Plant & Food Research
Rangahau Ahumāra Kai

Predicting grapevine yields and development

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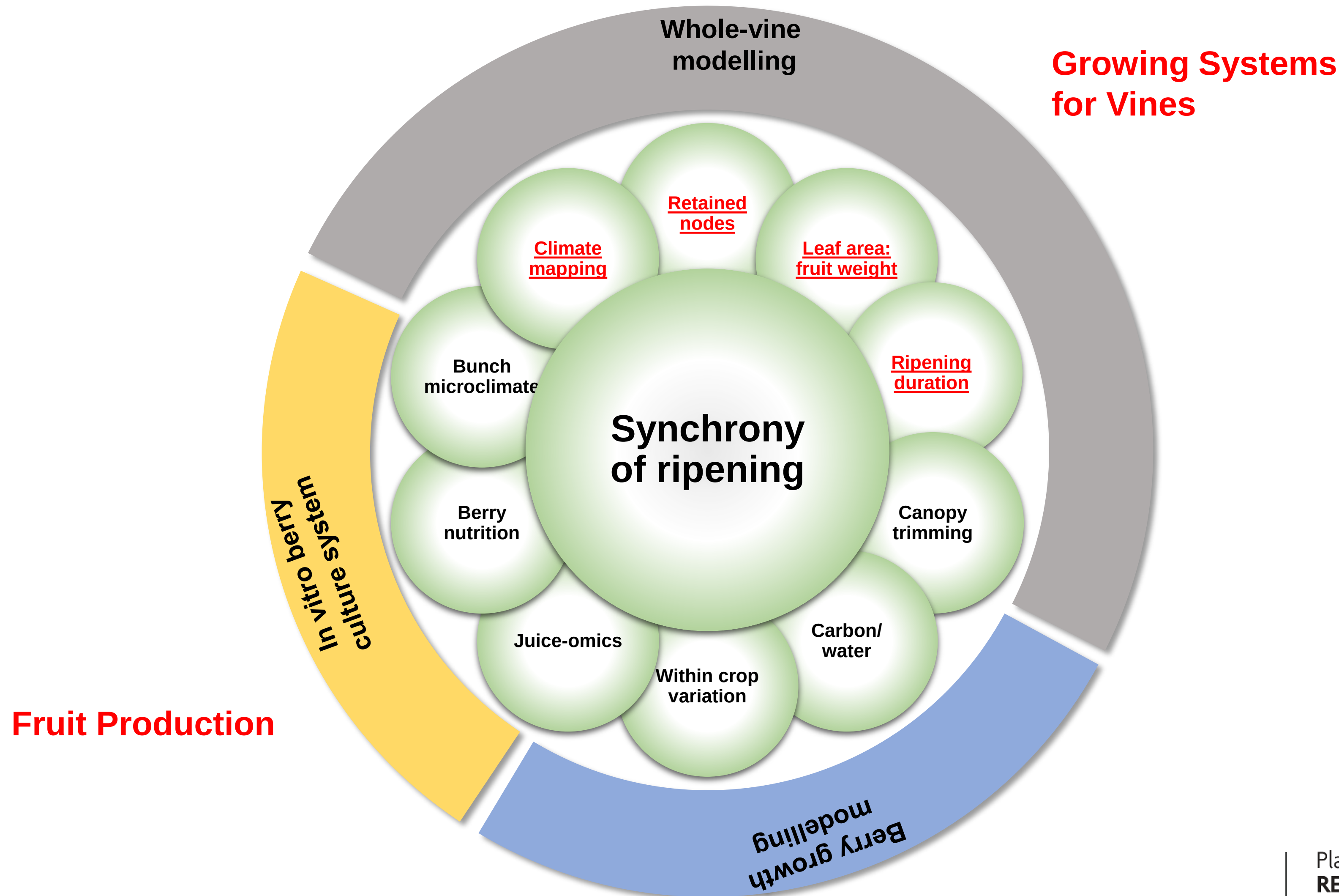
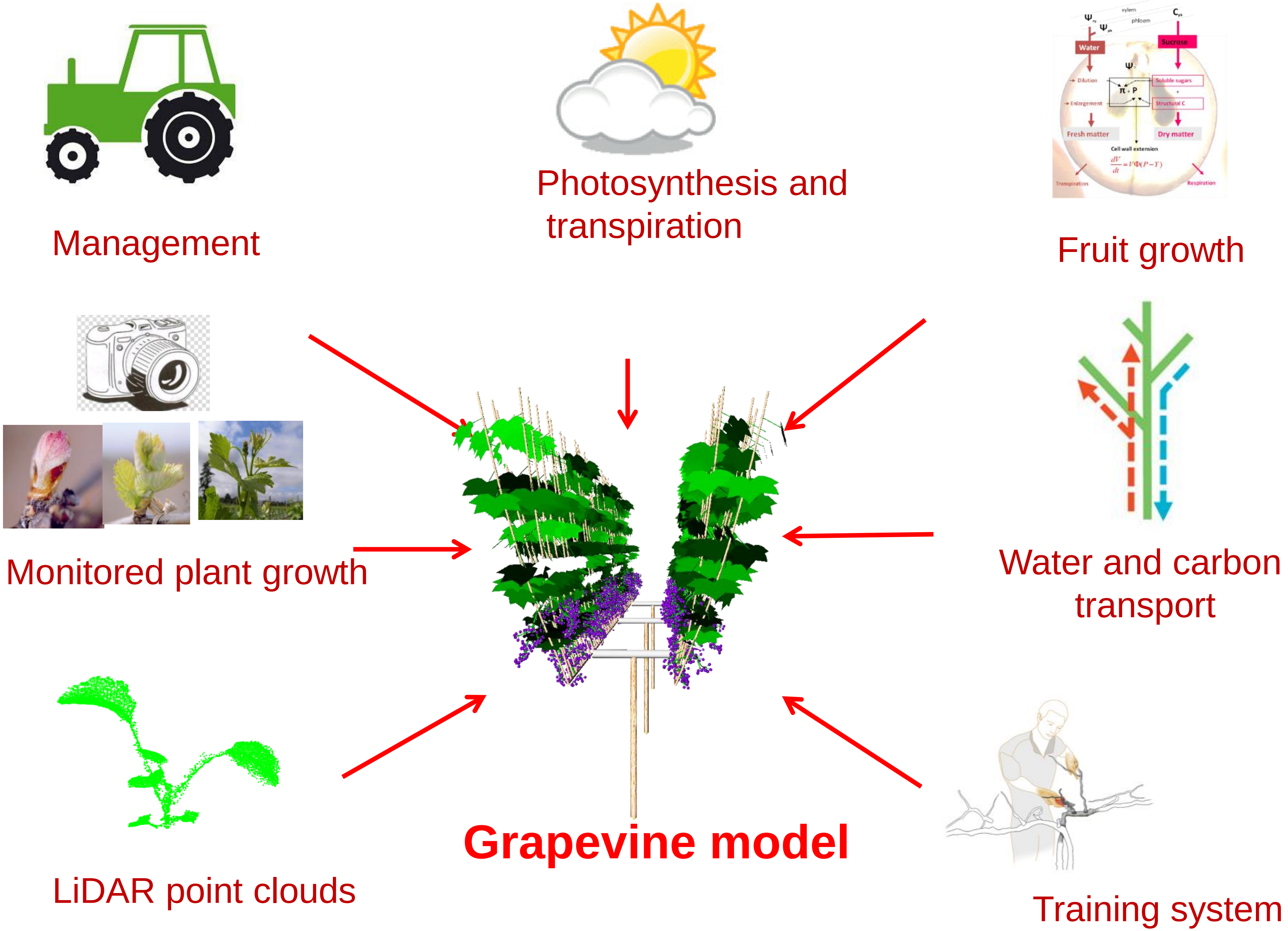
Winner 2017
The Prime Minister's Science Prizes

