Methodology development to create methods for acquisition and integration of historical, UAV sensors and IoT data for agriculture

- Historical data – many decades of accumulated experience and data
- Variable data acquisition and storage methods
- The arrival of new technologies is getting faster and faster
- Huge competition, growing range of available solutions
- Lack of resources (intellectual, technical, material).
- The influence of weather conditions and other environmental factors

TED4LAT

Funded by the European Union

Basic problem: integration of data in a unified environment, analysis and final product for the user

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AREI Remote Sensing expert

TED4LAT, No. 101079206

VIDZEME UNIVERSITY OF APPLIED SCIENCES

MEMBER OF E³UDRES²

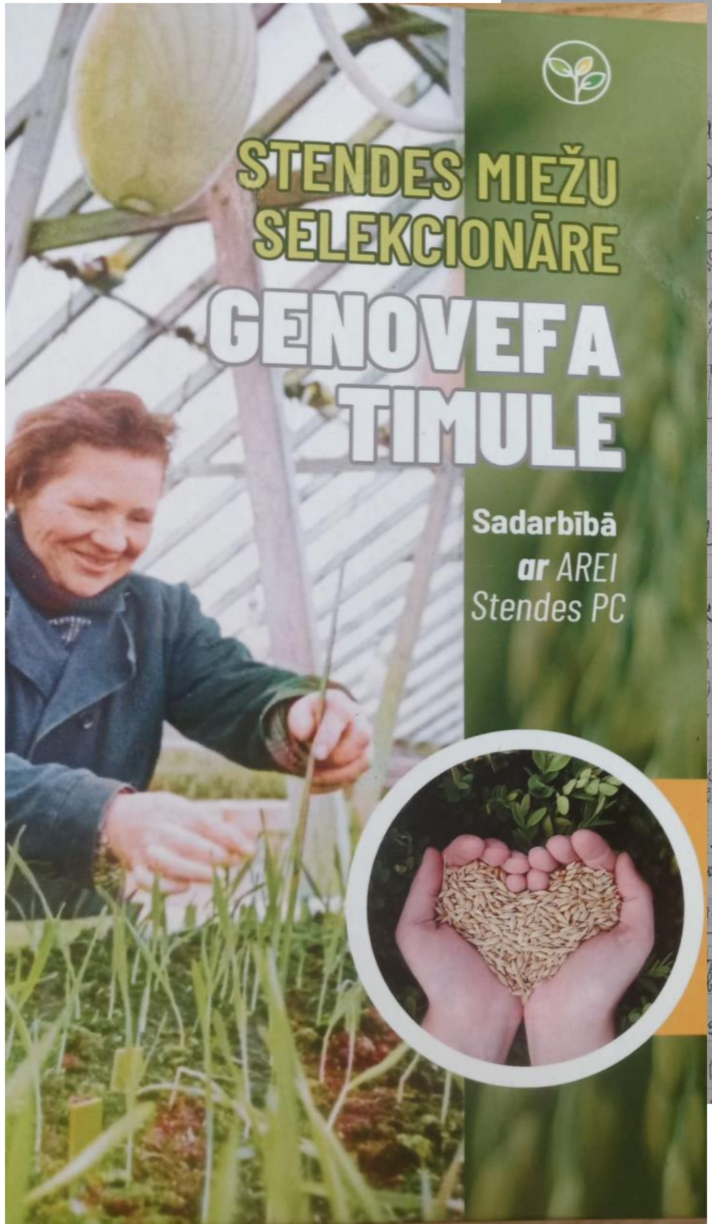
Vidzeme University of Applied Sciences cooperation with Institute of Agricultural Resources and Economics

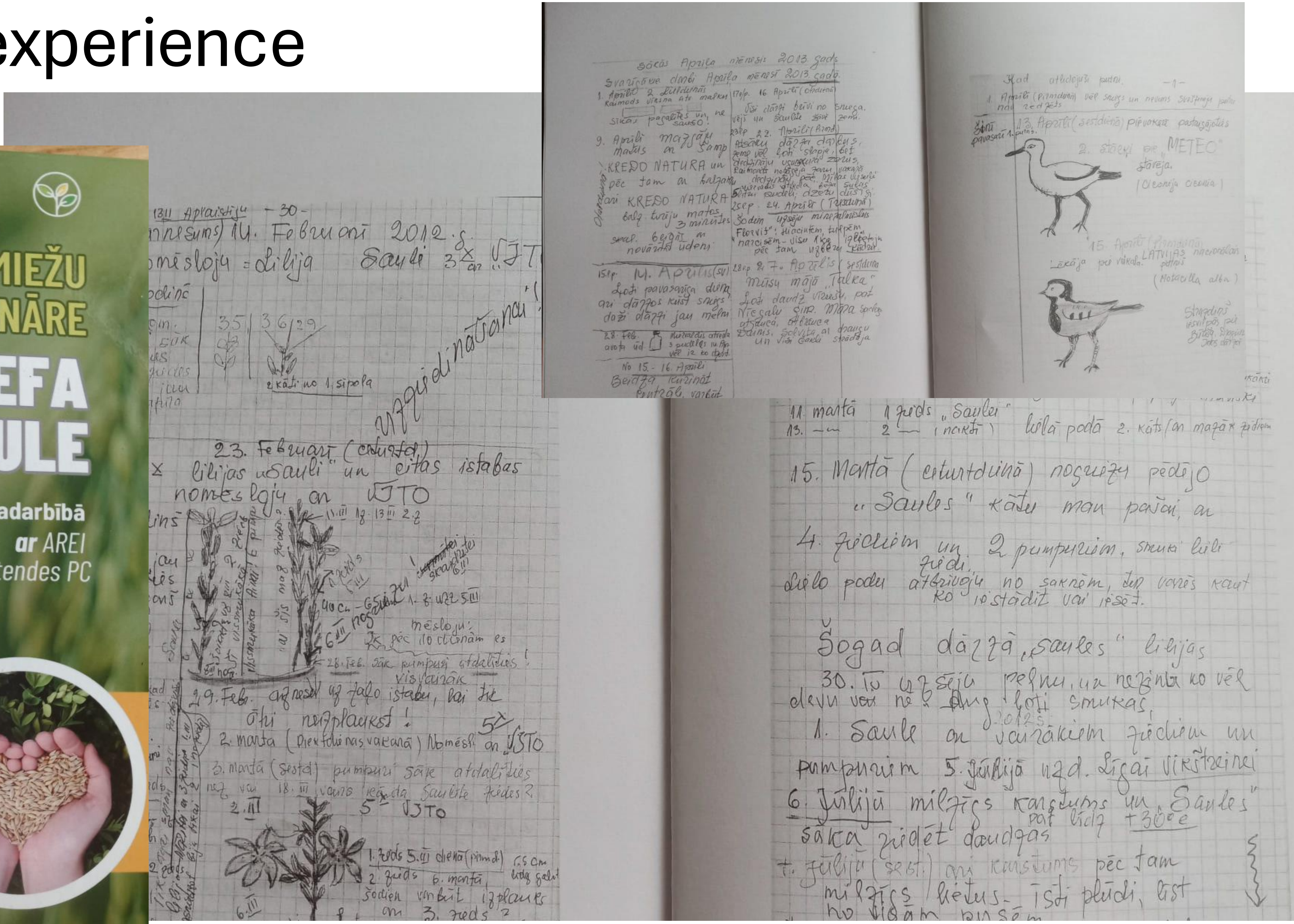
Education institution and an important bioeconomy industry research and leading field plant breeding institute with more than 100 years of history cooperation with high school.

History and operation

- More than 100 years of experience
- AREI scientists and specialists works:
  - In the bioeconomy sector
  - In the department of grain technology and agrochemistry
  - In field plant selection, agroecology and pre-election laboratory
- Priekuļi and Stende Research Centers, Technology Transfer Center and Agricultural Market Promotion Center
- AREI's activities are spread throughout Latvia, 4 main locations, as well as participation in international projects (experience in Lithuania, Estonia, Sweden, Norway)
- Much is being done in the field of knowledge transfer and learning new technologies, which is associated with various challenges
- Cooperation with Vidzeme University of Applied Sciences – what does it means: An experienced agricultural institute can pass on legacy knowledge, access new research, and develop future specialists, while gaining prestige, innovation, and practical experience. ***The long-term impact outweighs the short-term imbalance.***

