6P3 WP3 update: Improving methods and techniques for phenotyping

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#### WP3 tasks (from the project description):

- T3.1. Compare pros and cons of different flight altitudes and RGB vs multispectral imaging for different purposes (proxies for leaf area index plant height, vegetation indices, phenology) and provide data for the modeling in WP5.
- T3.2. Test out new drones and cameras as they become available and provide updated imaging protocols as technology is improving.
- T3.3. Test out and optimize low altitude UAV flights for high-resolution imaging to be used for the deep learning based automated feature detection tasks in WP4 (head counting in cereals, plant counts in potato).
- T3.4 Compare lab instrumentation and imaging technologies for seed phenotyping, focusing on seed morphology traits (test weight, thousand kernel weight) that can be linked with stress responses detected by UAV imagery in the field.

# Field trials and cameras used

- MASBASIS yield trial
  - -300 spring wheat lines at two reps
  - -Separate plots for biomass measurements
- Robot field yield trial
  - -24 historical spring wheat cultivars
  - -Two N-levels x 2 reps



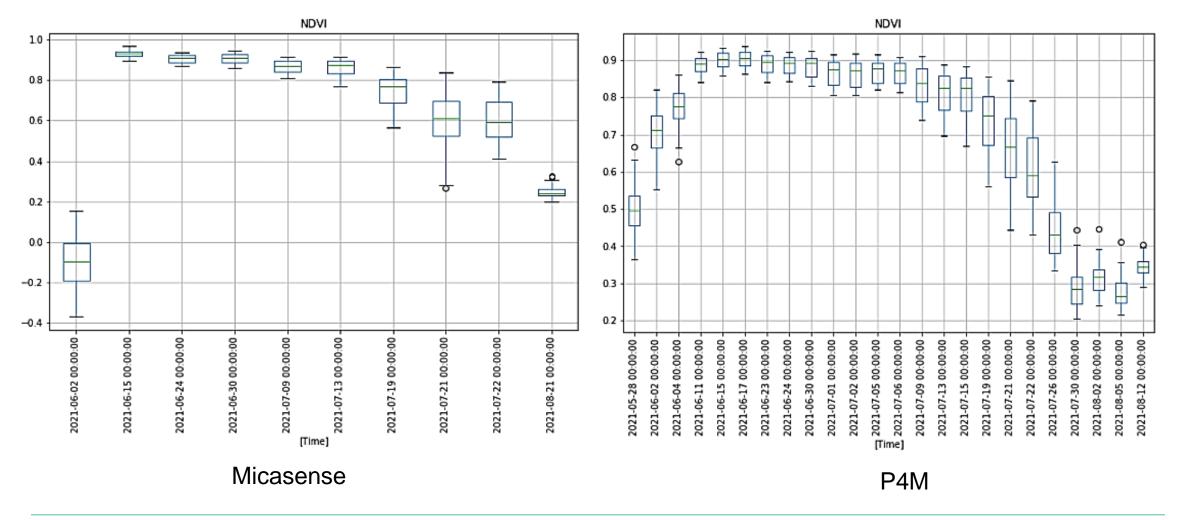


#### Overview of gathered data

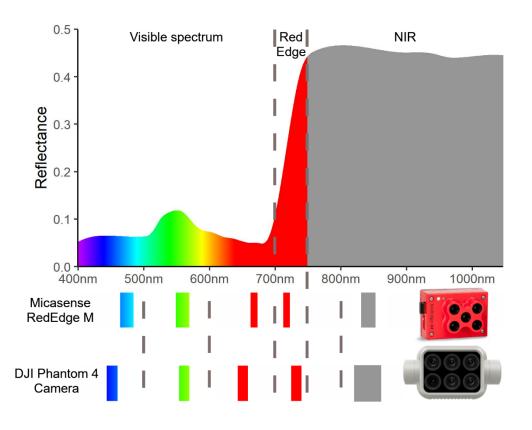
Data	Camera	Field
Spectral bands for trait prediction	Micasense RedEdge, P4M	MASBASIS
RGB for biomass and height estimation	P4M, P4	MASBASIS, Robot field
Different altitude for head detection	P4M, P4	Robot field
Hourly flight data during a day to investigate effects of sun angle	Micasense RedEdge, P4M	Robot field

#### Multispectral time series data - Robot field 2021





4 Plant phenotyping NMBU



	P4 Multispectral	Micasense RedEdge M
Red	650 ± 16 nm	668 ± 5 nm
Green	560 ± 16 nm	560 ± 10 nm
Blue	450 ± 16 nm	475 ± 10 nm
Red Edge	730 ± 16 nm	717 ± 5 nm
NIR	840 ± 26 nm	840 ± 20 nm

