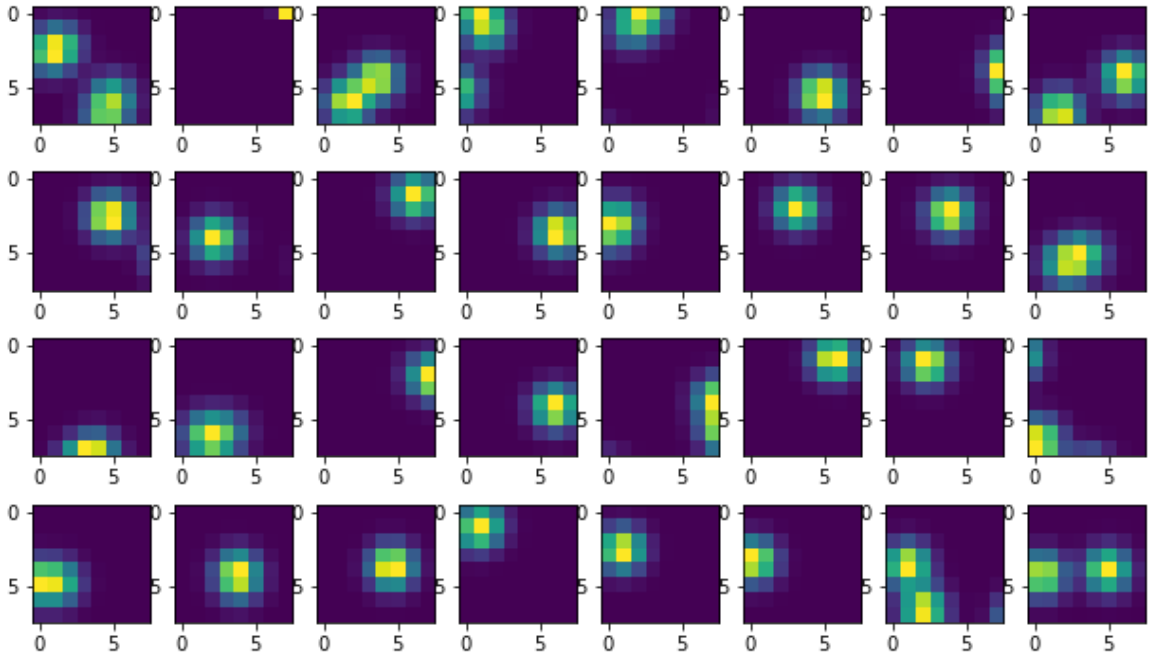


Data augmentation and generation

- More training data = better, but collection and annotation is expensive
- “Augmentation” allows us to increase the data set cheaply by applying easy transformations on the image: Rotation, scaling, flipping, adding noise, …
- Full image is too large. Cut it up in many small images and train on these.

Inputs

Outputs



Convolutional Neural Network

We use a **Convolutional neural network**, which belongs to the class of **Deep learning AI**

Why this type of network?

- A **LOT** of literature
- Proven performance (google, facebook, MS, amazon, …)
- Relatively easy to implement, adapt and tune

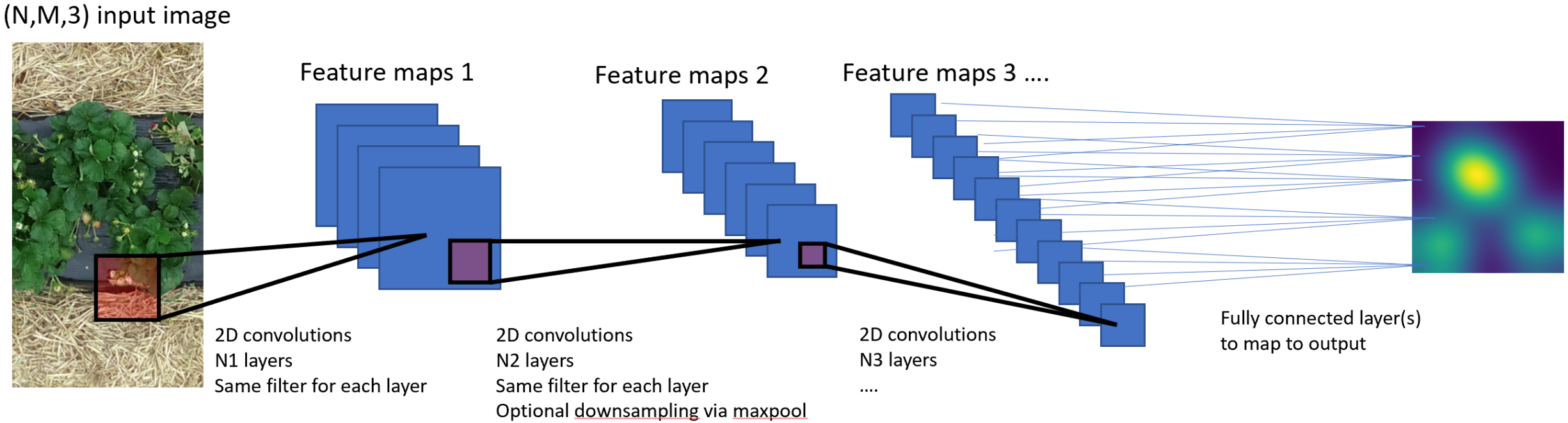
Alternatives possible? Yes, a lot, but this works well.

For more info: See literature, our papers or ask me!