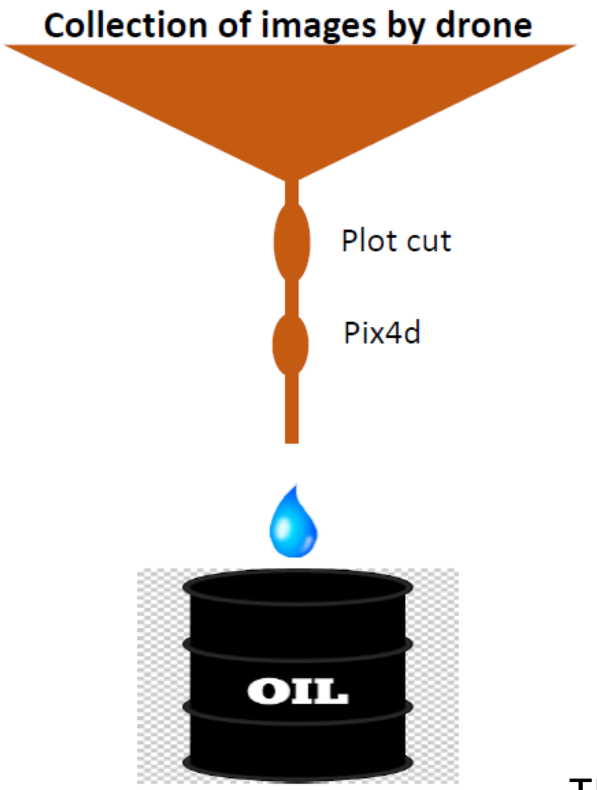
Historical experience





Current experience

Data pipeline from HTP with UAV



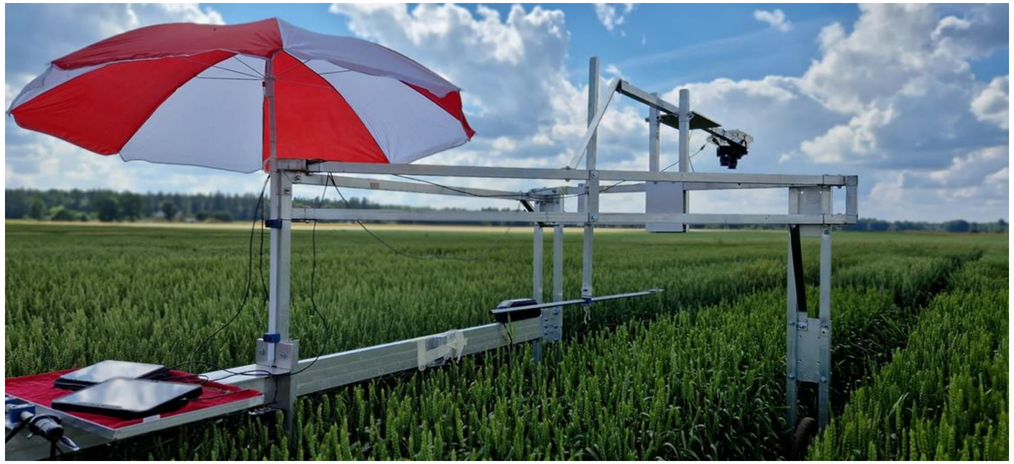
- Collection of «big data»
- Time consuming adjustments of images
- Large computer capacity needed
- Outcoming data difficult to integrate with other results

The view of Norwegian colleagues

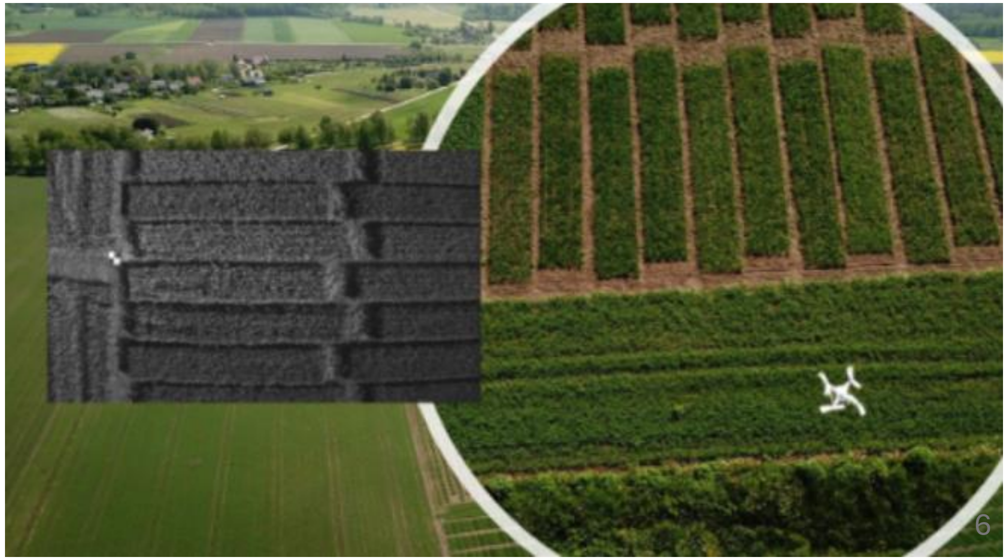
Graminor

International NOBAL Wheat Project

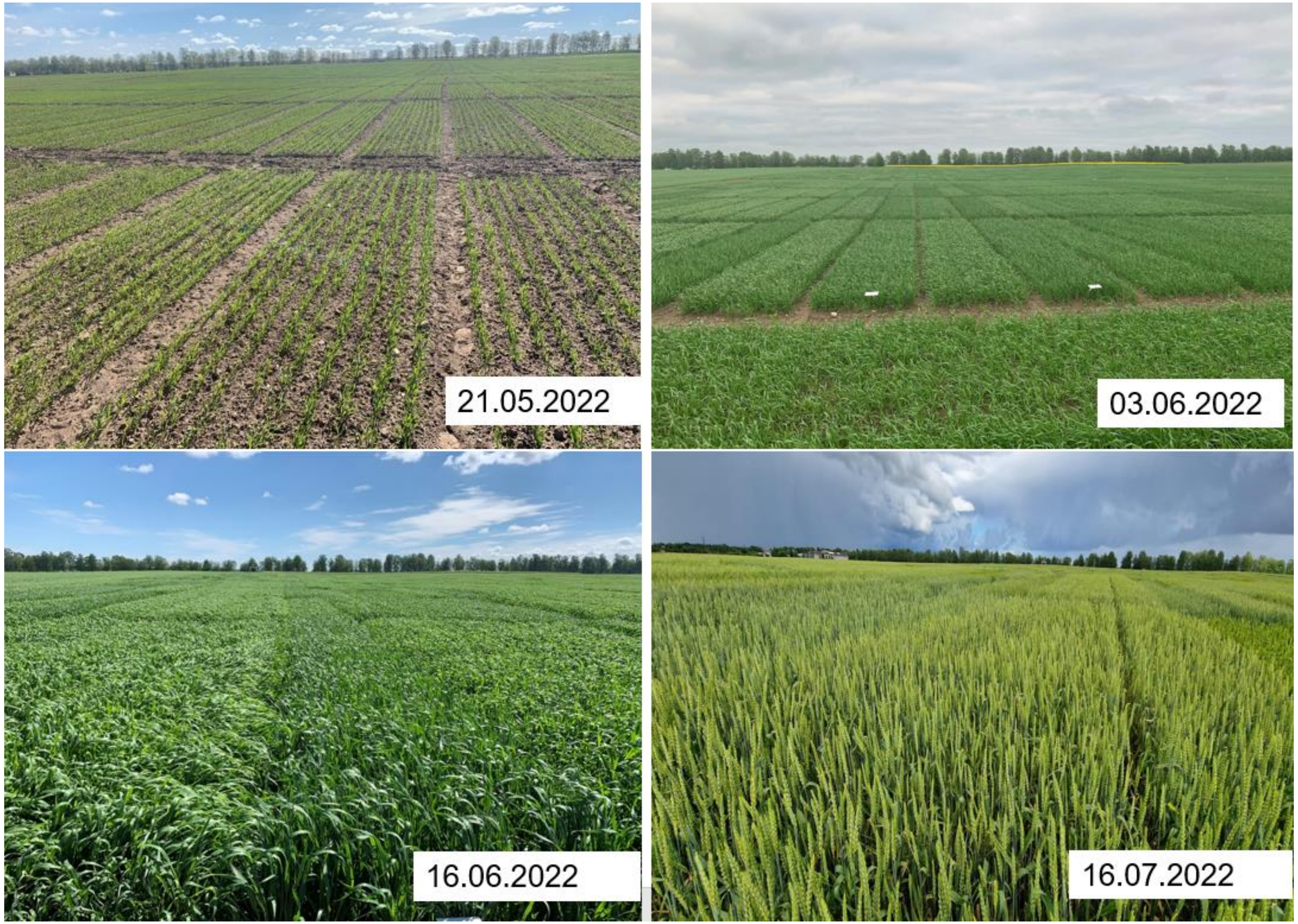
- A three-year project that gave us stability and confidence in what we do
    - Higher work efficiency
    - Improved competences
    - Better productivity
    - Innovative solutions
    - Cooperation experience
    - Market knowledge
    - Strategic thinking
    - New data collection methods
    - Improved data processing
- International cooperation
- Experienced consultants
- Networking opportunities



Phenomobile vs UAV



Data series (3 years x 10 missions) using UAV



Orthophoto map

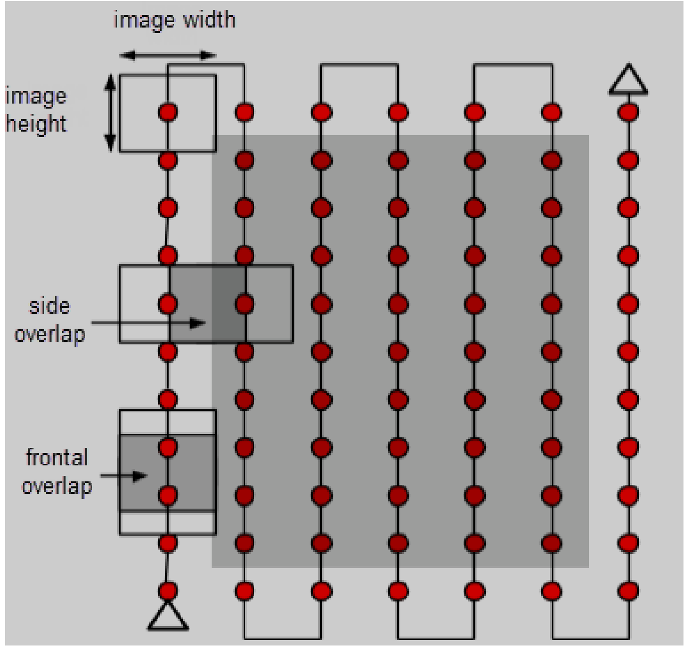
- Gets data when and where it is needed, with the necessary accuracy and resolution
- Compatibility with other resources in the GIS environment
- Required GSD* at least 1cm
- Shift of images between missions no more than 3cm

***GSD (Ground Sampling Distance)** it is also known as "ground surface resolution". This term is used in photogrammetry and remote sensing technologies to describe the spatial resolution of an image on the earth's surface. Basically, it indicates the distance on the ground represented by each pixel in the image.

