Agronomy program in Alaska and soil health research

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Mingchu Zhang, Ph.D. professor of agronomy/soil science

Department of Natural Resources and Environment,
Institute of Agriculture, Natural Resources, and Extension
University of Alaska Fairbanks

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Outline of the presentation

- Brief outline the agronomy/soil research activities in Alaska
- Modeling on small grain yield under climate change
- Report and discuss the soil health research in Alaska
  - Research on land use change
  - Problems encountered
  - Some considerations on soil health research in Alaska

U.S. EXPANSION AND THE ALASKA PURCHASE, 1867

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#040



Agronomy and soil research activities in Alaska

- Alaska current land for agriculture, total land suitable for agriculture.
  - 2237.9 hectares of small grain and most of them are feed barley with a crop value of $951,000
  - 16 million hectares of land suitable for agriculture, a potential breadbasket for USA under climate change scenario, range land 714,377 acres.
- Cereal crop variety test;
- Cover crop experiment;
- Soil health research;
- Cut flower nutrient test.

May 24, 2022


Bird damage



WINTERSTEIGER


Winter cover crop trial (started in summer 2022)

	Border Strip - Wooding Barley			Border Strip - Wooding Barley			Border Strip - Wooding Barley	
	101	Early Giant	201	17 MDCC-Hard	301	17 MDCC-Soft	401	Dixie
Clover	102	17 MDCC-Soft	202	Early Giant	302	Early Giant	402	17 MDCC-Soft
	103	17 MDCC-Hard	203	19 MDCC	303	Dixie	403	19 MDCC
	104	19 MDCC	204	Dixie	304	17 MDCC-Hard	404	17 MDCC-Hard
	105	Dixie	205	17 MDCC-Soft	305	19 MDCC	405	Early Giant
Winter	101	**Whistler**	**201**	**Amigo**	**301**	**WyoWinter**	**401**	**Windham**
peas	102	**WyoWinter**	**202**	**Lcicle**	**302**	**Whistler**	**402**	**Podell**
	103	**Amigo**	**203**	**Whistler**	**303**	**Windham**	**403**	**Amigo**
	104	**Lcicle**	**204**	**Blaze**	**304**	**Amigo**	**404**	**WyoWinter**
	105	**Windham**	**205**	**Podell**	**305**	**Blaze**	**405**	**Lcicle**
	106	**Blaze**	**206**	**WyoWinter**	**306**	**Podell**	**406**	**Whistler**
	107	**Podell**	**207**	**Windham**	**307**	**Lcicle**	**407**	**Blaze**
	Border Strip - Wooding Barley			Border Strip - Wooding Barley			Border Strip - Wooding Barley	

Taken in the University Farm
on July 7, 2021

Source: *Thomas J. Story / Sunset Publishing*

Source: Alaska peony growers' Association.