The New Zealand Institute for Plant and Food Research Limited

Research strategy – Grapevine modelling




Management
Photosynthesis and transpiration
Fruit growth
Monitored plant growth
Water and carbon transport
LiDAR point clouds
Grapevine model
Training system

Outlines

» Statistical yield prediction module based on historical data

» Integrating the yield prediction module into a plant growth model

» Following plans…

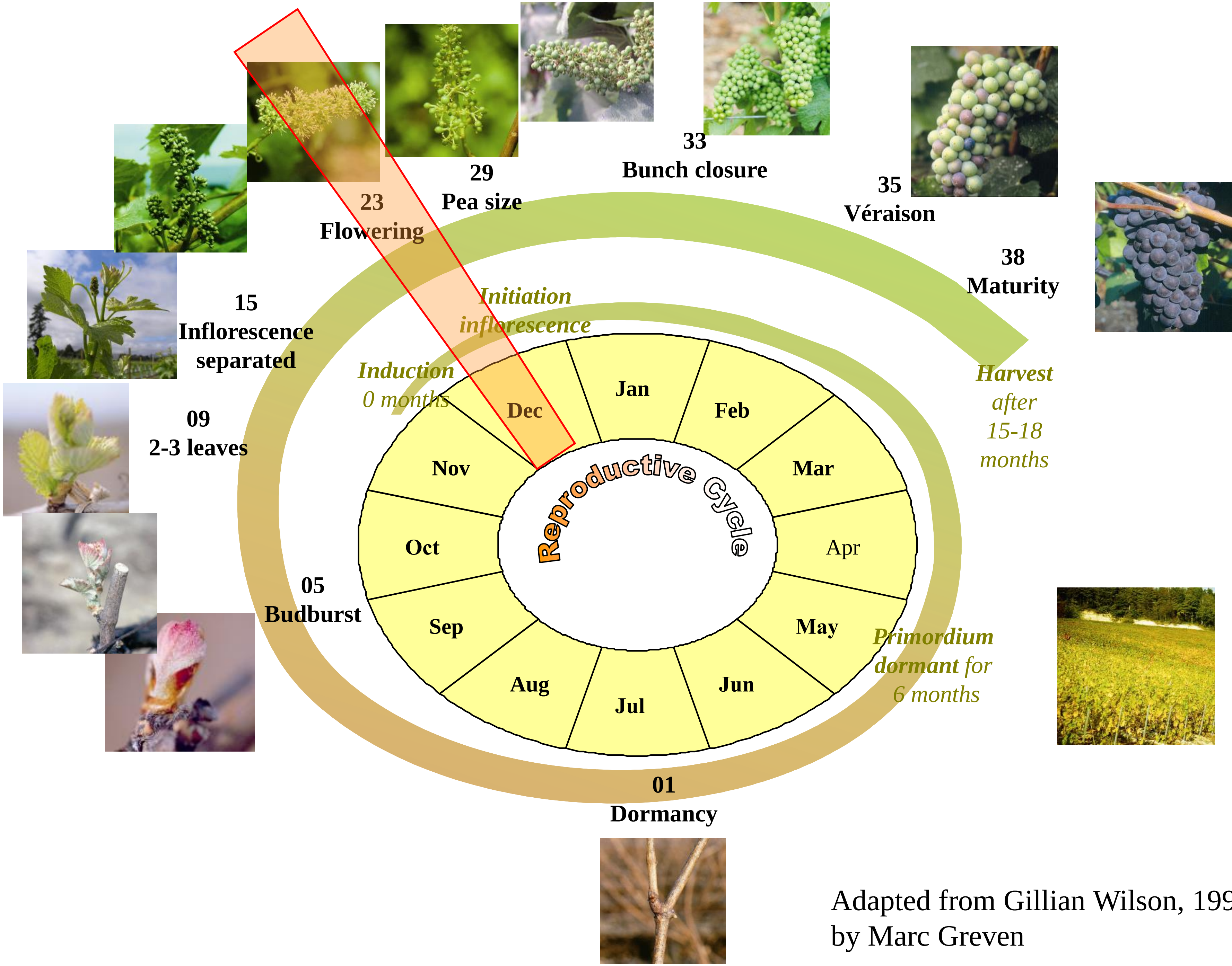
Background of yield prediction

» Yield prediction is a global priority for many multi-national wine producers

» Cool climates subject to large inter-annual yield variations (±35% for some varieties)