RGB (color photo) and Multispectral camera

- RGB (Red, Green, Blue)
- RE, NIR (Red Limit, Near Infrared)
- Photos are taken while flying, in consecutive series

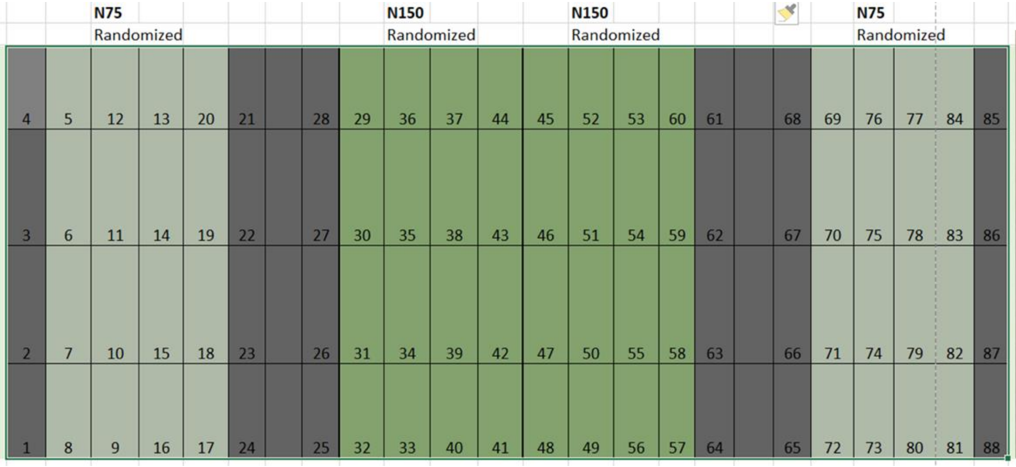
Correct protocols needed to collect data

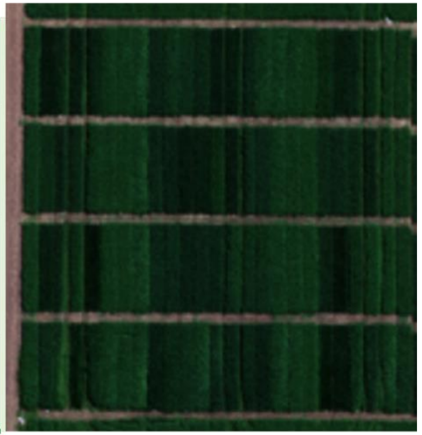


The gray area is the research area.
Image coverage not less than 70% and not more than 85%.
If you want to get a 2D orthophoto, then point the camera vertically down.
If a 3D object or surface model is required, the camera is turned at an angle of approximately 15 degrees from the vertical.

Current field planning «Excel type GIS »

- NUE trial design for 16 genotypes at 2 N levels
- Split field design - the field is divided into four main blocks, and the application of both N fertilization levels is randomly distributed among these four blocks.
- Crop trial design, 300 spring wheat genotypes
- Design of random blocks





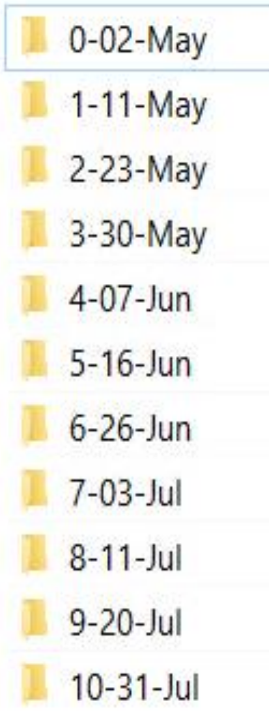
Replication 1; randomized																				Replication 2; randomized																			
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
NW244	NW68	NW278	NW171	NW174	NW254	NW151	NW173	NW77	NW228	NW2	NW15	NW66	NW246	NW181	NW232	NW264	NW261	NW300	NW49	NW117	NW60	NW71	NW263	NW181	NW111	NW261	NW299	NW300	NW256	NW13	NW23	NW251	NW7	NW228	NW46	NW94	NW28	NW190	NW164
NW255	NW146	NW263	NW203	NW27	NW104	NW1	NW170	NW201	NW122	NW129	NW163	NW280	NW148	NW190	NW175	NW165	NW35	NW119	NW72	NW86	NW249	NW145	NW69	NW99	NW129	NW34	NW182	NW128	NW19	NW52	NW104	NW213	NW246	NW82	NW232	NW275	NW220	NW225	NW162
NW89	NW109	NW107	NW76	NW248	NW74	NW47	NW120	NW229	NW177	NW231	NW45	NW200	NW86	NW117	NW82	NW98	NW266	NW53	NW196	NW253	NW109	NW264	NW283	NW143	NW108	NW17	NW217	NW147	NW169	NW252	NW211	NW216	NW176	NW248	NW199	NW173	NW260	NW219	NW27
NW283	NW256	NW150	NW299	NW270	NW56	NW84	NW63	NW191	NW222	NW265	NW206	NW37	NW209	NW288	NW32	NW155	NW133	NW154	NW187	NW56	NW185	NW126	NW243	NW209	NW67	NW2	NW64	NW103	NW206	NW132	NW201	NW112	NW151	NW153	NW170	NW77	NW63	NW140	NW286
NW290	NW79	NW157	NW81	NW118	NW115	NW22	NW61	NW12	NW172	NW91	NW142	NW277	NW75	NW260	NW24	NW136	NW88	NW143	NW253	NW231	NW68	NW12	NW110	NW218	NW192	NW237	NW35	NW154	NW31	NW32	NW267	NW203	NW135	NW274	NW156	NW118	NW158	NW294	NW47
NW199	NW213	NW215	NW285	NW14	NW55	NW85	NW25	NW243	NW126	NW292	NW121	NW73	NW30	NW197	NW139	NW102	NW50	NW58	NW252	NW149	NW97	NW73	NW239	NW235	NW171	NW130	NW95	NW184	NW11	NW88	NW6	NW122	NW234	NW187	NW150	NW226	NW167	NW174	NW210
NW226	NW130	NW42	NW116	NW257	NW161	NW43	NW262	NW297	NW245	NW127	NW31	NW29	NW168	NW198	NW268	NW9	NW132	NW279	NW237	NW223	NW40	NW250	NW138	NW189	NW106	NW33	NW89	NW10	NW83	NW96	NW276	NW265	NW75	NW262	NW277	NW224	NW233	NW36	NW272
NW110	NW286	NW131	NW141	NW48	NW269	NW90	NW214	NW21	NW274	NW189	NW233	NW212	NW178	NW144	NW7	NW296	NW225	NW219	NW83	NW93	NW53	NW58	NW279	NW25	NW57	NW196	NW18	NW270	NW240	NW76	NW115	NW255	NW137	NW15	NW159	NW1	NW291	NW131	NW259
NW87	NW4	NW18	NW193	NW8	NW112	NW52	NW294	NW291	NW247	NW69	NW3	NW51	NW6	NW185	NW59	NW11	NW249	NW16	NW34	NW208	NW141	NW166	NW172	NW288	NW133	NW16	NW70	NW247	NW43	NW241	NW107	NW186	NW79	NW157	NW195	NW238	NW30	NW59	NW8
NW239	NW180	NW160	NW40	NW218	NW184	NW295	NW64	NW234	NW65	NW179	NW250	NW156	NW78	NW224	NW135	NW60	NW271	NW211	NW227	NW55	NW29	NW50	NW287	NW20	NW205	NW257	NW297	NW178	NW148	NW230	NW21	NW42	NW161	NW124	NW183	NW142	NW80	NW221	NW5
NW208	NW158	NW275	NW230	NW240	NW183	NW36	NW99	NW13	NW95	NW223	NW152	NW272	NW251	NW166	NW217	NW17	NW19	NW236	NW159	NW163	NW292	NW4	NW105	NW282	NW81	NW41	NW3	NW62	NW298	NW245	NW152	NW165	NW289	NW92	NW65	NW229	NW193	NW54	NW285
NW238	NW241	NW242	NW106	NW96	NW235	NW20	NW134	NW169	NW207	NW186	NW70	NW10	NW128	NW204	NW114	NW5	NW167	NW210	NW289	NW160	NW236	NW61	NW48	NW113	NW212	NW91	NW295	NW134	NW293	NW168	NW9	NW74	NW271	NW278	NW87	NW191	NW273	NW22	NW39
NW80	NW103	NW111	NW221	NW33	NW284	NW205	NW62	NW195	NW94	NW182	NW216	NW93	NW273	NW258	NW140	NW26	NW38	NW41	NW145	NW227	NW204	NW125	NW120	NW280	NW144	NW84	NW268	NW180	NW215	NW200	NW101	NW14	NW66	[illegible]	NW175	NW254	NW136	NW146	NW102
NW267	NW113	NW105	NW282	NW123	NW101	NW188	NW137	NW124	NW67	NW162	NW276	NW192	NW147	NW71	NW287	NW259	NW108	NW44	NW281	NW72	NW85	NW24	NW244	NW197	NW100	NW284	NW98	NW116	NW38	NW222	NW266	NW114	NW207	[illegible]	[illegible]	[illegible]	[illegible]	NW51	NW90
NW153	NW149	NW138	NW23	NW202	NW100	NW194	NW57	NW28	NW164	NW92	NW293	NW39	NW125	NW46	NW176	NW298	NW97	NW220	NW54	NW119	NW179	NW78	NW155	NW214	NW202	NW45	NW123	NW198	NW127	NW139	NW290	NW121	NW49	NW296	NW258	NW44	NW26	NW281	NW194

Proximal phenotyping (growth stages)

- GS21 Beginning of jam formation:
  - Cereals begin to form side shoots, which will be an additional source of grain.
- GS65 Full flowering:
  - The plant is in full bloom and all the flowers have opened.
- GS73 Beginning of milk ripening:
  - The grains begin to fill with a milky liquid, but are not yet fully ripe.