XKCD.com

Convolutional Neural Network

We use a **Convolutional neural network**, which belongs to the class of **Deep learning AI**



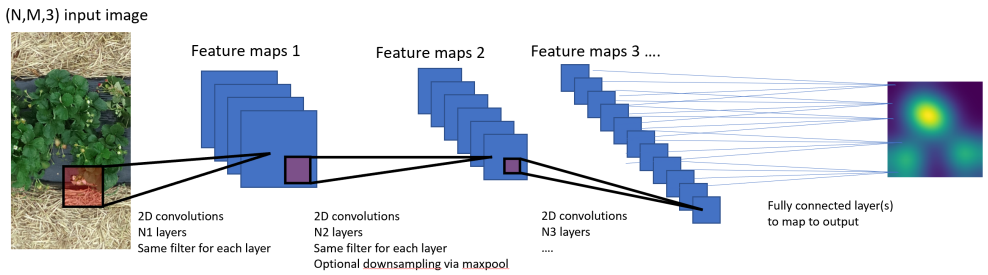
- Color RGB inputs get convolved with many local spatial filters
- The output serves as input for the next layer => convolution layers
- Downsampling via pooling (max over 2x2 regions), random dropout for stability
- Fully connected layer at the end to map to the output image
- Training by backpropagation, ADAM optimizer and L2 error function

Walach, Elad & Wolf, Lior. Learning to Count with CNN Boosting. Proc. ECCV 2016, pp. 660-676.

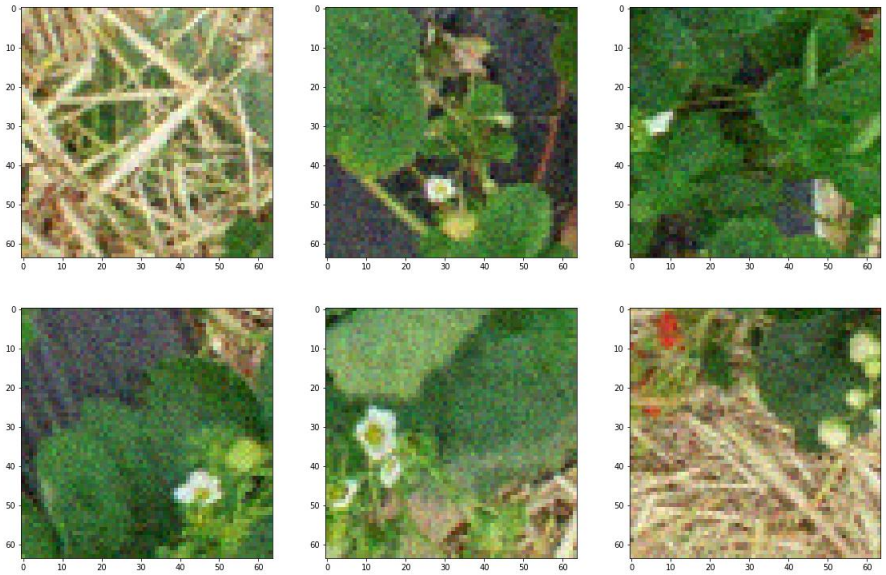
Karen Simonyan and Andrew Zisserman. Very Deep Convolutional Networks for Large-Scale Image Recognition, 2015. arXiv:1409.1556 [cs.CV]

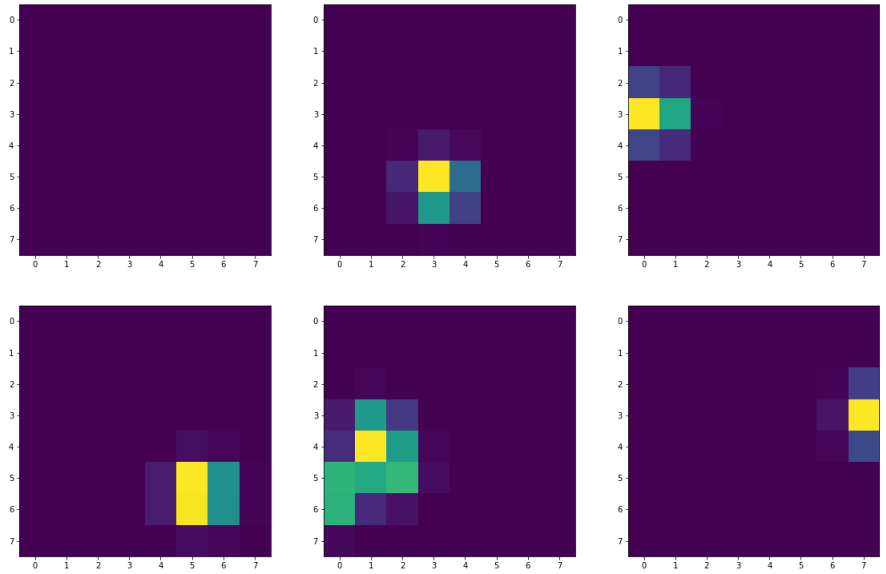
CNN strategy

- **Input**: image patches, augmented
- **Output**: Density image obtained by blurring and downsampling point annotations
- **Counting**: Integrate the density image