» Advance warning of yield variances very helpful for business planning

» Climate change poses various threats and opportunities

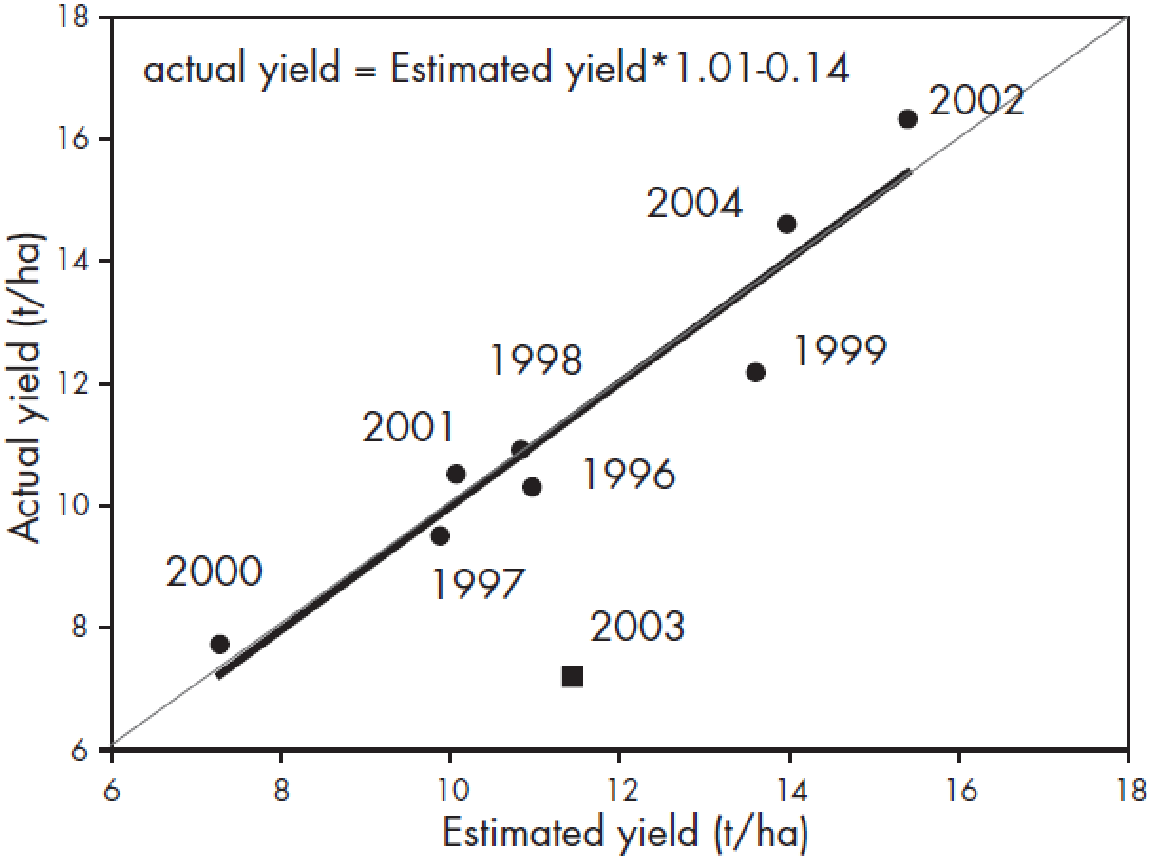


Adapted from Gillian Wilson, 1996
by Marc Greven

Yield model by Mike Trought

- Estimated Yield (t/ha) =

  (2.728*initiation temperature) + (2.918*flowering temperature) – 29.48



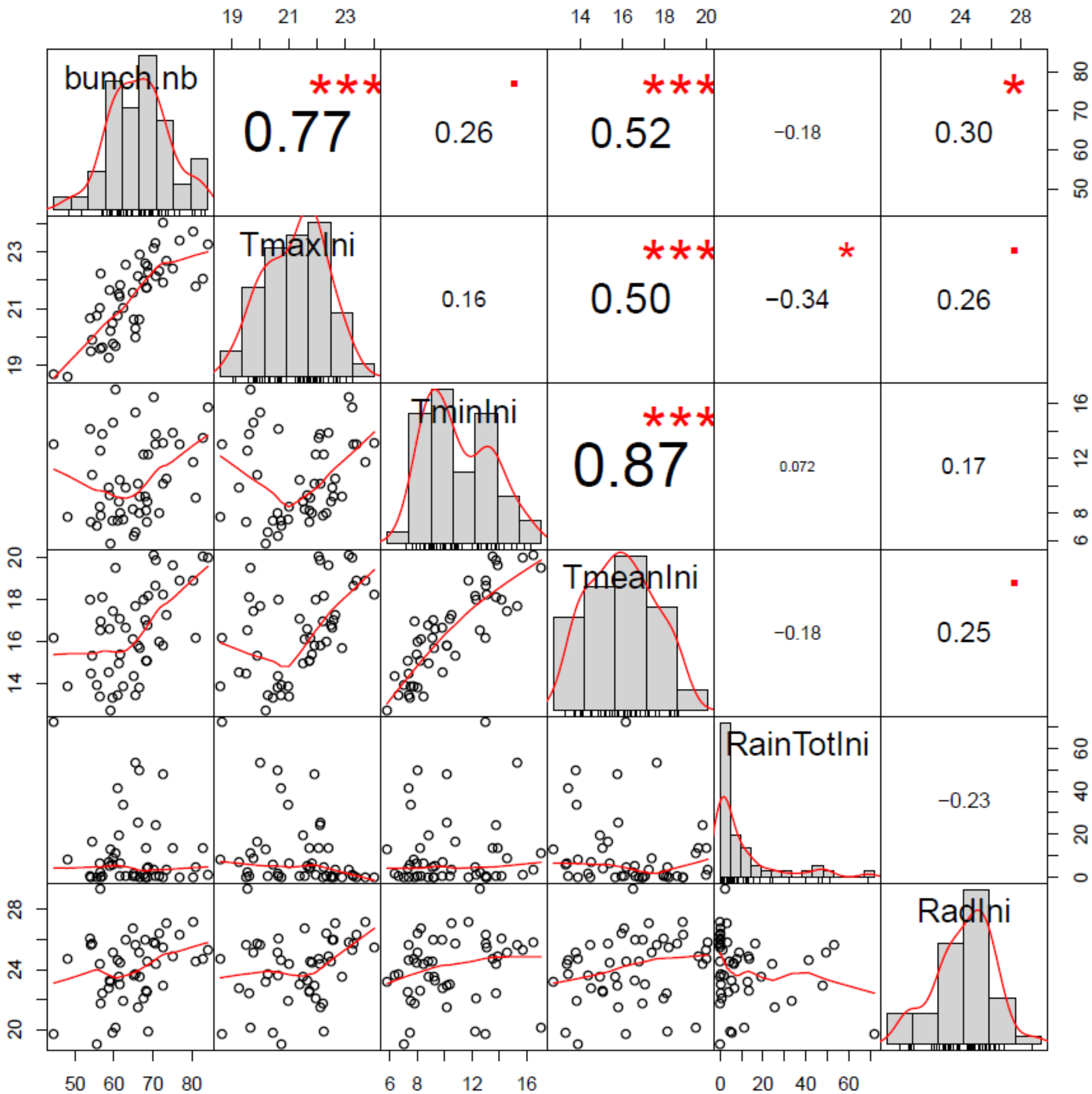
Trought 2005

Long-term phenology and yield monitoring – Rob Agnew & Victoria Raw

Improvement for the yield prediction model

- Collating the long-term phenology and yield monitoring data into a consistent dataset (takes long time…)
- Organising the nearby meteorology data, e.g. maximum and minimum temperature, radiation, rain
- Test the effects of all climatic factors and their interactions on each yield components, e.g. bunch number, berry number, berry weight
- Find the best periods for predicting those yield components using flowering and véraison as guide
- Derive the final prediction equation with the combinations of different factors