A challenge for an IT specialist, specific knowledge in agriculture is required

UAV missions

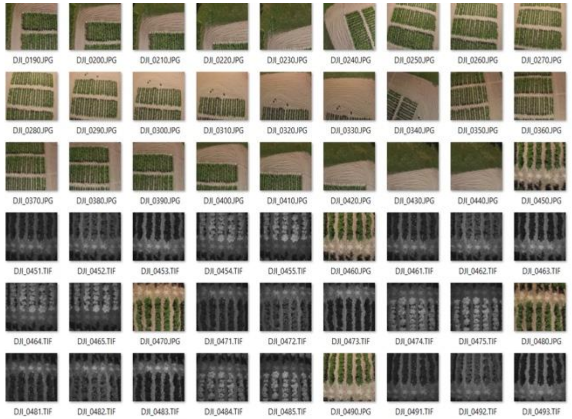


The experiment (Stargate project)

Another excel (the design)

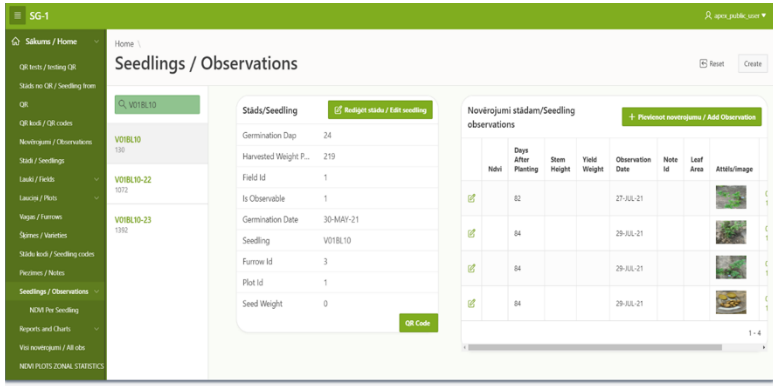
Real field view

Data collection

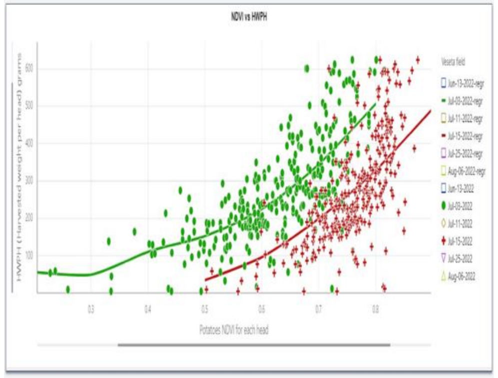


Processing (the GIS project)

Database

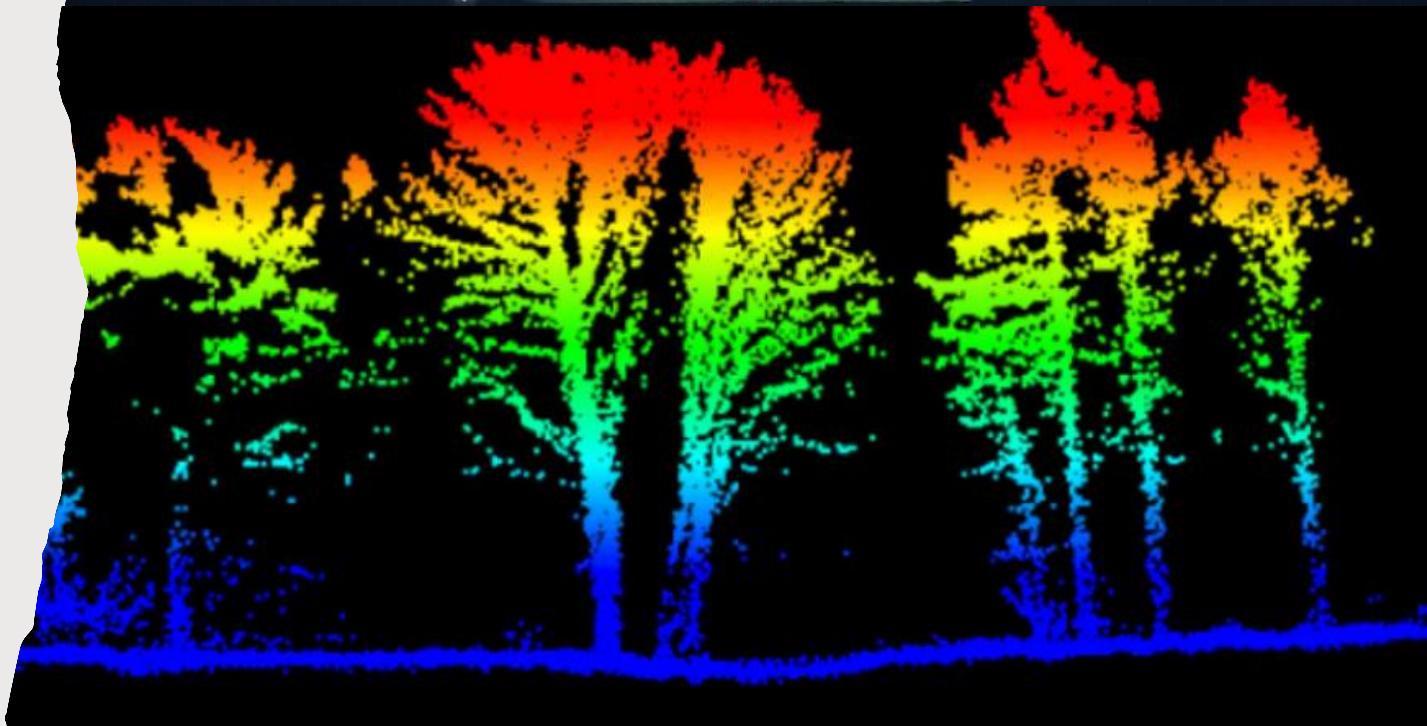


Results



LiDAR capabilities

- Several levels of light beam reflection
- Classification
- Resources for research
  - https://levelfivesupplies.com/100-real-world-applications-of-lidar-technology/



Technical resources

- We have
  - DJI Matrice 300
  - Sentera Multispectral
  - Pix4D Mapper
  - QGIS
- Purchased, but needs to be learned
  - DJI Zenmuse L2 LiDAR*
- New learning challenges
  - AI (Artificial Intelligence)
  - GIS (Geographic Information Systems)

LiDAR(Light Detection and Ranging) is a technology that uses laser beams to measure distances and create three-dimensional (3D) images and models of the surrounding environment.

Problem

- Economic productivity and competitiveness are essential for improving national well-being. The advantages are in high value-added sectors. **The untapped potential of technology is still an underutilized growth opportunity.**
- **We live in an era where technology and society are evolving faster than most companies can adapt.** Survival will not depend on strength or intelligence, but on the ability to adapt.
- **Technology is evolving exponentially, while society's ability to use it is lagging behind.** There is a growing digital divide between technological transformation and the ability of companies to apply it in production and management to drive efficiency and innovation.

•January 2019 DOI: 10.22364/pctni.06 In book: Produktivitātes celšana: tendences un nākotnes izaicinājumi = Raising Productivity: Trends and Future Challenges. Juris Binde

Research question and focus

- How can a scalable and flexible system be designed to integrate diverse data sources (multispectral, LiDAR, IoT sensors) with actual manual field observations, meteorological information, harvest data and historical data for precision agriculture?
- Focus: System architecture and modularity.

Problem statement:
Integrating multispectral, LiDAR, sensor, and historical data into a unified geospatial model for precision agriculture presents key challenges. The gap between technical experts and agricultural professionals highlights the need for a unified approach, shared understanding, and clear methodology for data acquisition and transformation in an ever-evolving technological landscape.

Aim of this work:
- UAV mapping and optimization in precisin agriculture;
- Development of comprehensive methodology for designing and rapidly adjusting data acquisition, processing, and maintenance systems for data science applications in precision agriculture.