Two major researches

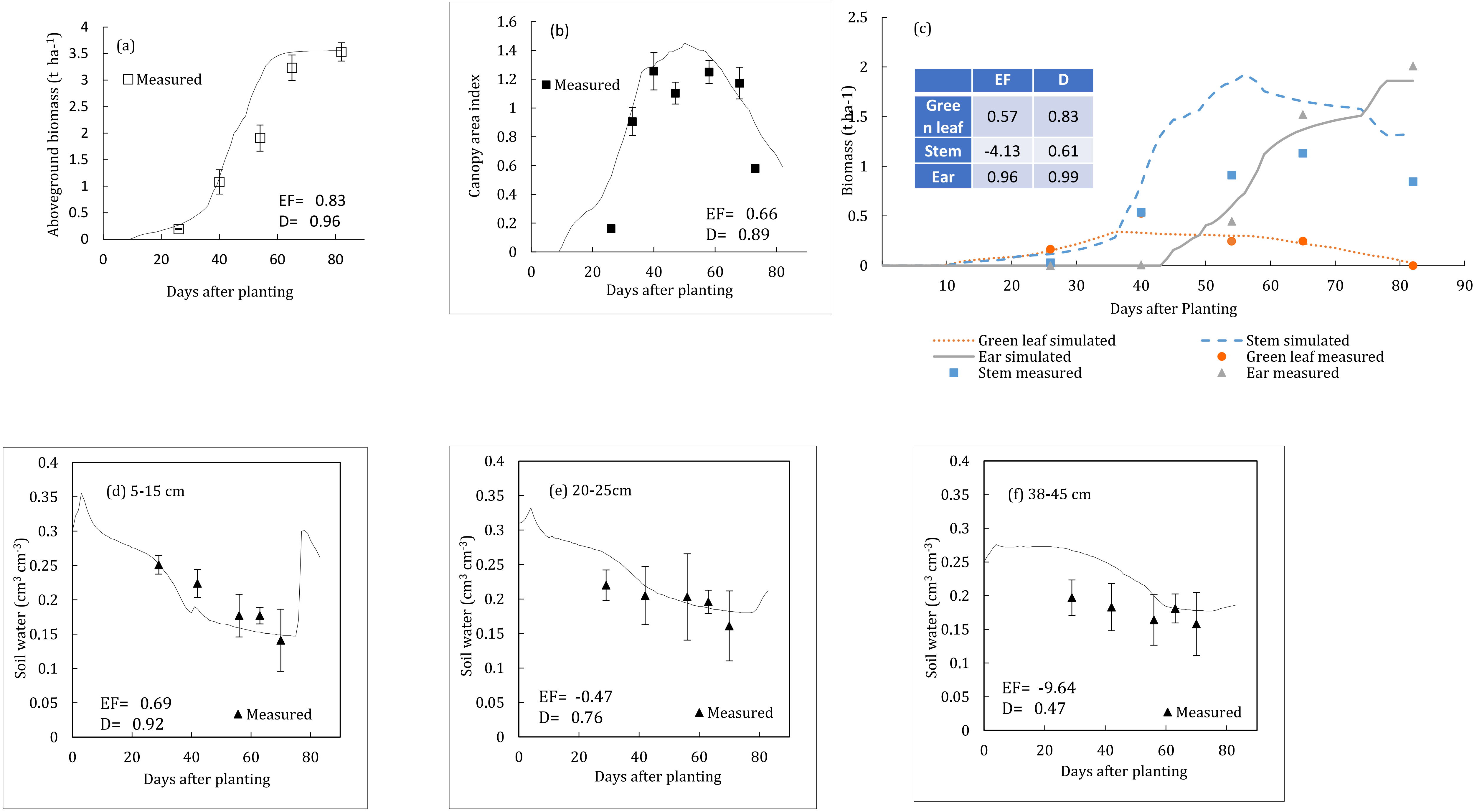
- Small grain evaluation and modeling
  - Passed 20+ years field research accumulated large database.
  - It allows modeling (simulation or machine learning) of the data under environment changes.
- Soil health research
  - Early land use change on soil health.
  - Current exploration for new approaches.