Correlation between bunch number and weather factors at different periods



Zhu et al., 2020
OENO one

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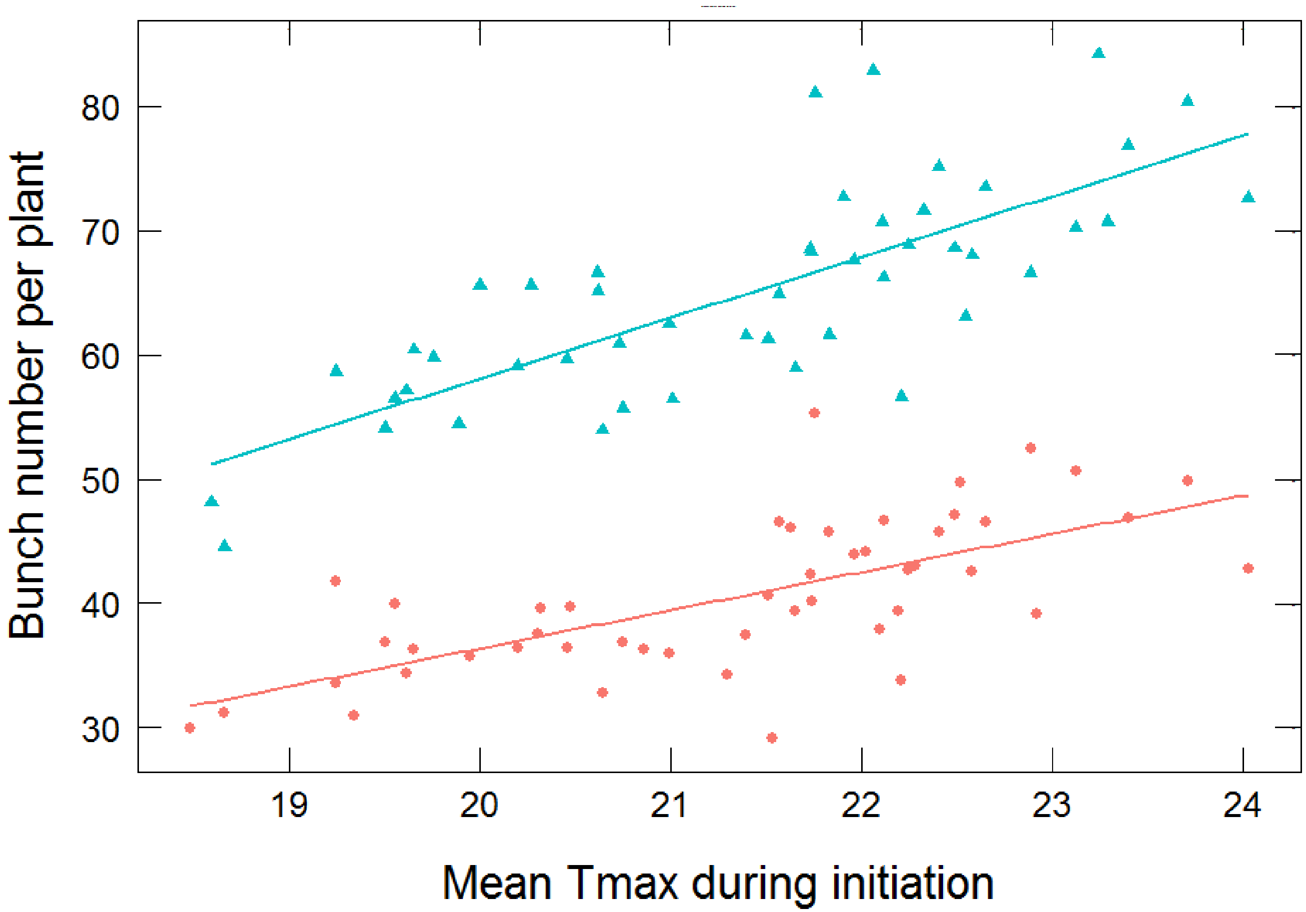
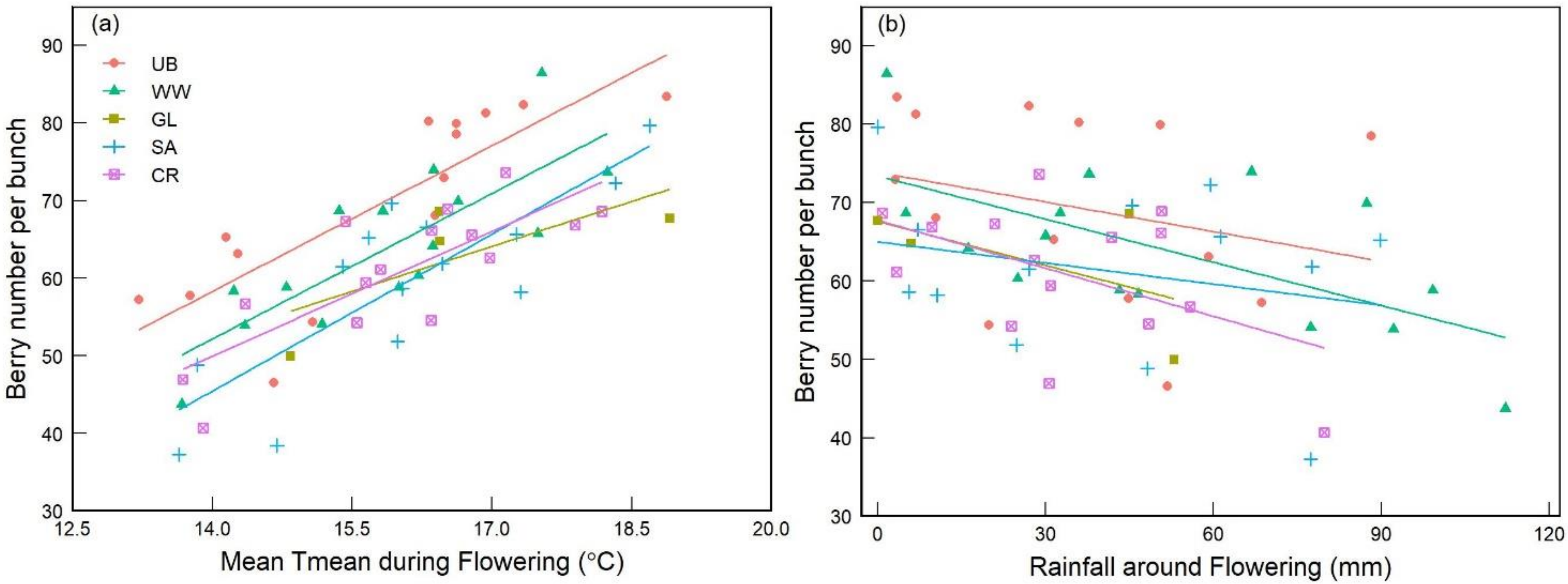
Critical periods