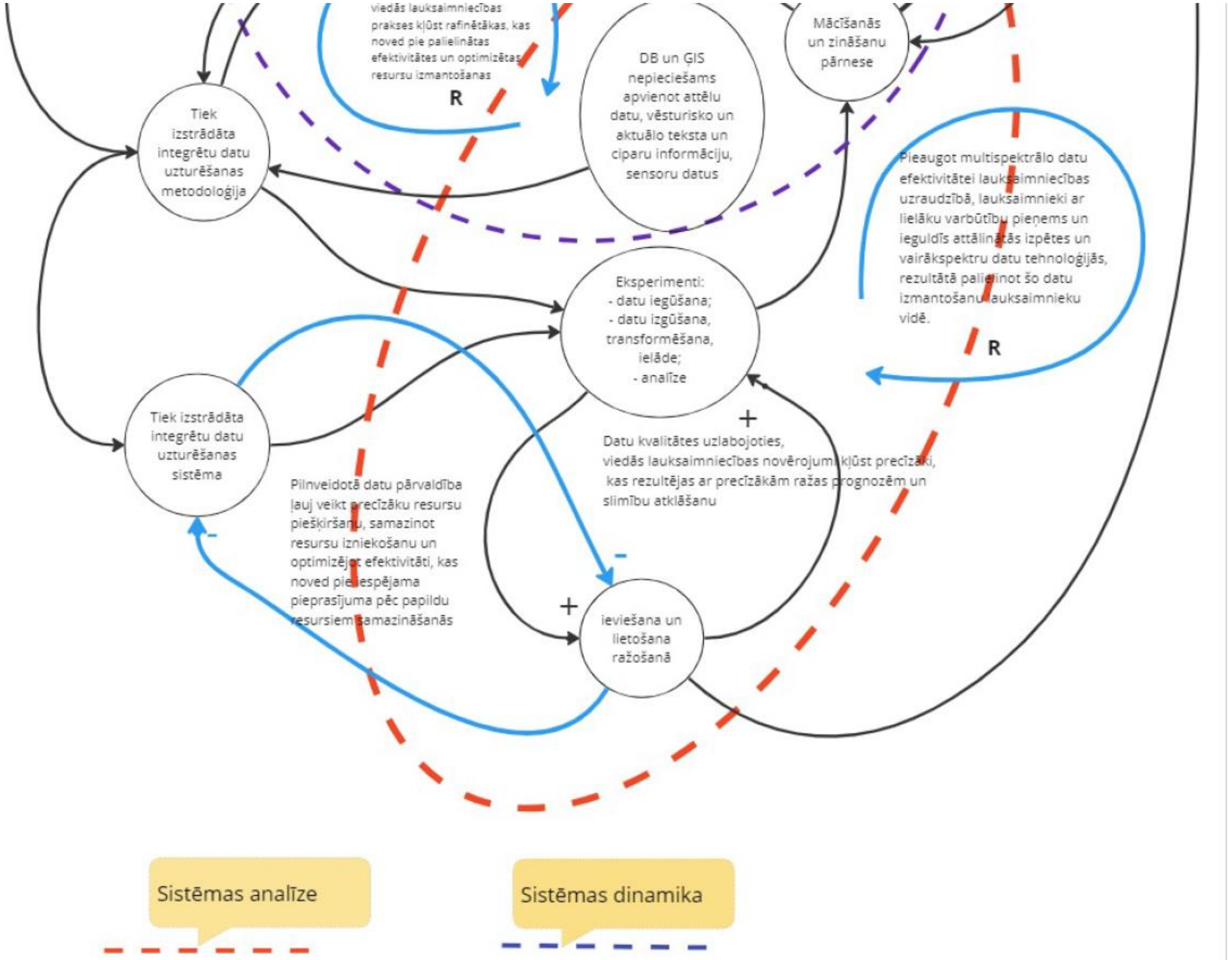
All stakeholders must come to a common understanding

- This is the first version – general understanding
- The goal must be formulated to the end, separate tasks must be allocated
- Tools and methods must be chosen
- The author's new contribution must be specified

A transparent, universally understandable concept must be validated and verified

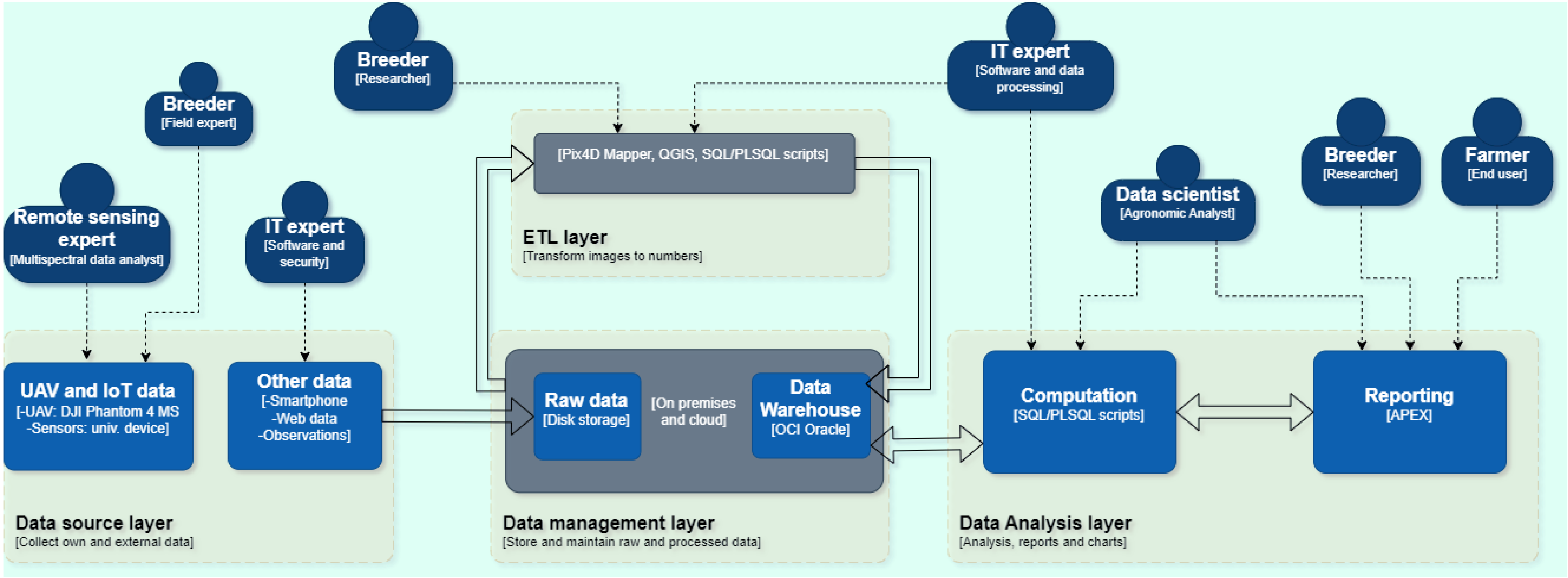
How to perform these tasks?

- Requirements model, the creation of which has several (as many as necessary) iterations
- Financing and implementation