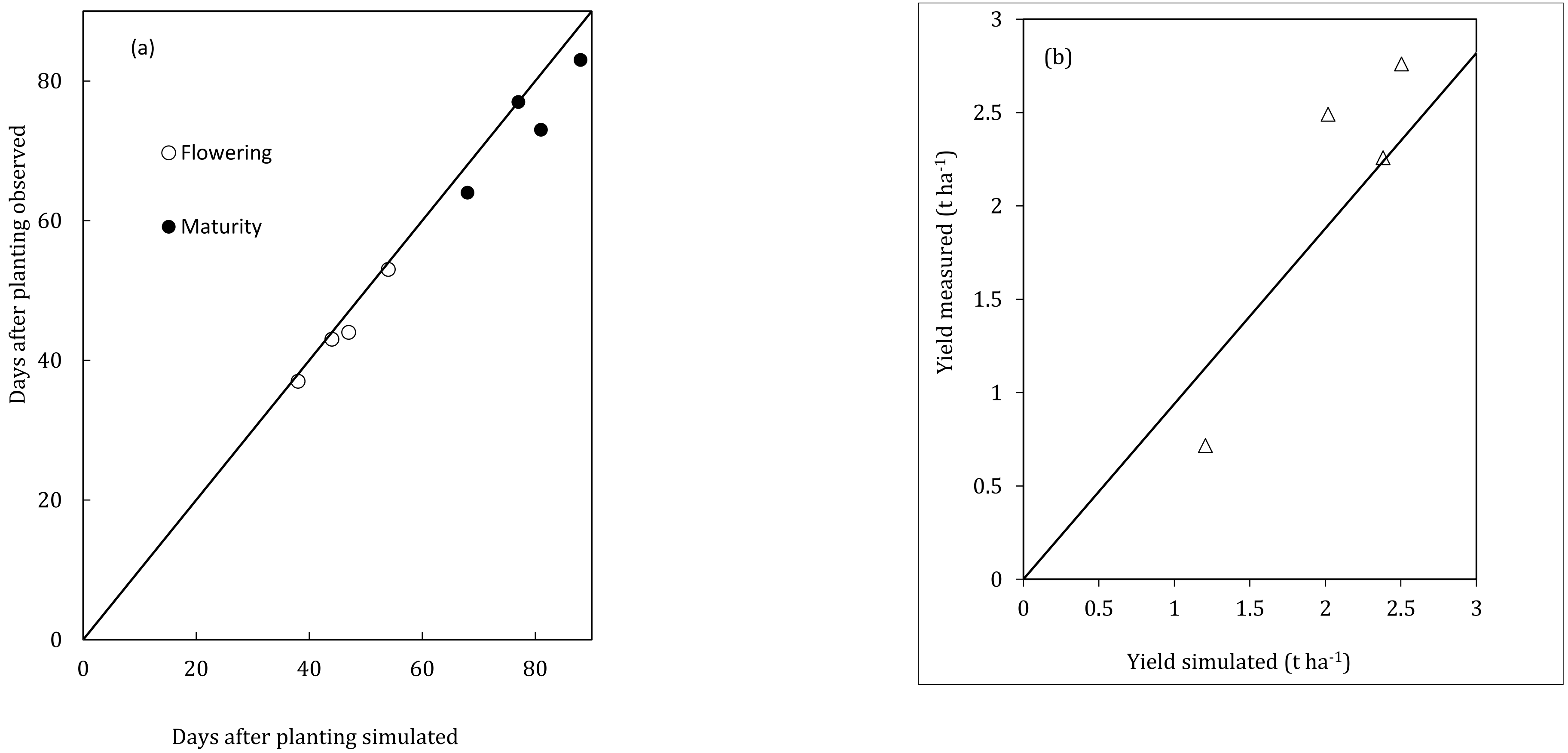
Modeling of cereal crop on a data set from 20+ years for growth stages and climate impact

- Projections of spring wheat growth in Alaska: Opportunity and adaptions in a changing climate. Climate Service 22 (2021) 100235.
- Forecasting flowering and maturity times of barley using six machine learning algorithms. J. of Agricultural Science and Technology, B 9 (2019) 373-391
- Growing season and phenological stages of small grain crops in response to climate change in Alaska. American Journal of Climate Change, 2021 10:490-511
- Impact of heading shift of barley cultivars on the weather patterns around heading and yield in Alaska. Atmosphere 2022, 13:310
- Temperature and precipitation changes impact the yield of small grain cultivars from 1978 to 2018 in Fairbanks and Delta Junction, Alaska. Arctic, Antarctic, and Alpine Research 2022, 54:386-395.

For DSSAT (Decision Support System for Agrotechnology Transfer) simulation

- DSSAT: a site-specific model simulating Plant, Environment and Management (PxExM) conditions under a changing driver, CO_2, temperature, and precipitation. There are four steps:
  - Field data collection (2018) with spring wheat "Ingal", data collected including: growth stages, biomass yield, and grain yield, weather data etc.
  - Model calibration, using 2015-2018 data.
  - Model validation, using data of 2011-2014, and model test using qualifiers, RMSE, normalized RMSE, d-index, and model efficiency,.
  - Model application: RCP 4.5, and RCP 8.5 for the time periods of 2020 - 2049, 2050 – 2079, and 2080 – 2099.