The network learns to **map images to flower densities**





Experiment: Train on a single orthophoto

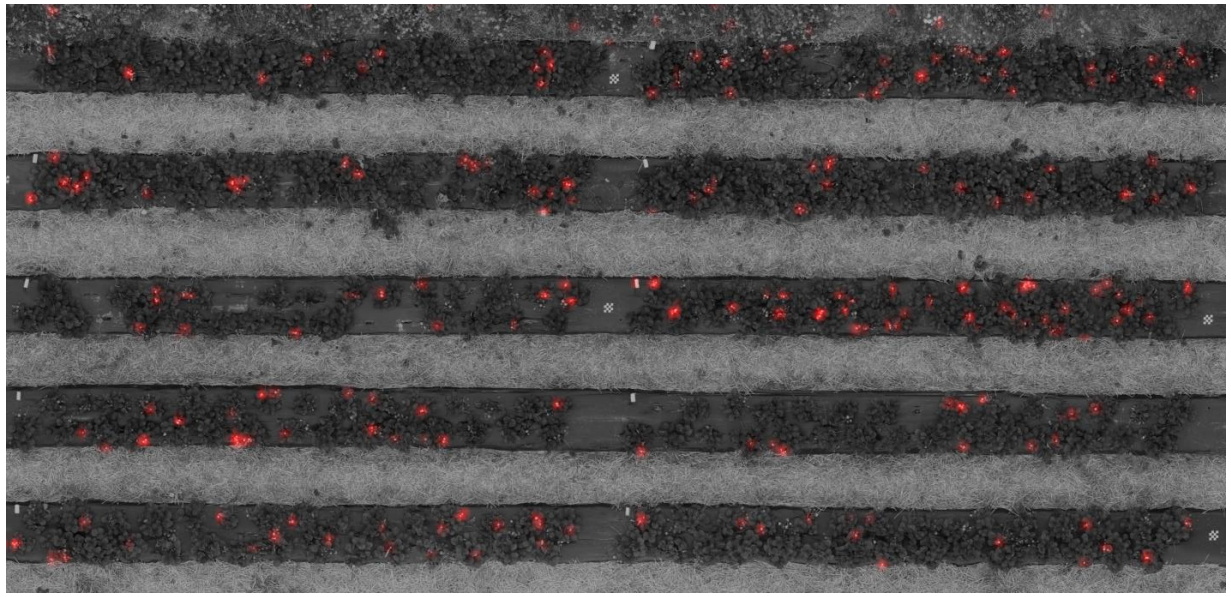
Training

Testing

Result on test image

Orthophoto

BW orthophoto
Flower density overlay in red

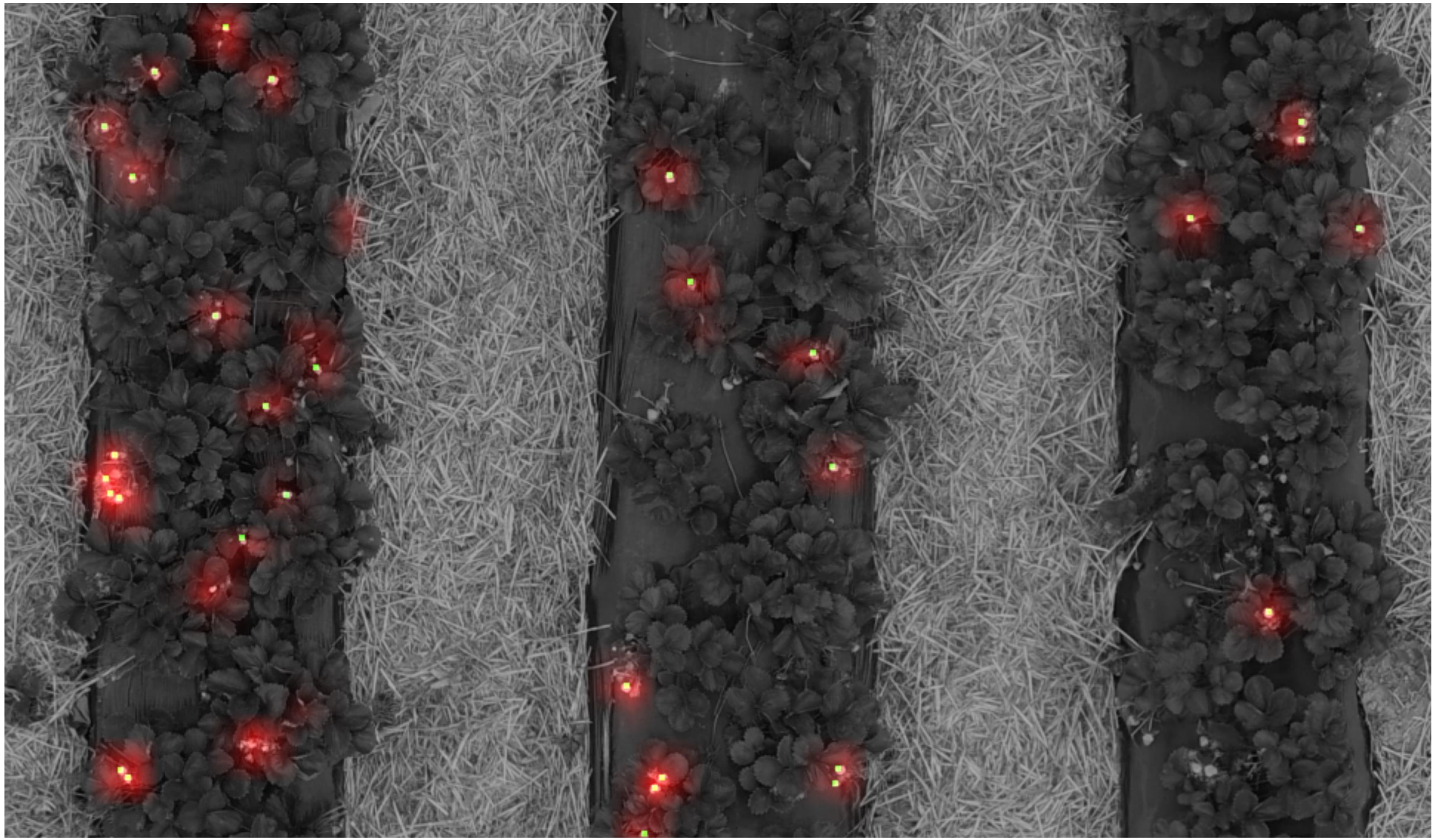


Full orthophoto: Zoomed selection

BW orthophoto

Flower density

Ground truth point annotation



Counting result and preliminary conclusions

Manual count:	**254**
Counted by neural network:	**267**

- AI method has a 5% deviation from manual count