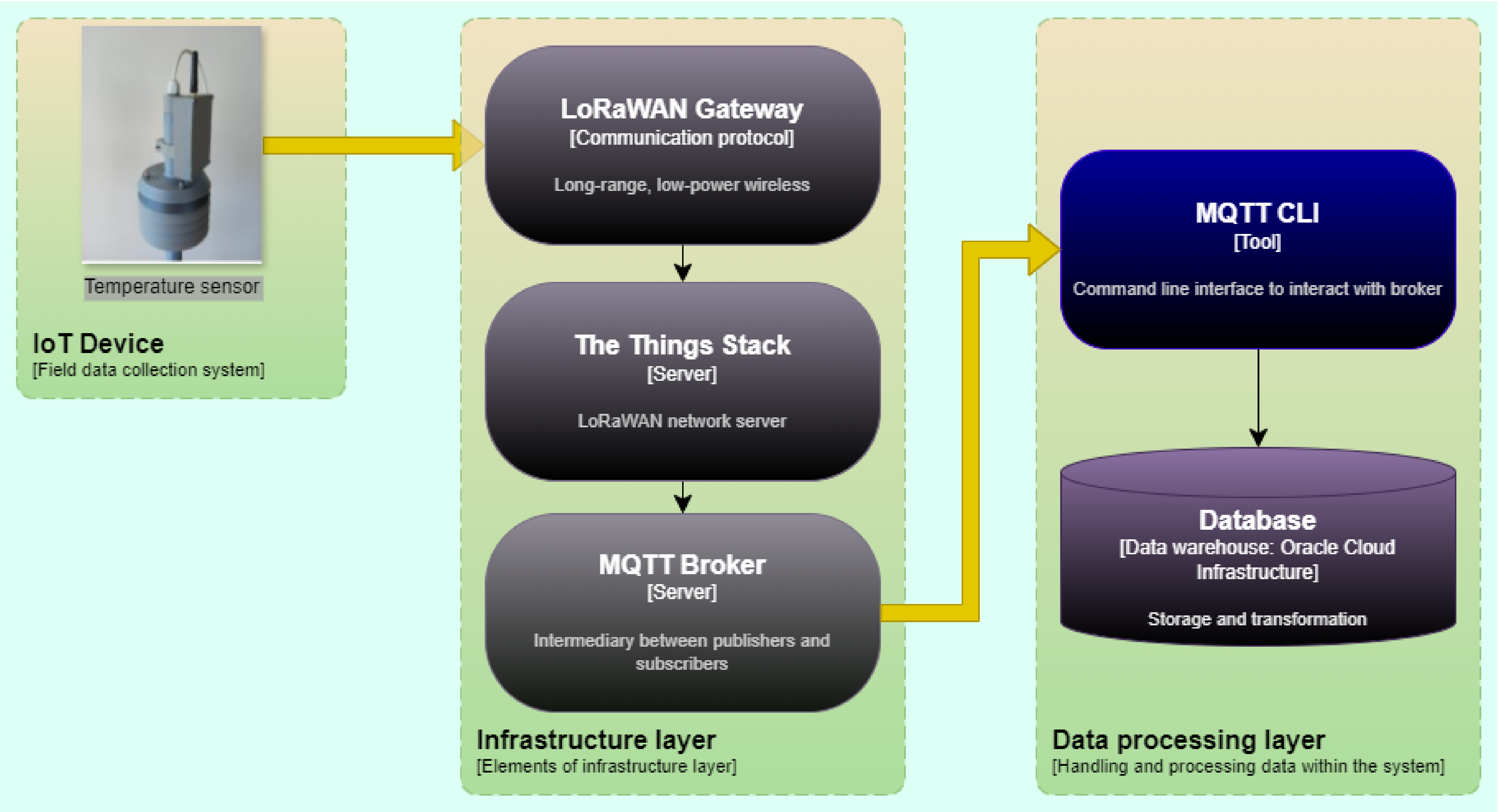
Thanks to Egils Ginters

Architecture for multispectral data acquisition, integration and analysis



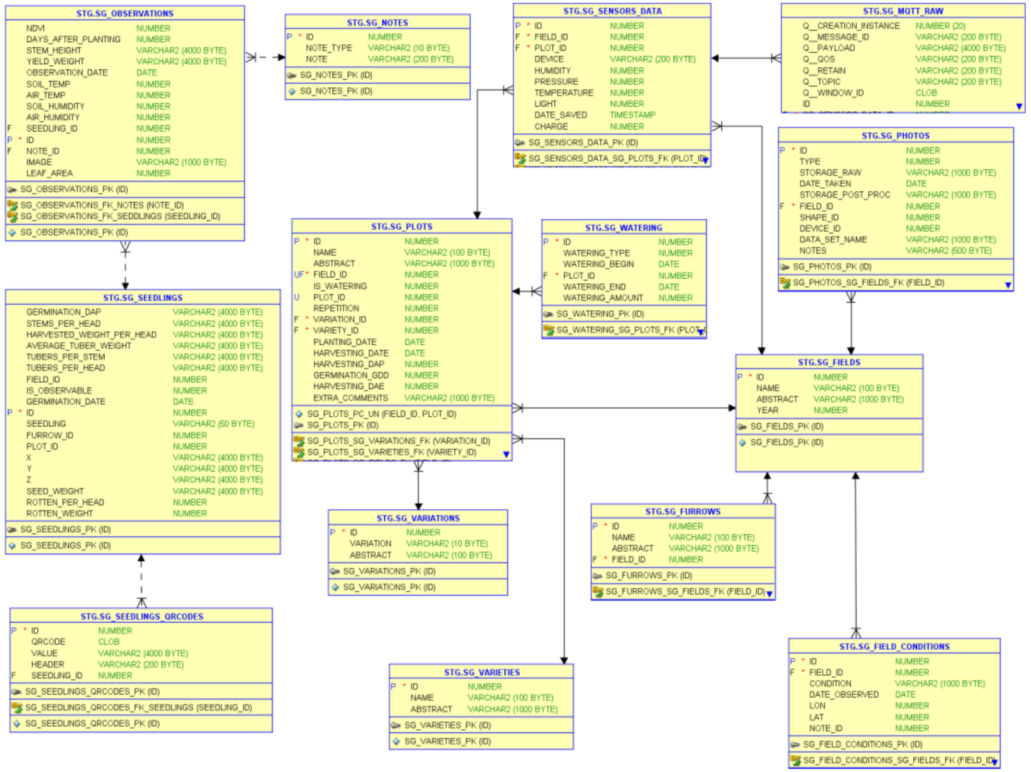
Thanks to Sandro Bimonte

IoT data processing architecture



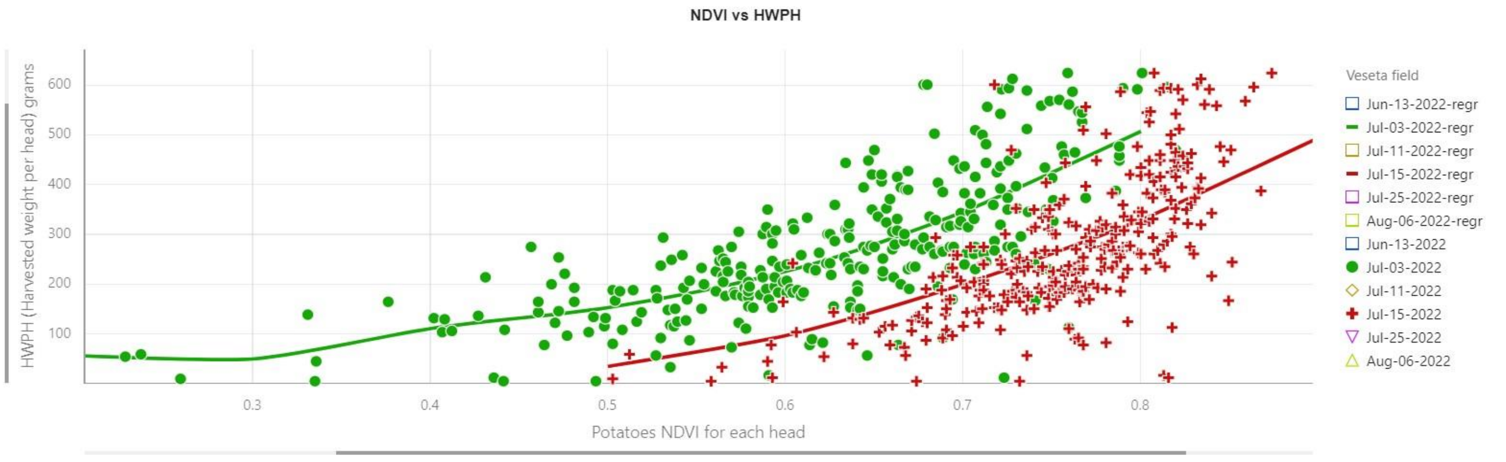
Database: OCI as platform and flexible Data model

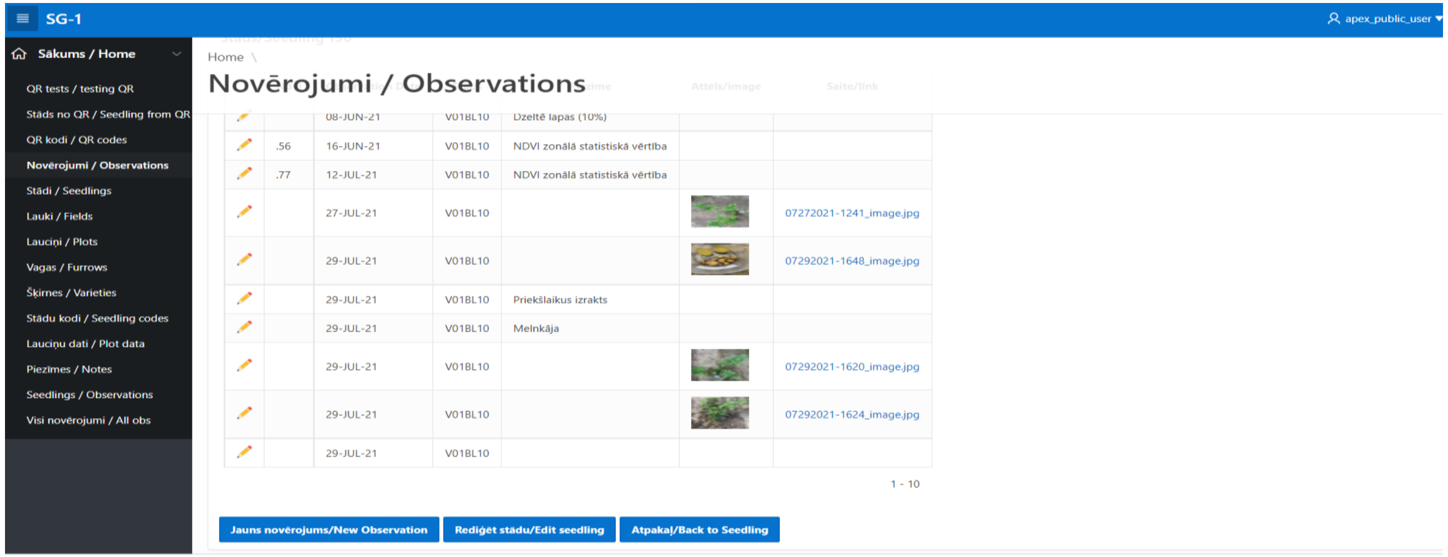
Generativity.
It is a technology's capability of producing new outputs without input from the originator.
Scalability.
Ability to handle growing volumes of data and increasing complexity of processes as precision agriculture advances.
Accesibility.
Easy access for different users, with varying levels of expertise.
Interoperability.
Compatible with various tools, databases, and platforms, allowing users to integrate other technologies or data sources easily.



Sun, R., Gregor, S., Fielt, E. (2021). Generativity and the paradox of stability and flexibility in a platform architecture: A case of the oracle cloud platform, Information & Management 58(8), 103548. https://www.sciencedirect.com/science/article/pii/S0378720621001221

User interface, charts, reports





What is it, or a container terminal?

Integrated data, available in the database, geospatialy correct positions, offered to the user as an easy-to-use product in a GIS environment. Blue containers show harvested

Novelty

- **Flexibility and adaptability, user-oriented design:** Unlike existing solutions, which often provide rigid frameworks for specific problems, this methodology offers a scalable and modular approach, allowing users to **rapidly adjust** systems to evolving data sources, tools, and technologies in agriculture.

Key novel aspects include:

- **Customizable and Dynamic System Design**: The methodology emphasizes the ability to quickly integrate new tools, such as UAV-based multispectral imaging, LiDAR, IoT sensors, and historical data. This flexibility is crucial for addressing the constantly changing technological landscape in precision agriculture.
- **Modular and Service-Oriented Architecture**: It introduces a modular structure that can be adapted to different agricultural tasks with minimal disruption, enhancing the ease of customization for various use cases and tools.
- **Focus on Real-Time Data Integration**: By providing a framework for seamless integration of diverse, multimodal data (e.g., geospatial, sensor, historical data), the methodology oriented to support real-time decision-making and data processing.
- **Cross-Disciplinary Knowledge Transfer**: The research addresses the gap between IT specialists and agricultural professionals, offering methods to enhance collaboration, reduce friction, and promote knowledge sharing across domains.
- **Rapid Customization for Emerging Technologies**: Unlike other systems that may become outdated as new tools are introduced, this methodology allows users to modify and expand the system as new technologies and data sources emerge.
- **AI-ready**: Consolidated data is now accessible through a unified interface, optimized for downstream use with language models (LMs) and deep learning (DL) tools.
- **Agile and DevOPS:** Methodologies not only for system development but as well for data collection and processing methods.