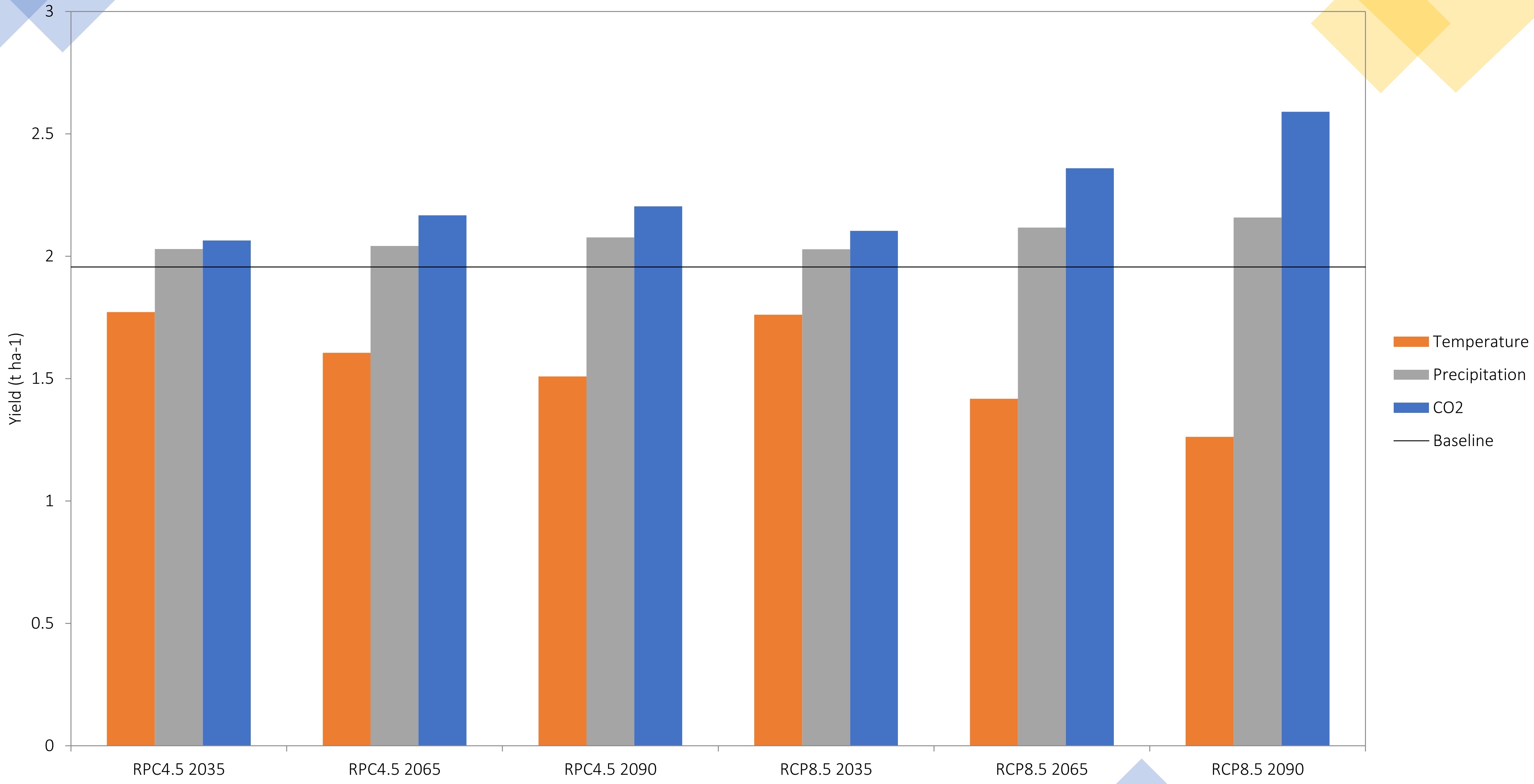

(a)
Measured
EF= 0.83
D= 0.96
Aboveground biomass (t ha-1)
Days after planting
(b)
Measured
EF= 0.66
D= 0.89
Canopy area index
Days after planting
(c)
EF
D
Green leaf
0.57
0.83
Stem
-4.13
0.61
Ear
0.96
0.99
Biomass (t ha-1)
Days after Planting
Green leaf simulated
Stem simulated
Ear simulated
Green leaf measured
Stem measured
Ear measured
(d) 5-15 cm
EF= 0.69
D= 0.92
Measured
Soil water (cm3 cm-3)
Days after planting
(e) 20-25cm
EF= -0.47
D= 0.76
Measured
Soil water (cm3 cm-3)
Days after planting
(f) 38-45 cm
EF= -9.64
D= 0.47
Measured
Soil water (cm3 cm-3)
Days after planting