Yield component	Factors	Thermal days before 50% flowering	Thermal days after 50% flowering
Bunch number per vine	TmaxIni	15.90	1.27
	RadIni	10.42	0.14
Berry number per bunch	TmeanFlow	7.08	0.02
	RainTotFlow	10.50	2.69
	TmaxIni	7.92	30.37
Berry weight	TmeanFlow, RainTotFlow, RadFlow, RainTotVer		
Bunch weight	TmeanFlow, RainTotFlow, RainTotVer		

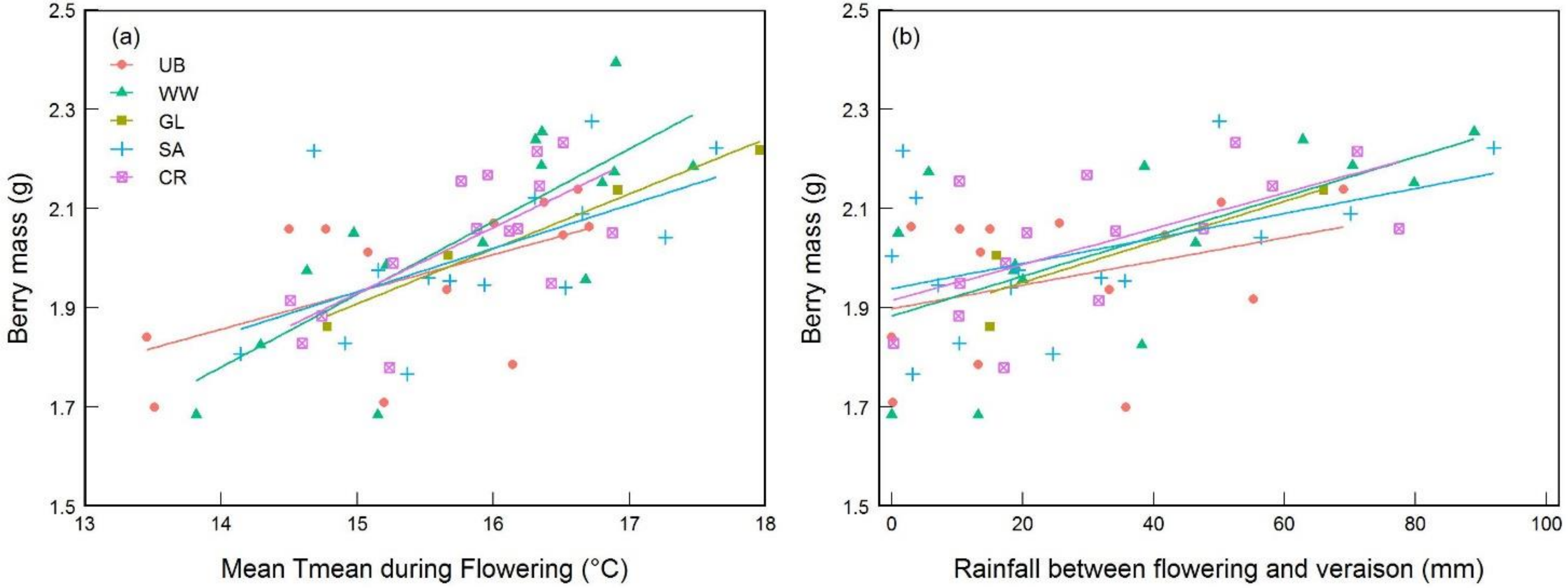
Bunch number vs TmaxIni



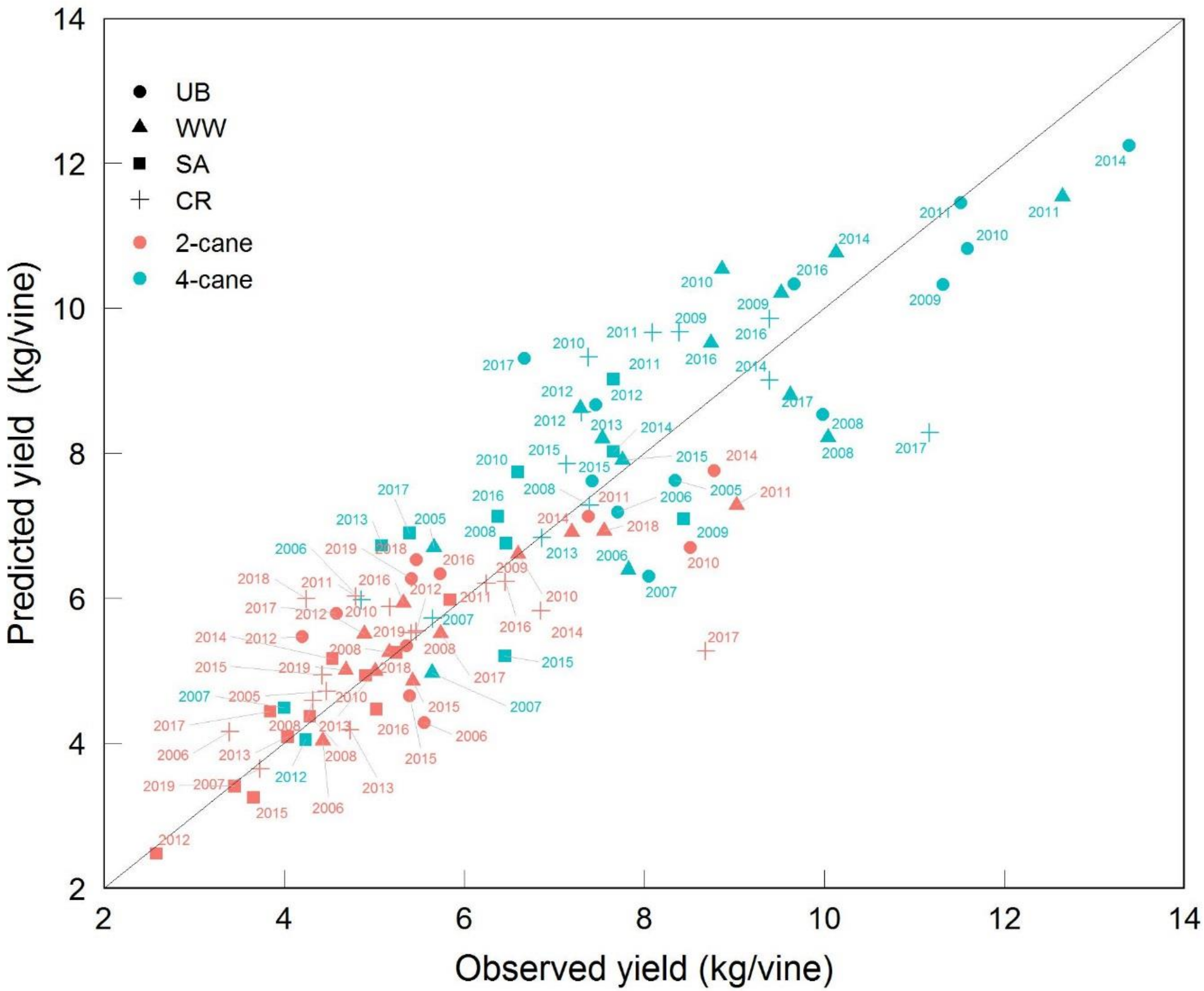
Berry number vs Ta and Rainfall



Berry mass vs Ta and Rainfall



Yield prediction



Current highlights

- Daily Tmax (not Tmean) is most influential factor on berry number and bunch mass