Development methodology

- Software and systems development
- Roadmap for smart agriculture development
- What innovations could be applied

Decade	**Methodology / Trend**	**Key Innovations**
1970s–1980s	Waterfall	Sequential Phases
1990s	Spiral, Iterative	Risk-driven Development, Incremental Delivery
2000s	Agile	Scrum, XP, User Feedback Loops
2010s	DevOps	CI/CD, Infrastructure as Code (IaC), Docker, Kubernetes
2020s	Cloud-Native, SRE	Microservices, GitOps, Observability
2020s–2025	Platform Engineering	Internal Developer Platforms, Developer Experience (DevEx)
2025+	AI-Driven Development, Autonomous Systems	AI Coding, AIOps, Self-Healing Systems

Era	Methodology / Focus	Key Characteristics
Pre-2000s	Traditional Methods	Manual data collection, intuition-based decisions
2000s	Basic Digitization	Introduction of GPS, spreadsheets, simple sensors
2010s	Precision Agriculture	IoT sensors, satellite imagery, variable-rate tech
2020s	Smart Agriculture	AI, ML, cloud platforms, mobile apps, drones
2025+	Autonomous & AI-Guided Farming	Robotics, AI decision systems, edge computing, predictive models, blockchain traceability

Future innovations in Smart Agriculture development methodologies

- AI-Powered Soil & Crop Health Diagnostics
  - Multi-modal Sensing with Predictive Analytics
  - Combining drone imagery, soil sensors, and satellite data analyzed by AI for early disease, nutrient deficiency, or pest detection.

Area	Potential Innovation	Description / Application in Smart Ag
AI-Driven Adaptive Planning	*Real-time AI Optimization of Crop Plans*	Systems that dynamically adjust planting, watering, and fertilization schedules based on live sensor and weather data.
Digital Twins of Farms	*Full-Farm Simulation Environments*	Virtual replicas of entire farms to test interventions, crop rotations, or machinery changes without risking real assets.
Swarm Robotics Coordination	*Autonomous Drone and Robot Swarms*	Coordinated fleets of drones/robots that collaboratively manage large fields, perform planting, pest control, and harvesting.
Blockchain for Traceability & Incentives	*Decentralized Crop Provenance & Carbon Credits*	Transparent supply chains and incentivization of sustainable practices using blockchain tokens or smart contracts.
AI-Powered Soil & Crop Health Diagnostics	*Multi-modal Sensing with Predictive Analytics*	Combining drone imagery, soil sensors, and satellite data analyzed by AI for early disease, nutrient deficiency, or pest detection.
Edge AI with Low Power Sensors	*On-Device AI for Real-Time Decision Making*	Sensor devices that process data locally to reduce latency and reliance on cloud, enabling instant interventions.
MLOps for Ag Models	*Continuous Training and Deployment of Crop Prediction Models*	Robust pipelines to update AI models as new data arrives, ensuring accuracy and adaptability.
Human-AI Co-Governance Frameworks	*Farmers and AI Systems Collaborate on Decisions*	Methodologies that formalize trust, oversight, and feedback between human farmers and AI recommendations.
Augmented Reality (AR) for Field Management	*AR Interfaces for Real-Time Field Data Visualization*	Allowing farmers to visualize soil moisture, pest presence, or growth metrics overlayed on actual crops through AR glasses or mobile apps.
Sustainability-Focused Dev Methodologies	*Incorporating Environmental Impact Metrics into Dev Cycles*	Frameworks that mandate measuring water use, emissions, and biodiversity impact during software/technology development.

Conclusions

•Respect Legacy, enable Iransition
Rather than disrupting long-standing practices, focus on *empowering them through structured transformation*. Avoid struggling against entrenched ways of working. Instead, develop and apply a **robust data and knowledge migration methodology**, supported by intuitive tools that make the transition natural, not forced. This approach fosters adoption, preserves valuable expertise, and ensures continuity.

•Build an Interdisciplinary Core Team
The complexity of modern data systems demands diverse perspectives. Forming an **interdisciplinary team** - blending domain experts, technologists, data scientists, and operations specialists - ensures that solutions are both technically good and practically relevant.

•Innovate at the intersections
The **future of data collection and processing is interdisciplinary innovation**. True scalability and intelligence emerge when we integrate **sensors, robotics, environmental science, AI**, and **productivity tools** into unified, adaptive systems. These hybrid solutions enable dynamic monitoring, real-time analysis, and informed decision-making, even in complex environments.

```
--------------------------------------------------------------------------------
-- Main PL/SQL Script for Seedling Processing
--------------------------------------------------------------------------------

DECLARE
    r           VARCHAR2(100);        -- Holds value read from source table
    qry         VARCHAR2(200);        -- Dynamic SQL query
    qryW        VARCHAR2(200);        -- Dynamic SQL query for weight
    w           NUMBER;               -- Seed weight
    nID         NUMBER;               -- Placeholder for row ID
    npID        NUMBER;               -- Not used in current logic
    nF          NUMBER := 0;          -- Furrow counter
    nCn         NUMBER;               -- Column counter within row
    nSeedling   NUMBER;               -- Seedling flag
    vSeedling   VARCHAR2(20);         -- Transformed seedling name
    nWeight     NUMBER;               -- Extracted seed weight
    dSDate      DATE;                 -- Germination date
    vInsSQL     VARCHAR2(500);        -- SQL insert statement
BEGIN
    -- Loop through each relevant row in the source table
    FOR i IN (
        SELECT id
        FROM LAUKA_PLANOJUMS_12052023
        WHERE id < 53 AND id > 1
        ORDER BY id
    ) LOOP
        nCn := 1; -- Reset column index for each row

        -- Loop through all columns except excluded ones
        FOR c IN (
            SELECT column_name AS cn
            FROM user_tab_columns
            WHERE table_name = 'LAUKA_PLANOJUMS_12052023'
            AND column_name NOT IN ('ID', 'COLUMN_61', 'COLUMN_62', 'COLUMN_63', 'COLU
        ) LOOP

            -- Dynamically get column value for current row
            qry := 'SELECT ' || c.cn || ' FROM LAUKA_PLANOJUMS_12052023 WHERE id = :1'
            EXECUTE IMMEDIATE qry INTO r USING i.id;

            IF r IS NOT NULL THEN
                -- Check if value is a short string and not a number or date
                IF LENGTH(r) < 10 AND is date(r) = 0 AND is number(r) = 0 THEN
```

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Phenotypic Variation and Relationships between Grain Yield, Protein Content and Unmanned Aerial Vehicle-Derived Normalized Difference Vegetation Index in Spring Wheat in Nordic–Baltic Environments

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Knowledge transfer, publications

Current challenges

- Submit publication
- LiDAR data processing workflows (methodology for AREI)
- Literature review