A correlation of measured and simulated (a) growth phases, and (b) yield of Ingal grown in Fairbanks during 2011-2014

Validation statistics for flowering day after planting (dap) maturity dap and yield (kg/ha) of Ingal grown In Fairbanks during 2011-2014

	Mean Observed	Mean Simulated	%RMSE	D-index	EF
Flowering	44	46	3.9	0.98	0.91
Maturity	74	78	6.9	0.88	0.45
Yield	2056	2028	17.9	0.92	0.78



3
2.5
2
1.5
1
0.5
0
Yield (t ha-1)
RPC4.5 2035
RPC4.5 2065
RPC4.5 2090
RCP8.5 2035
RCP8.5 2065
RCP8.5 2090
Temperature
Precipitation
CO2
Baseline

What we found

- Simulated changes in temperature, especially minimum temperature strongly impact on spring wheat yield
- Current spring wheat cultivar “Ingal” yield in the simulated climate scenarios (RCP 4.5, RCP 8.5) for 2035 s and 2065 s decreased 1 to 4% due to high growing season GDD, and fast growth of “Ingal”.
- Required extensive field measurement in order to run DSSAT simulation model.
- Adaptive measurement for the results: breeding new cultivars, or seeding late.

For Machine Learning modeling

- Different from other simulation, machine learning is pattern recognition or grouping.
- There are different ways for pattern recognition, but we evaluated six common used ones
  - Linear Discriminant Analysis (LDA),
  - Support Vector Machines (SVMs),
  - *k*-nearest neighbor (kNN),
  - Naïve Bayes (NB),
  - Recursive Partitioning and Regression (RPART), and
  - Random Forest (RF).

What have we found?

- Results showed:
  - Machine learnings are useful tools to predict flower and maturity dates, but no single algorithm outperformed others over all data set.
  - LDA and SVMs are better than the other for the data used, but k-NN is the worst one for the data set.
  - More work is needed in AI crop yield modeling, such as deep learning, and application of past plant/soil knowledge in modeling.

Soil health research

- Soil health: The continued capacity of the soil to function as a vital living ecosystem that sustains plants, animals and human.)USDA-NRCS, 2012, Soil Renaissances, 2014).

- Soil quality: the capacity of a soil to function within ecosystem boundaries to sustain biological productivity, maintain environmental quality, and promote plant and animal health. (Doran and Parkin, 1994).

Soil quality and soil health

- Even though the two concepts differ, the methods of evaluation are pretty similar, that is using tangible soil test parameters.
- pH, EC, organic matter content, CEC, etc.

Methods of evaluating soil quality/health in early studies (J. of Land Use Science, 2012:109-121)

- Land uses: CRP, agriculture, and forest
- DI = 100(Xi - Xo)/Xo
- DI – deterioration index of individual measurement;
- Xi – mean of replicate of an analytical item in other land uses rather than natural condition;
- Xo – mean of replicates of an analytical item in the baseline soil, which is natural forest soil in our study;

$ADI = \Sigma DI/N$

- ADI – average of deterioration index of all measurements;
- N – total number of analytical items.

$W = 100 \times DIi / \sum_{i=1}^{n} DIi$

- W weight of individual DI in ΣDI multiplied by 100.

Soil physical, chemical, and biological properties from different land uses in central Alaska.