- This in a region with a lot of confusion (other flowers, clutter, budding flowers, flowers sideways or upside down, green fruits with petals, …). Manual count has errors also…
- Training and testing on two parts of the same image, so conditions are similar
- Only visible flowers

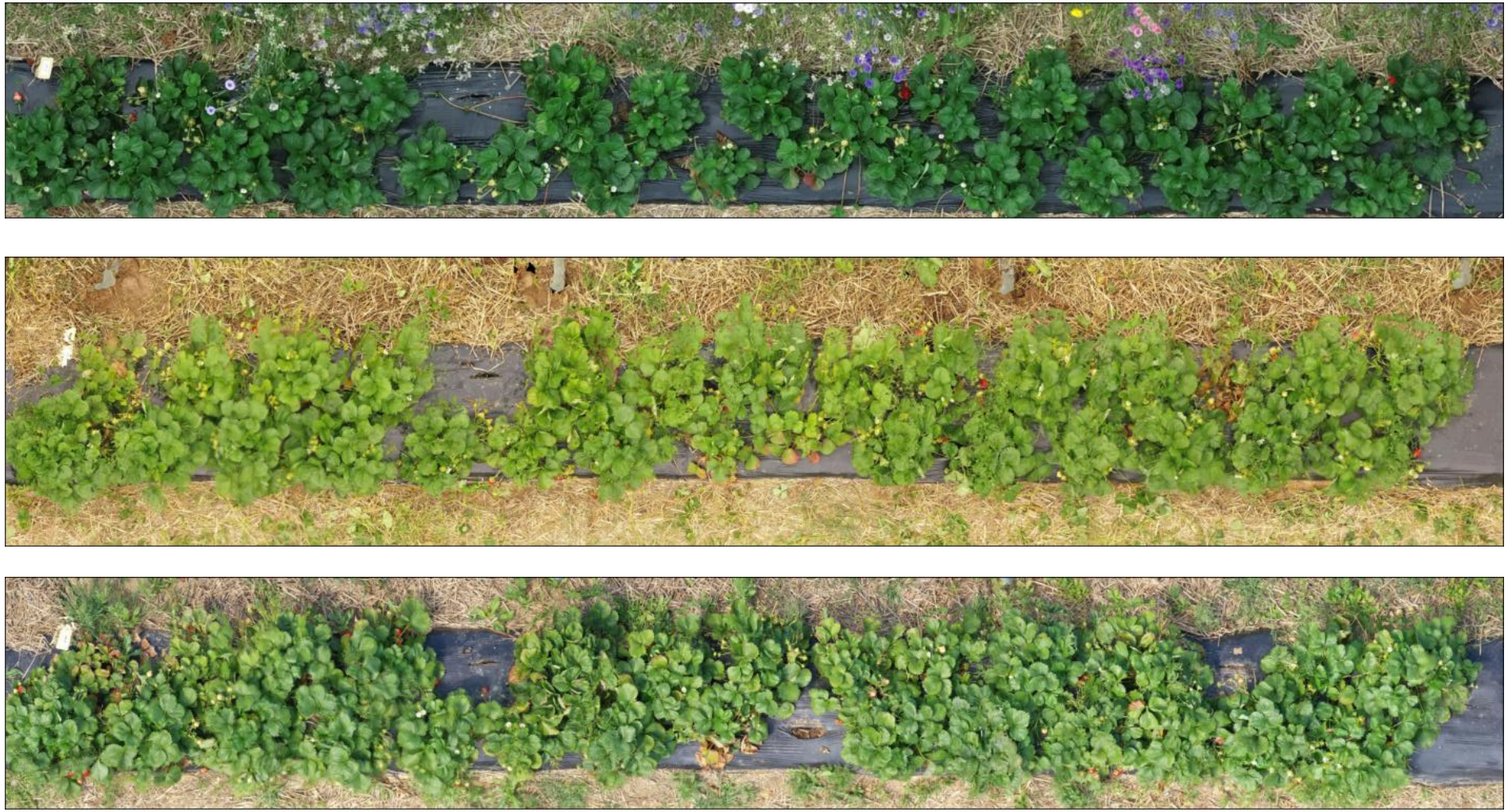
Part 2: Lessons learned

Several practical issues were encountered:

- Differences in imaging conditions can have a large effect
- Stitching can introduce errors
- Only visible flowers can be counted