TED4LAT

Standard operating procedures for UAV phenotyping. url: https://excellenceinbreeding.org/sites/default/files/manual/EiB_M4_%20SOP-UAV-Phenotyping-12-10-20.pdf.
Biomass Prediction with 3D Point Clouds from LiDAR. url: https://openaccess.thecvf.com/content/WACV2022/papers/Pan_Biomass_Prediction_With_3D_Point_Clouds_From_LiDAR_WACV_2022_paper.Pdf.
Soumya Debnath, Manik Paul, and Tanmoy Debnath. "Applications of LiDAR in Agriculture and Future Research Directions". In: J Imaging 9.3 (Feb. 2023), p. 57. doi: 10 . 3390 / jimaging9030057. url: https : //doi.org/10.3390/jimaging9030057
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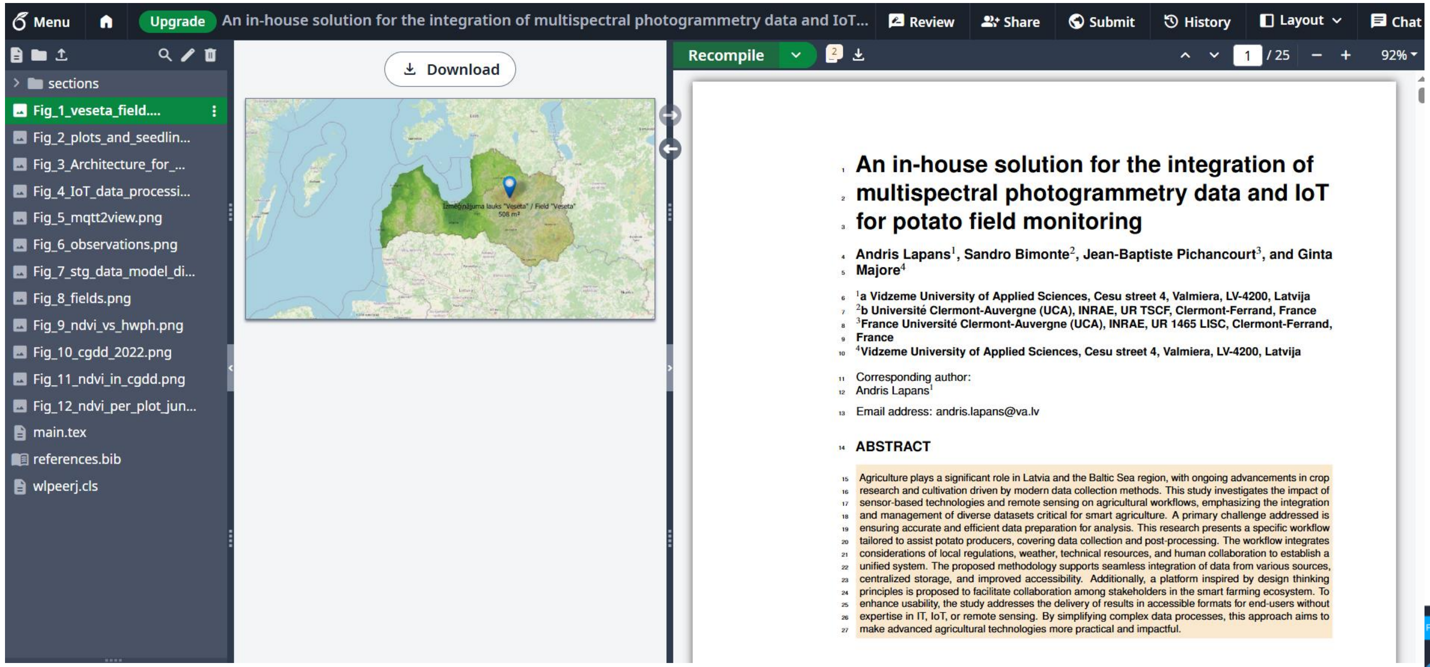
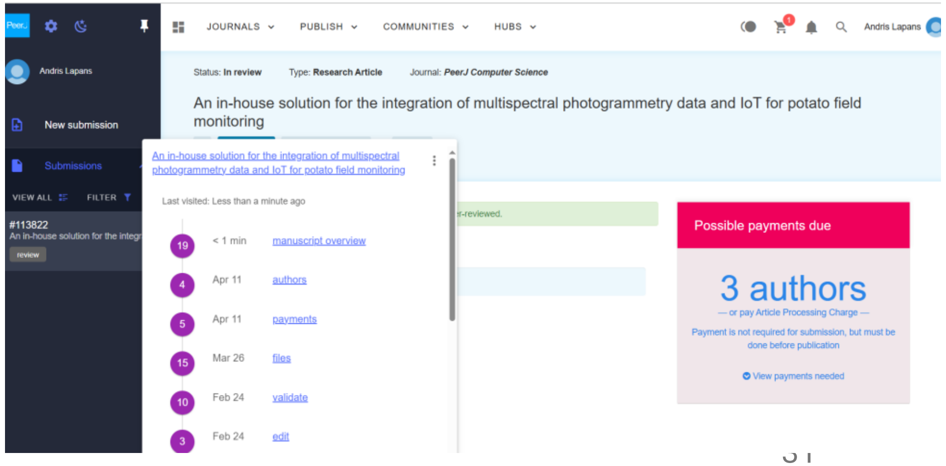
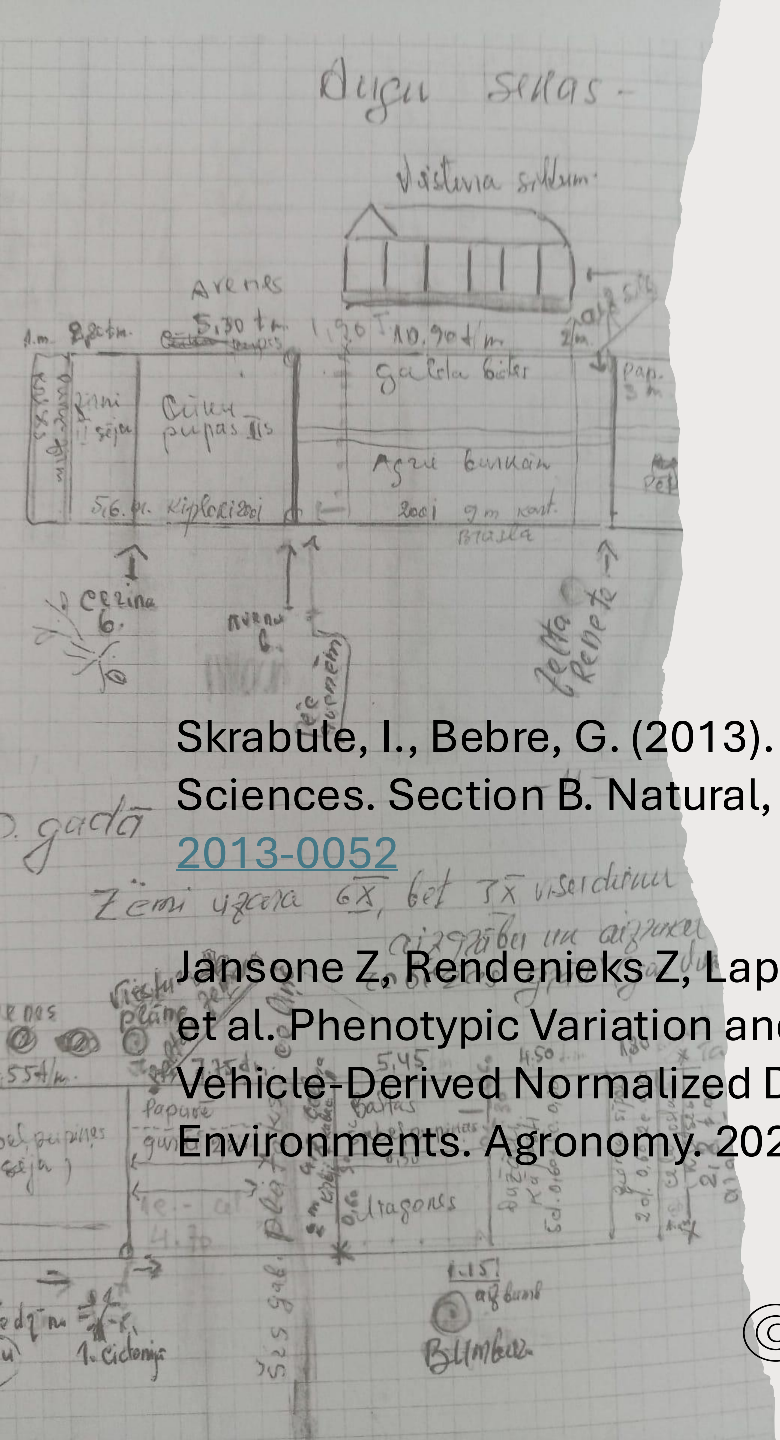
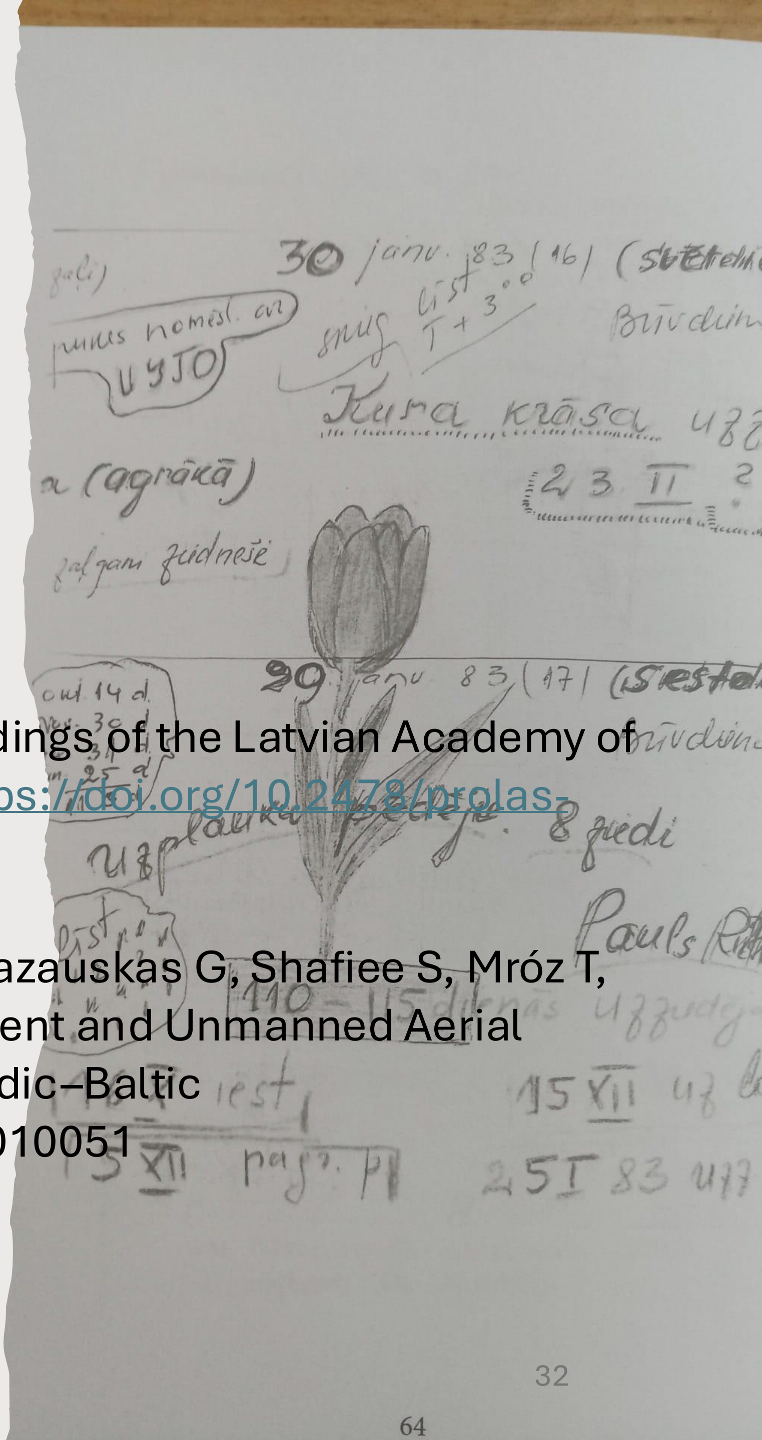
Publication in process





Questions?





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