Analytical Item	Land Uses			Statistical Analysis	
	Arable soils	CRP soils	Forest soils	*P*	LSD (0.05)
Physical properties					
Bulk density (Mg m^{-3})	0.67	0.73	0.82	0.15	NS
Wet aggregate stability 6 mm (%)	19.5	26.9	24.5	0.06	6.3
Chemical properties					
Organic matter					
Surface organic matter (Mg ha^{-1})	4.6	19.4	290.5	<0.0001	59.5
Organic C in mineral soil (g kg^{-1} soil)	60.4	49.4	42.5	0.035	13.4
Total nutrients in mineral soil					
Total N (g kg^{-1} soil)	0.32	0.25	0.19	0.0073	0.07
C:N ratio	18.9	19.8	22.4		
Total P (g kg^{-1} soil)	0.082	0.068	0.056	0.0032	0.014
pH	5.3	5.4	5.3	0.63	NS
EC (dS/m)	0.13	0.11	0.10	0.66	NS
CEC ($cmole_c$ kg^{-1} soil)	25.1	18.0	17.9	0.01	5.0
Mineral N					
NO_3^--N (mg kg^{-1} soil)	0.8	0.1	<0.1	NS	NS
NH_4^+- N (mg kg^{-1} soil)	5.8	2.6	0.5	<0.001	1.8
Melhich-3 extractable ions					
P (mg kg^{-1} soil)	40	10	4	0.0002	16
K (mg kg^{-1} soil)	117	126	76	0.0014	26
Na (mg kg^{-1} soil)	17	12	17	0.078	5
Ca (mg kg^{-1} soil)	2170	1295	1175	0.0004	475
Mg (mg kg^{-1} soil)	290	176	188	0.0005	55
Zn (mg kg^{-1} soil)	5	4	2	0.0002	1
Cu (mg kg^{-1} soil)	2	2	2	0.47	<1
Fe (mg kg^{-1} soil)	541	555	596	0.02	39
Mn (mg kg^{-1} soil)	16	9	17	0.03	6
Biological properties					
Microbial C (mg C/kg soil)	119.5	171.4	98.2	0.028	53.6
Microbial N	21.7	21.9	9.4	<0.001	5.1
Microbial C:N ratio	5.5	7.8	10.4		

Deterioration index (DI, %) of CRP and agricultural soils, and contribution (weight) of each soil parameter to total DI.

Analytical items	CRP soil				Agricultural soil			
	DI	W1	W2	W3	DI	W1	W2	W3
Surface OM	-63.6	-4.1	-22.6		-98.2	-3.7	-21.3	
Total C	23.8	1.5	8.4	6.9	52.7	2.0	11.4	9.4
Total N	42.4	2.7	15.5	12.3	78.5	2.9	17.0	14.3
Total P	23.3	1.5	8.3	6.8	48.5	1.8	10.5	8.7
M3-P	251.8	16.1			1094.3	40.8		
M3-K	90.9	5.7	31.9	26.2	76.3	2.8	16.6	13.6
Min-N	318.7	20.3			588.5	21.9		
Min-N released	715.4	45.6			541.2	20.2		
Micro. N	47.5	3.0	16.8	13.7	112.9	4.2	24.5	20.2
Micro. C	122.1	7.8	43.3	35.3	132.2	4.9	28.7	23.6
CEC	-3.6	-0.2	-1.3	-1.05	58.7	2.2	12.7	10.5
Sum (ΣDI) (1)	1567.9	100			2685.6	100		
Average (ADI) (1)	142.5	7.7			244.1	7.7		
Sum (ΣDI) (2)	282.0		100		461.6		100	
Average (ADI) (2)	35.1		12.5		57.7		12.5	
Sum (ΣDI) (3)	345.6			100	559.8			100
Average (ADI) (3)	49.4			14.3	80.0			14.3

W1 - weight of the total of each analytical item;

W2– weight of each analytical item in summation of DI excluding M3-P and Min-N, Min-N released;