- Optimized critical periods for Tmax mainly before 50% flowering either in the previous or current season
- Mean Radiation also an important input variable
- Rainfall around flowering - negative effect
- Rainfall post-flowering - positive effect
- Statistical model explained 65-85% of the seasonal variations in yield per vine

Publication on VineFacts

- First bunch number prediction in VineFacts on 17 October 2019
- Berry weight, bunch weight and yield per vine on 23 January 2020
- The accuracy of the prediction was evaluated after harvest in April, 2020
- Bunch number prediction for 2020-2021 published in April 2020

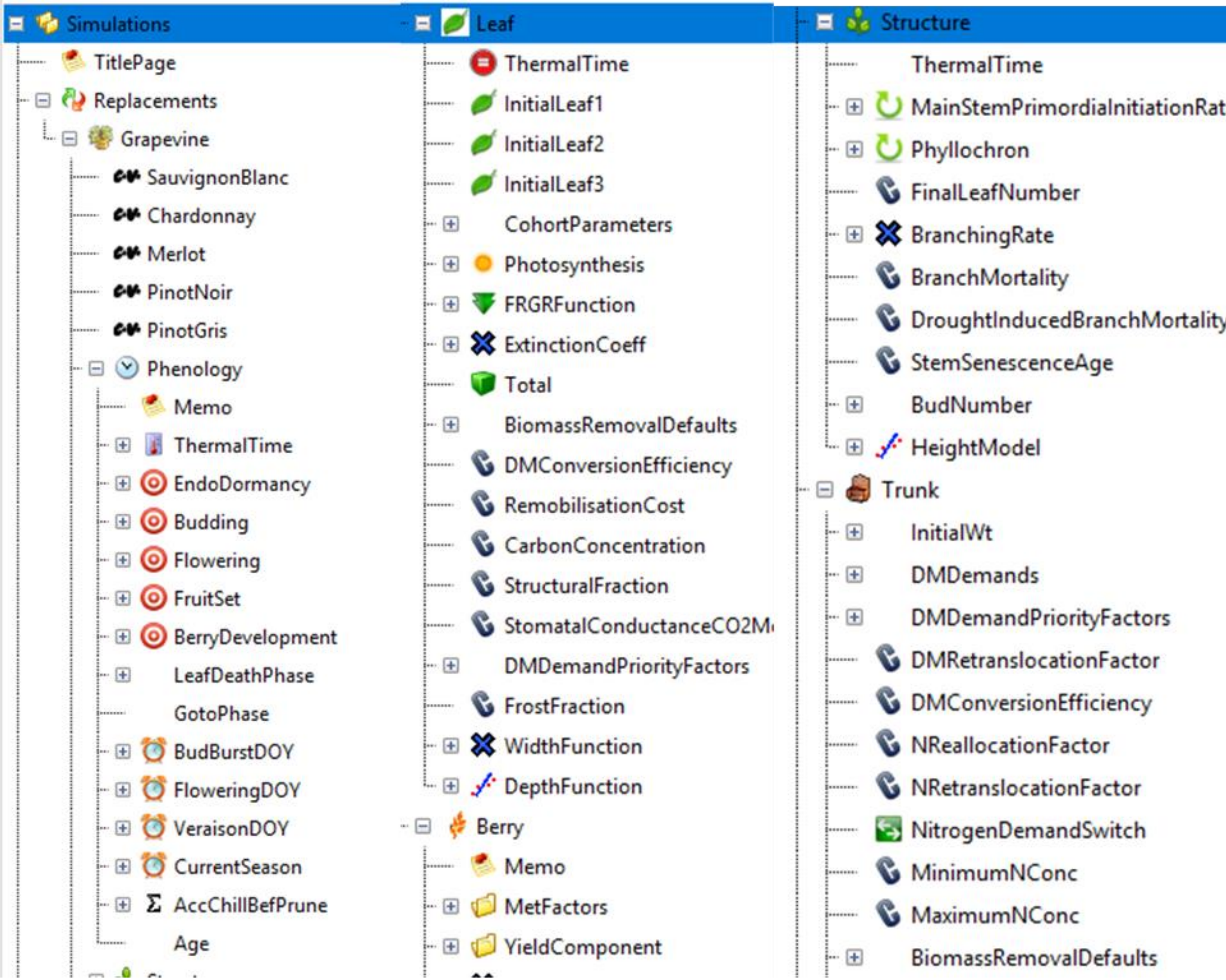
Bunch number for two-cane vines in 2019-2020