#### Camera comparison

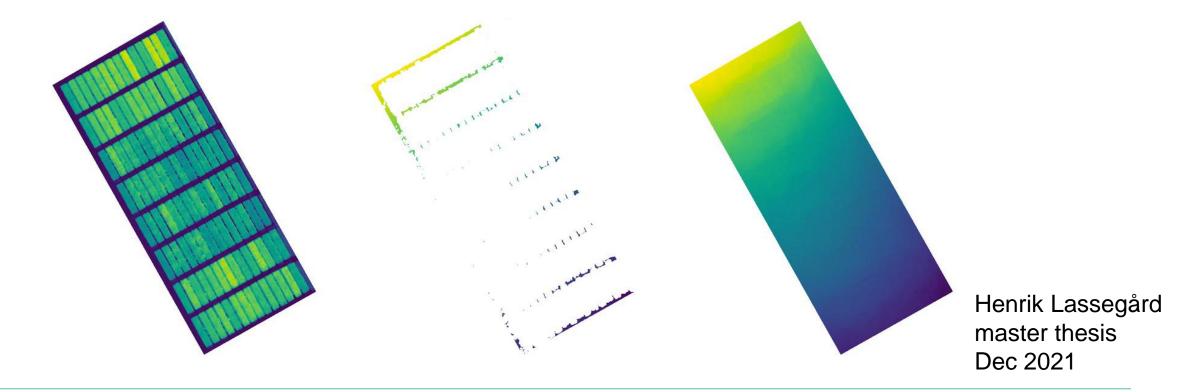


- Weekly flights during the season
- Tested for prediction of in-season biomass and grain yield using machine learning
- Some minor differences in performance:
  - P4M performs best around crop physiological maturity
  - RedEdge-M has its peak performance at heading stage.
- Overall, no significant difference in trait prediction performance

Shafiee et al., submitted

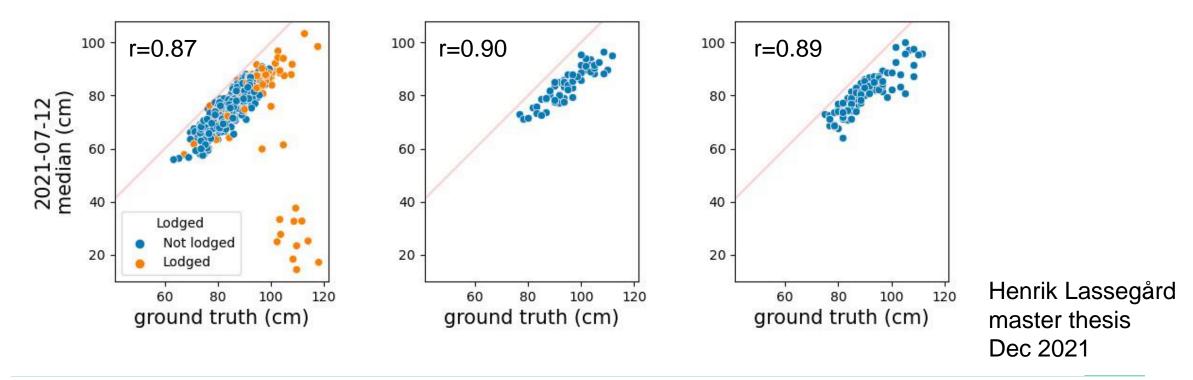
5 Plant phenotyping NMBU

- Phantom 4, 20 m altitude, 80% frontal and 85% side overlap
- Plant height = digital surface model (DSM) digital terrain model (DTM)



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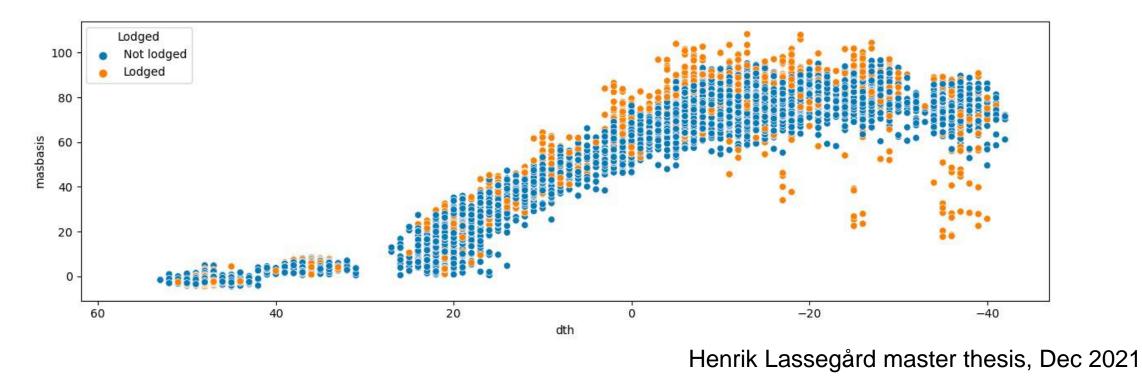
- Comparison with ground truth in 3 different trials
- Median values show good correlations, but underestimates true plant height