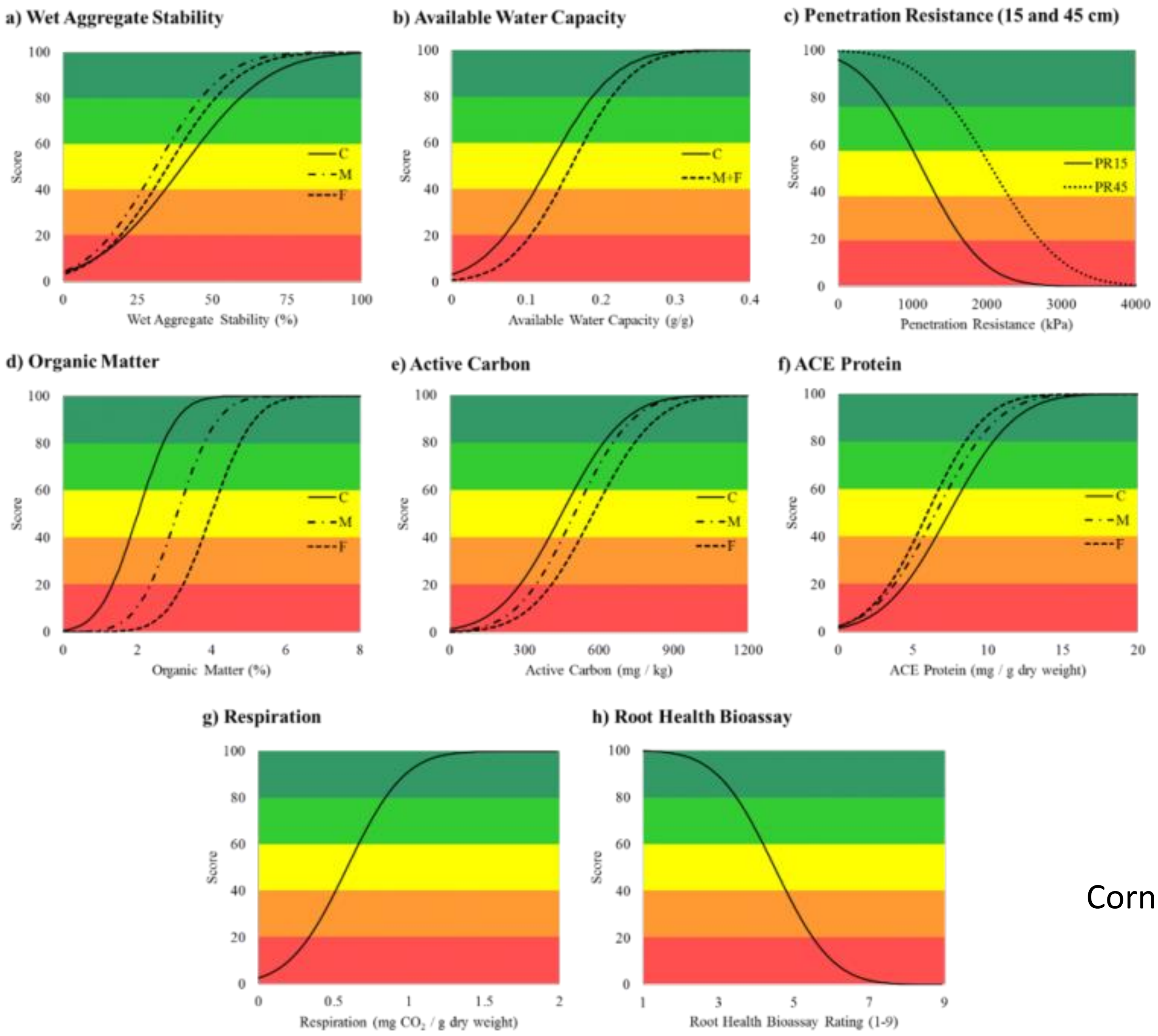
W3 - weight of each analytical items in summation of DI excluding M3-P, Min-N, Min-N released, and Surface OM.


I don't know much about birds but I can easily identify the husband in this picture 😂😂😂😂😂

Cornell approach

- Based on the large quantity of data of the past so that optimal range of soil scores can be found. (Cornell' soil health score curve), more is better, less is better, optimal is better.

- Crop/management/regional specific?



Cornell soil health curve

What are needed for developing curves

- Large amount of past experiment data.
- Based on which, database development is needed.
- For Alaska, systematic agriculture related research started in 1970s, data are scattered and need to be collected.
- Therefore, development of curve is very preliminary.

Soil health is also crop specific

- Crop differences dictate soil health indicators, it has reported by numerous research papers.

  - DuPont ST, Kalcsits L, Kogan C (2021) Soil health indicators for Central Washington orchards. PLoS ONE 16(10): e0258991. https://doi.org/10.1371/journal.pone.0258991)