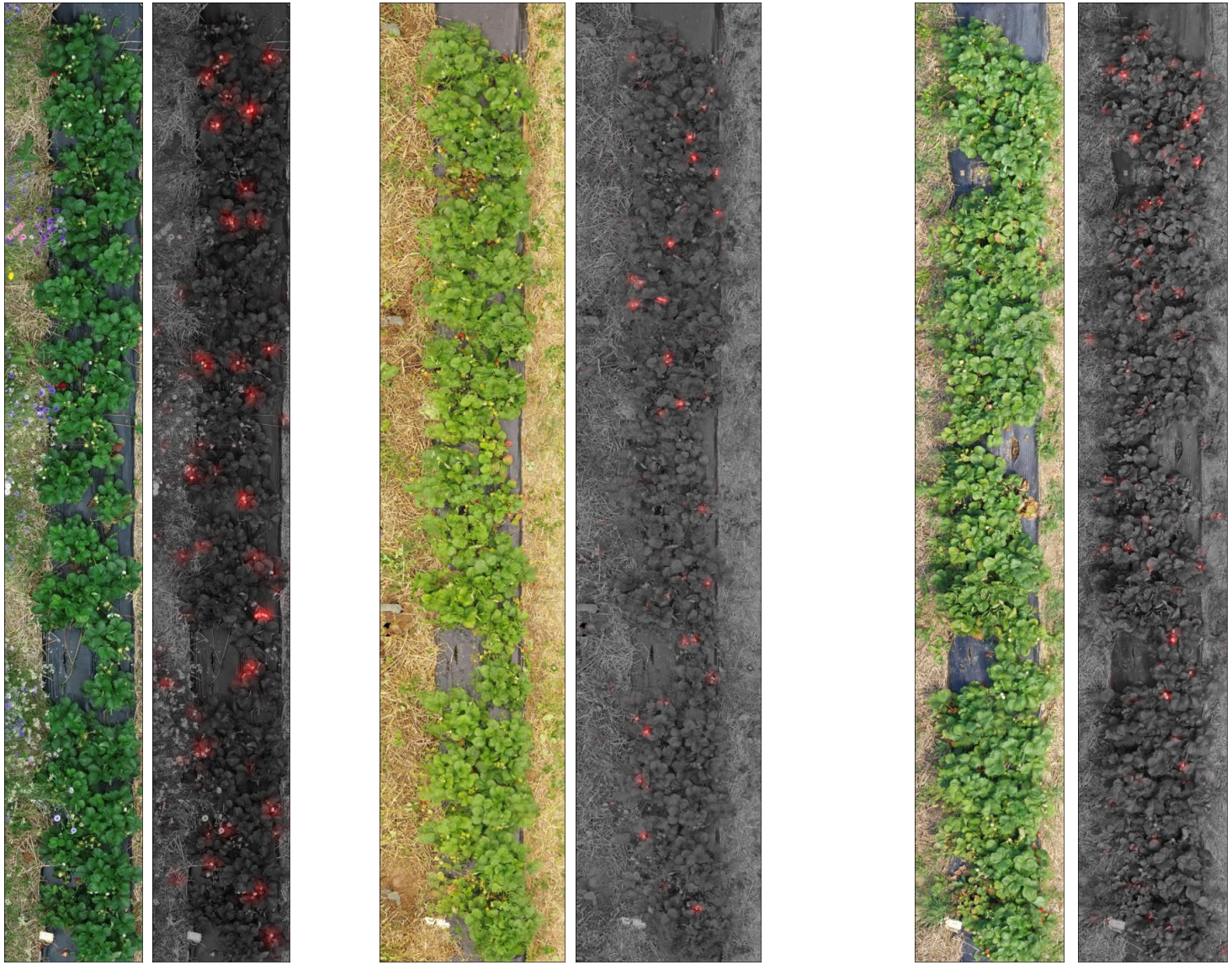
Dependence on conditions

The same plot on 3 different days, 2 weeks apart



Dependence on conditions

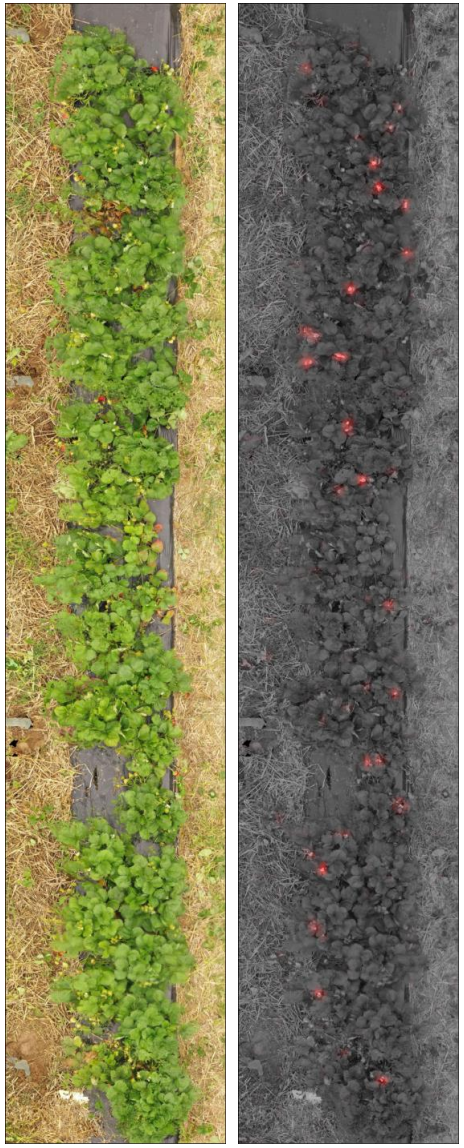
Predictions by the CNN are wrong on days 2 and 3