Vineyard	Long-term average bunch No./vine	Predicted bunch No./vine compared to Avg.	Actual bunch No./vine compared to Avg.	Accuracy of Actual compared to predicted
Central Rapaura	41.4	37.1 90%	33.5 81%	10% lower
Seaview Awatere	34.9	32.5 93%	32.3 93%	1% lower
Upper Brancott	42.8	38.3 89%	33.0 77%	14% lower
Western Wairau	41.7	37.5 90%	40.1 96%	7% higher

Bunch number for two-cane vines in 2020-2021

Vineyard	Long-term average bunch No./vine	Predicted bunch No./vine in 2021	Predicted bunch No./vine in 2021 as % of LTA
Central Rapaura	41.4	45.6	110%
Seaview Awatere	34.9	38.7	111%
Upper Brancott	42.8	44.0	103%
Western Wairau	41.7	44.3	106%

Integrating into a plant growth model



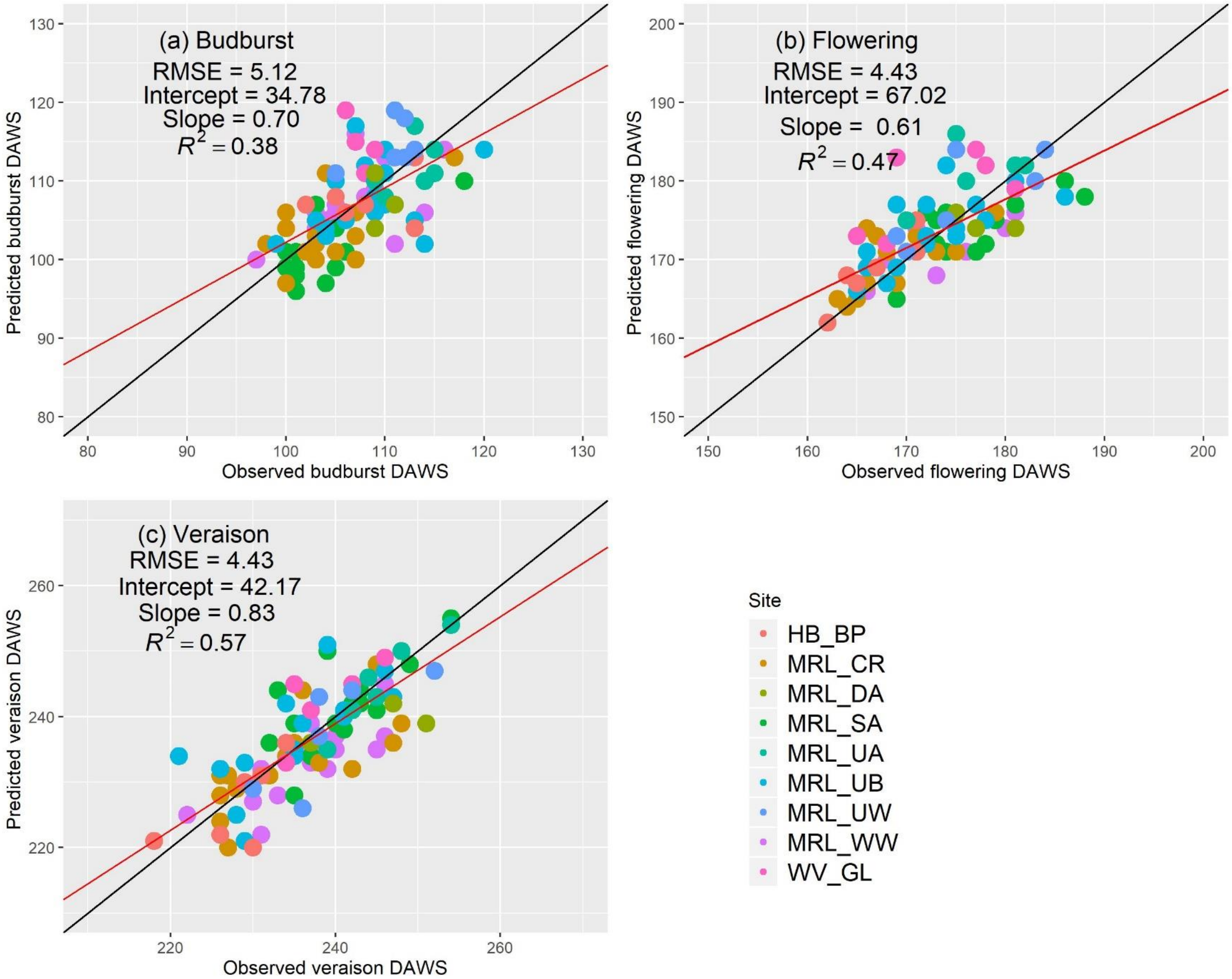
Overview of APSIM grapevine model

- **A**gricultural **P**roduction **S**ystems s**IM**ulator (APSIM)
- A vine and inter-row strip configuration to represent the vineyard setup.
- Strip light interception model
- New carbon allocation method
- A new yield module
- Flexibility in setting different training systems