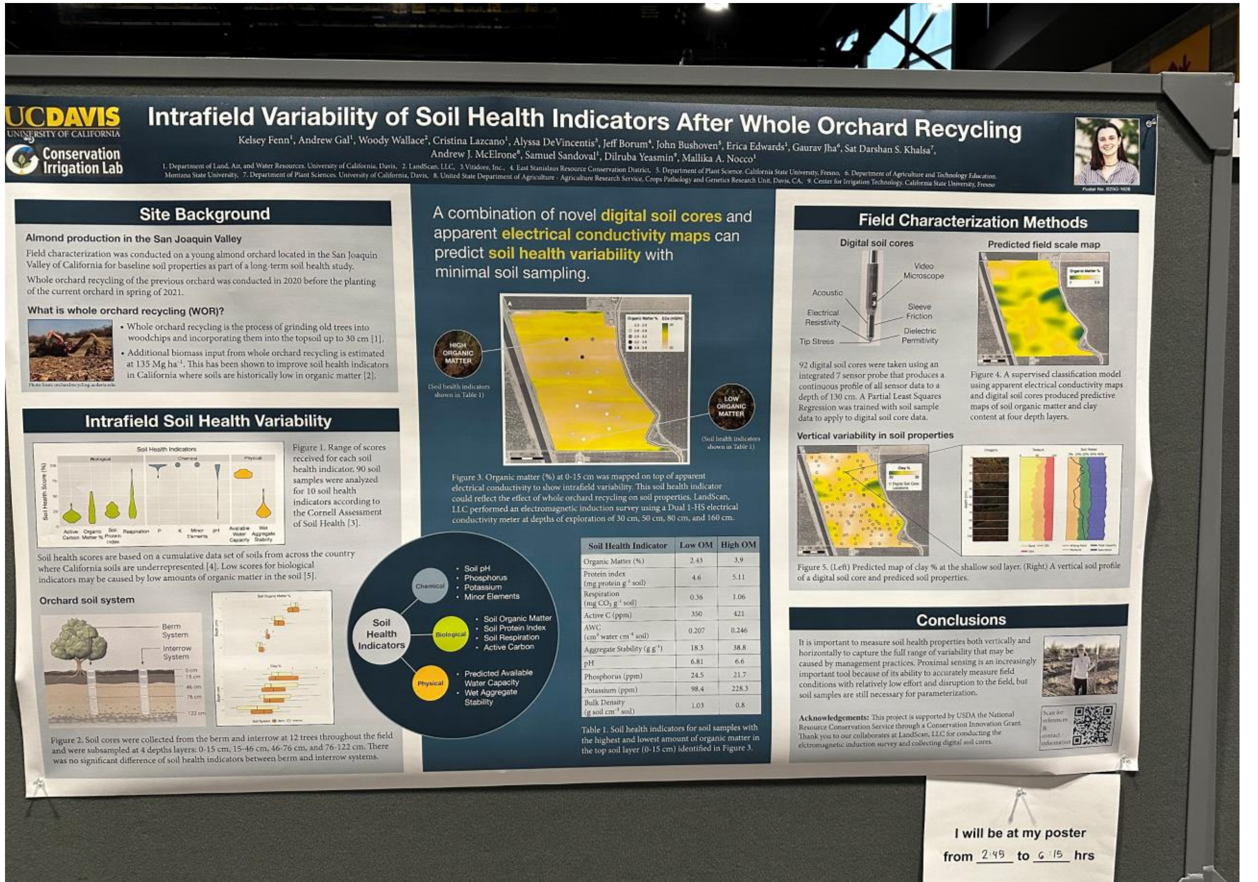
  - Soil quality index for cacao cropping systems, 2018. Quintino Araujo, et al. Archives of Agronomy and Soil Science, https://doi.org/10.1080/03650340.2018.1467005

Issues for soil health

- Scientific study to sustain soil productivity vs. commercial indicators for land prices (Development in agricultural soil quality and health: reflections by the research committee on soil organic matter management, MM Wander et al. 2019 Frontier in Environmental Science, 7:109)

- Heterogeneity issues, poster

from AGU Chicago, Dec. 11-16, 2022



Current research in soil health in Alaska

- Conduct long term field experiment,
  - Example of cover crop trial started in 2016 with 1-, 2- and 3-years rotations followed by potato.
- Do multiple soil analysis in order to develop minimum datasets, and build database.
  - Soil samples were analyzed in four different labs, including routine, soil health tool, Haney test, biological test, USDA-NRCS lab test.
- Relating test results with potato yield.
- Developing minimum data set as soil health indicators, this is an ongoing process.

Conclusion remarks

- AI technology is powerful, yet algorithm improvements for predicting crop growth are still needed.

- Soil health indicators are site and crop specific.