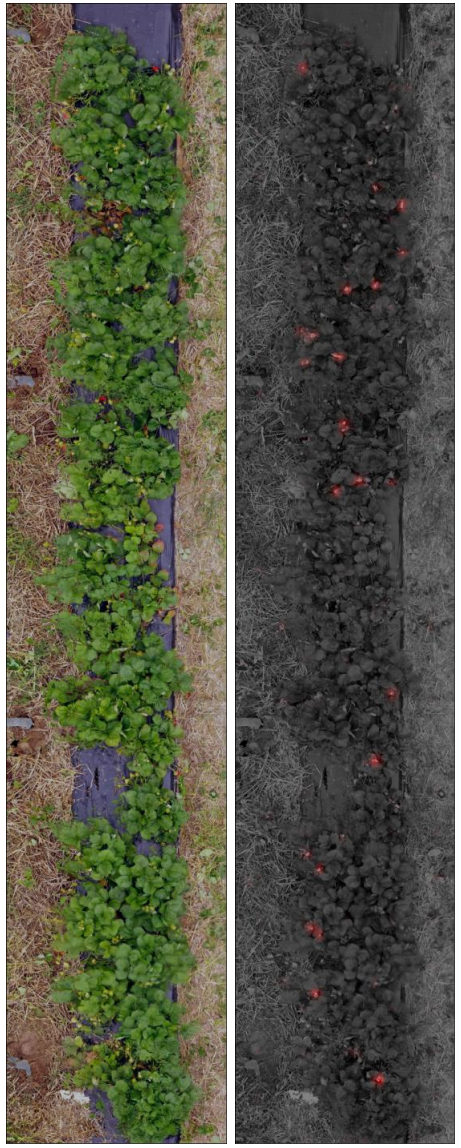


Plot ID	Flight	Visual	CNN
15-4	1	34	33
	2	27	39
	3	16	47
	4		
	5		
17-5	1	28	28
	2	26	29
	3	6	46

Dependence on conditions

What if we preprocess the images with color balance and exposure correction?





Plot ID	Flight	Visual	CNN	CNN c.b.
15-4	1	34	33	33
	2	27	39	26
	3	16	47	11
	4			
	5			
17-5	1	28	28	28
	2	26	29	22
	3	6	46	7

Significant improvement!

- Preprocess images **BEFORE** training
- If possible, include a calibration panel for white balancing
- Watch out with automatic exposure correction and overexposure!

Stitching problems

Extracts from orthophoto with stitching problems due to wind caused by low altitude

How many flowers are here? If we can’t solve it, we can’t teach it to a CNN either…







Manual counting

- Only visible flowers can be counted on an image
- A fraction of flowers is occluded
- Manual counts of flowers were performed on the same plots each flight day to derive this ratio
  - **Varying ratios due to varying plant history**
  - **Significant variation in time**
  - **Depends on variety**

- Extrapolation and prediction is work in progress

Plot ID	Manual	Image	Ratio
15-4	62	48	77%
15-6	36	26	72%
19-3	33	18	55%
18-7	46	24	52%
19-6	30	13	43%
18-6	40	17	43%
17-3	38	15	39%
17-5	70	27	39%
16-6	48	18	38%
19-5	38	14	37%
18-4	44	15	34%
16-5	101	26	26%