7 Plant phenotyping NMBU

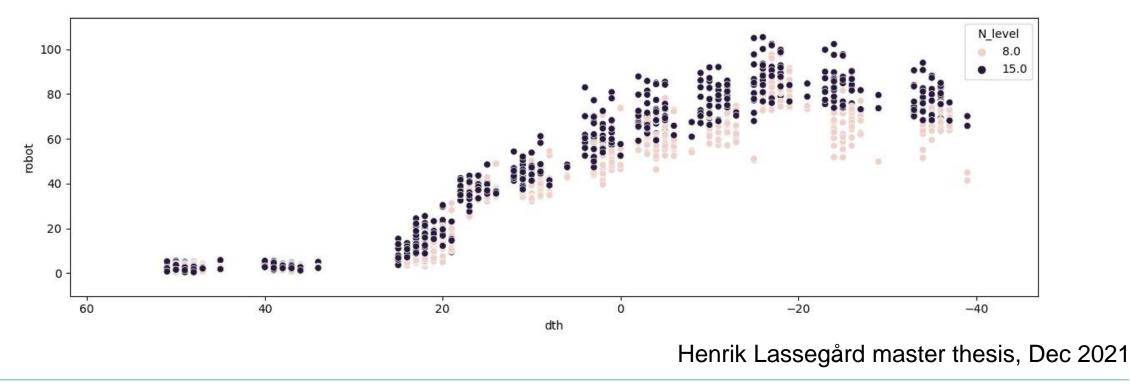


• Growth dynamics can be followed in high resolution based on time series data





 Effect of N-level fertilization on plant height estimation – challenging to capture true plant height in less dense canopies.



#### Plans for 2022 season

- Focus on head detection using low-altitude UAV flights
- Testing of 8 m altitude flights in 2021, RGB imaging with Phantom 4:



 Collaboration with the Global Wheat Head Detection Challenge

AAAS Plant Phenomics Volume 2021, Article ID 9846158, 9 pages https://doi.org/10.34133/2021/9846158 Plant Phenomics

#### Database/Software Article

#### Global Wheat Head Detection 2021: An Improved Dataset for Benchmarking Wheat Head Detection Methods

Etienne David <sup>(5)</sup>,<sup>1,2</sup> Mario Serouart <sup>(6)</sup>,<sup>1,2</sup> Daniel Smith <sup>(6)</sup>,<sup>3</sup> Simon Madec <sup>(5)</sup>,<sup>1,3</sup> Kaaviya Velumani <sup>(5)</sup>,<sup>2,4</sup> Shouyang Liu <sup>(6)</sup>,<sup>5</sup> Xu Wang <sup>(6)</sup>,<sup>6</sup> Francisco Pinto <sup>(7)</sup>,<sup>7</sup> Shahameh Shafiee,<sup>8</sup> Izzat S. A. Tahir <sup>(6)</sup>,<sup>9</sup> Hisashi Tsujimoto <sup>(6)</sup>,<sup>10</sup> Shuhei Nasuda <sup>(6)</sup>,<sup>11</sup> Bangyou Zheng <sup>(6)</sup>,<sup>12</sup> Norbert Kirchgessner <sup>(6)</sup>,<sup>13</sup> Helge Aasen <sup>(6)</sup>,<sup>13</sup> Andreas Hund <sup>(6)</sup>,<sup>13</sup> Pouria Sadhegi-Tehran <sup>(6)</sup>,<sup>14</sup> Koichi Nagasawa <sup>(6)</sup>,<sup>15</sup> Goro Ishikawa <sup>(6)</sup>,<sup>16</sup> Sébastien Dandrifosse <sup>(6)</sup>,<sup>17</sup> Alexis Carlier <sup>(6)</sup>,<sup>17</sup> Benjamin Dumont <sup>(6)</sup>,<sup>18</sup> Benoit Mercatoris <sup>(6)</sup>,<sup>17</sup> Byron Evers <sup>(6)</sup>, <sup>6</sup> Ken Kuroki <sup>(6)</sup>,<sup>19</sup> Haozhou Wang <sup>(6)</sup>,<sup>19</sup> Masanori Ishii,<sup>19</sup> Minhajul A. Badhon <sup>(6)</sup>,<sup>20</sup> Curtis Pozniak <sup>(6)</sup>,<sup>21</sup> David Shaner LeBauer <sup>(6)</sup>,<sup>22</sup> Morten Lillemo <sup>(6)</sup>,<sup>8</sup> Jesse Poland <sup>(6)</sup>, <sup>6</sup> Scott Chapman <sup>(6)</sup>,<sup>31,12</sup> Benoit de Solan <sup>(6)</sup>,<sup>1</sup> Frédéric Baret <sup>(6)</sup>,<sup>2</sup> Ian Stavness <sup>(6)</sup>,<sup>20</sup> and Wei Guo <sup>(6)</sup>

https://doi.org/10.34133/2021/9846158





### Image-based seed phenotyping – starting in 2022



- Establish links between stress captured by UAV imagery and seed traits
- Comparison of lab instrumentation





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