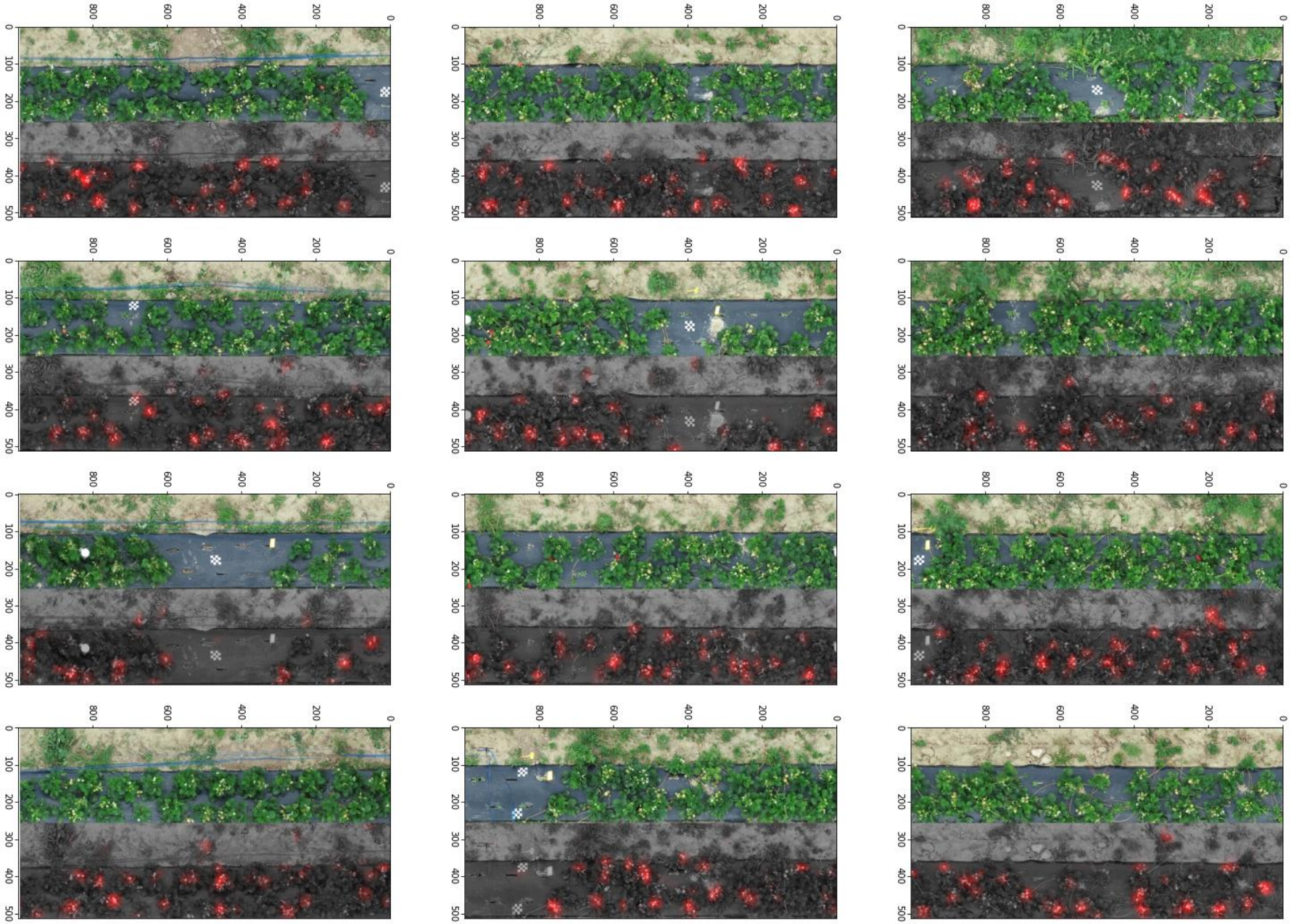
Additional experiments

Portola strawberries

Manual: **342**

CNN : **348**

Difference: **2%**



Additional experiments 2

Portola flight 2

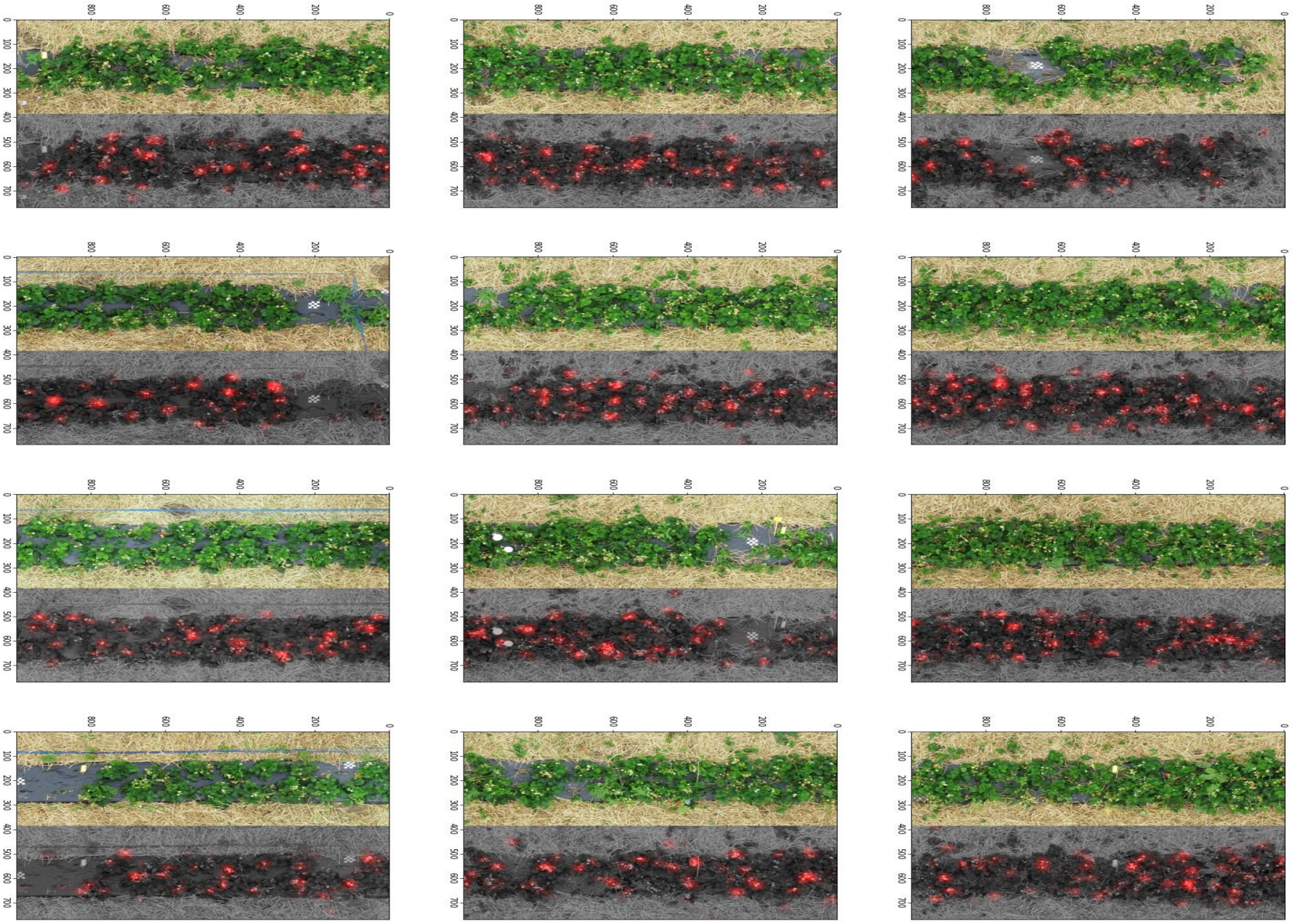
Manual: **763**

CNN : **702**

Difference: **8%**

Notes:

CNN with **colorbalance correction**



High altitude

Flight 5 (17 Sep 20)

Altitude: 20m

Resolution: 5472x3648

Too low gives stitching issues

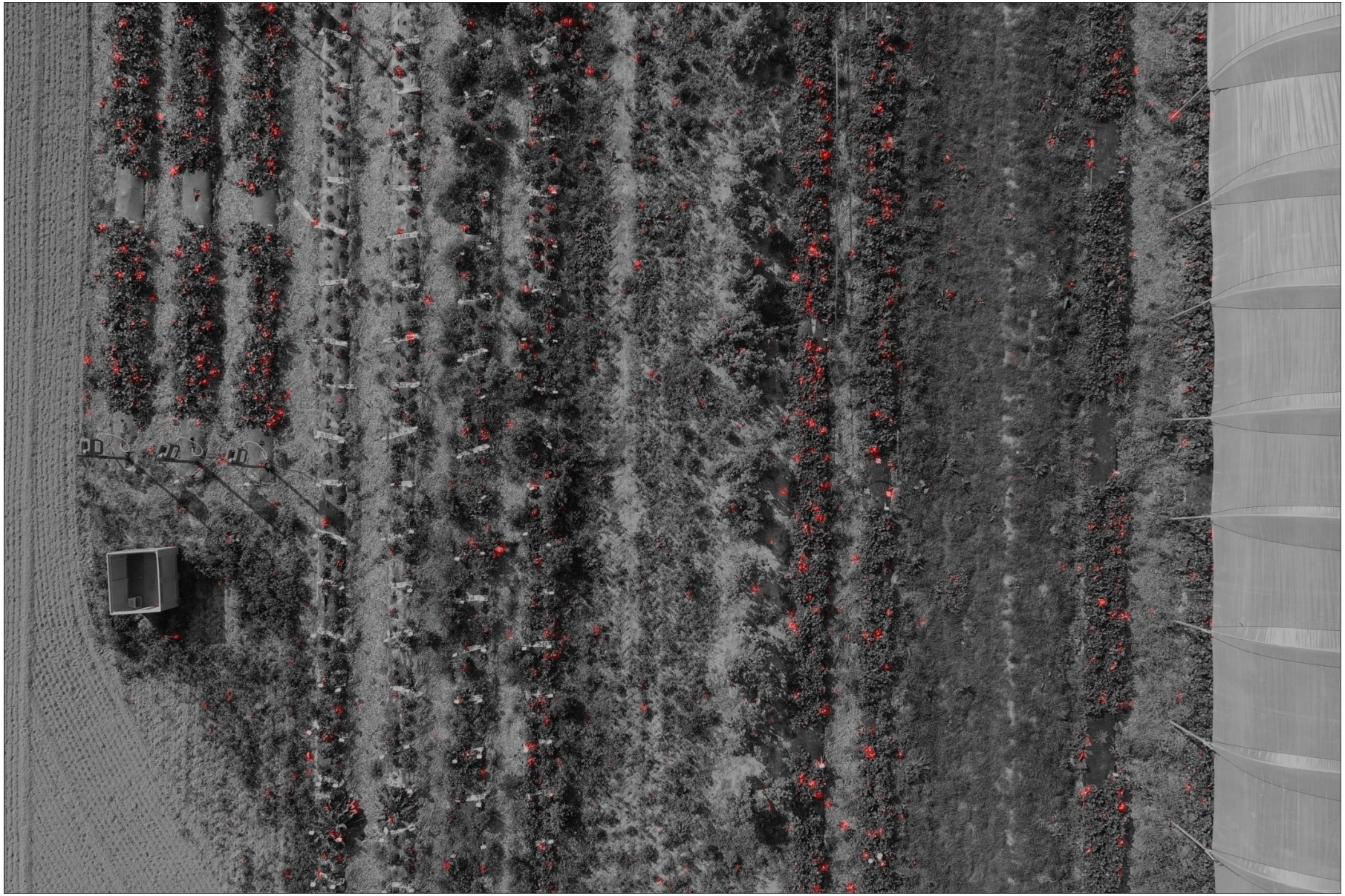
What about very high? How far can we push this method?

High altitude

Flight 5 (17 sep 20)

Altitude: 20m

Resolution: 5472x3648



Conclusions

- CNN density map prediction is a viable approach to count flowers in fields.
- Too low (2m): stitching and wind issues. Too high (20m): Flowers become very small. 10m altitude works very well. This depends on camera resolution.
- Sensitive to light exposure and color balance (also an issue for humans!):
  - **Try to take images at favorable conditions (e.g., no long shadows)**
  - **Color balance the images before training. Inclusion of a calibration panel might be beneficial.**
- In favorable conditions, the predictions are very accurate.
- Technique can be modified to other problems: counting of other types of objects or target detection.
- Fast: A trained neural network counts a full orthophoto with 100 million pixels in 10 seconds on a regular PC with a GPU. Image acquisition and processing is the main bottleneck.