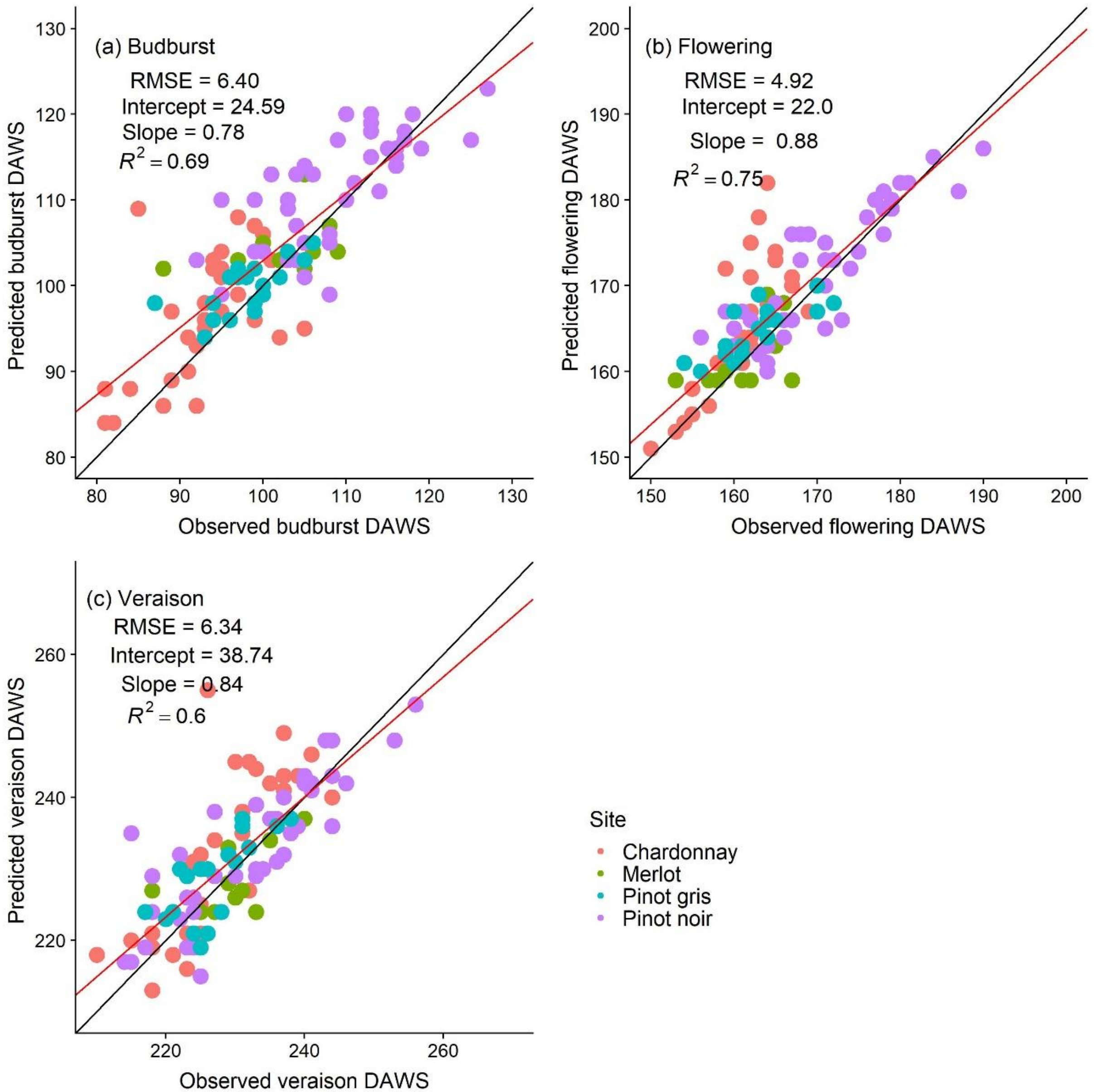
Model functionality

- Phenology (budburst, flowering, fruitset, véraison)
- Light interception
- Photosynthesis
- Leaf number, leaf size, and leaf area on primary shoot and lateral shoot
- Carbon allocation between different organs and carbon storage
- Yield formation
- Soil water dynamics (under development)

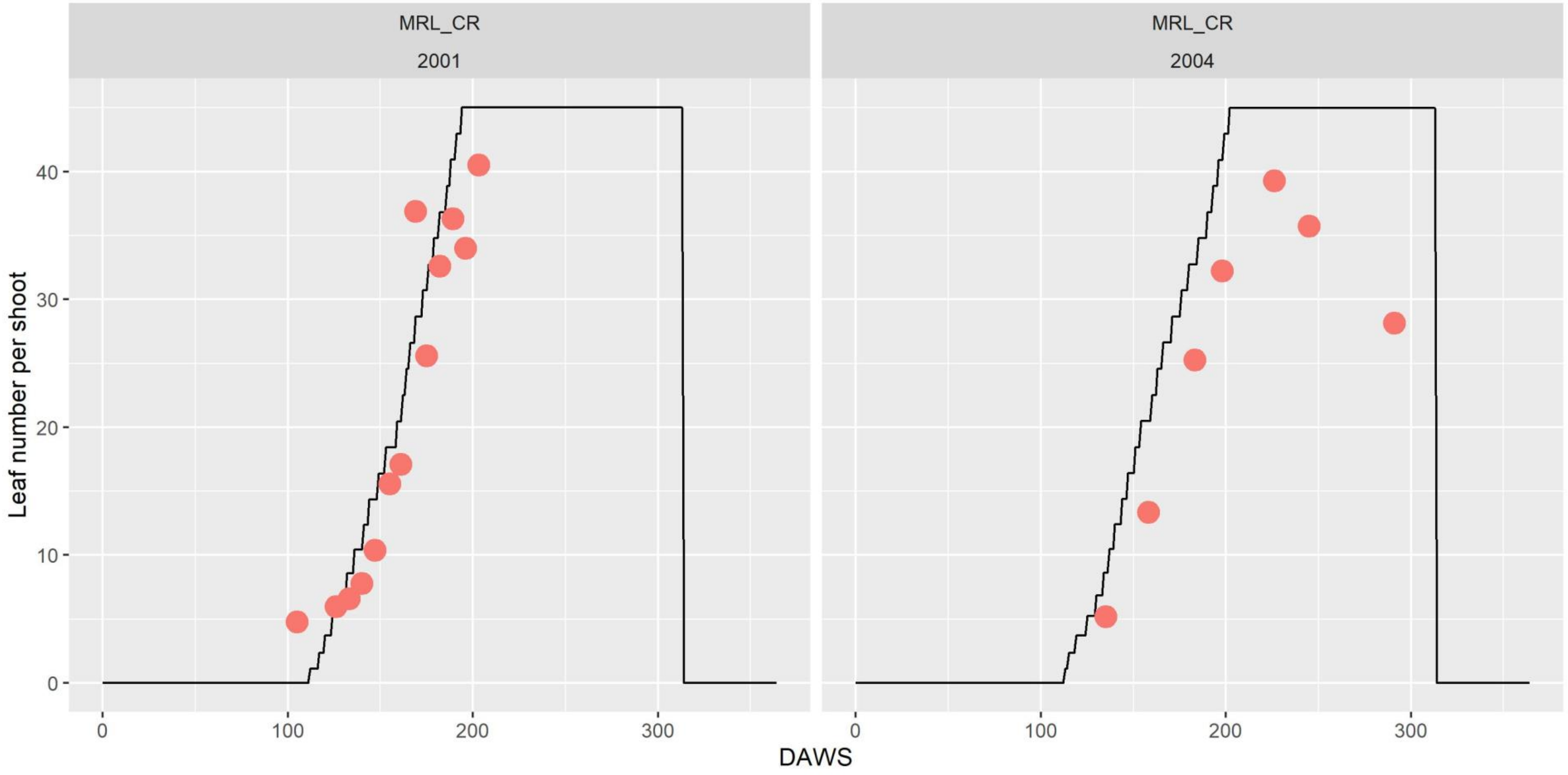
Phenology prediction



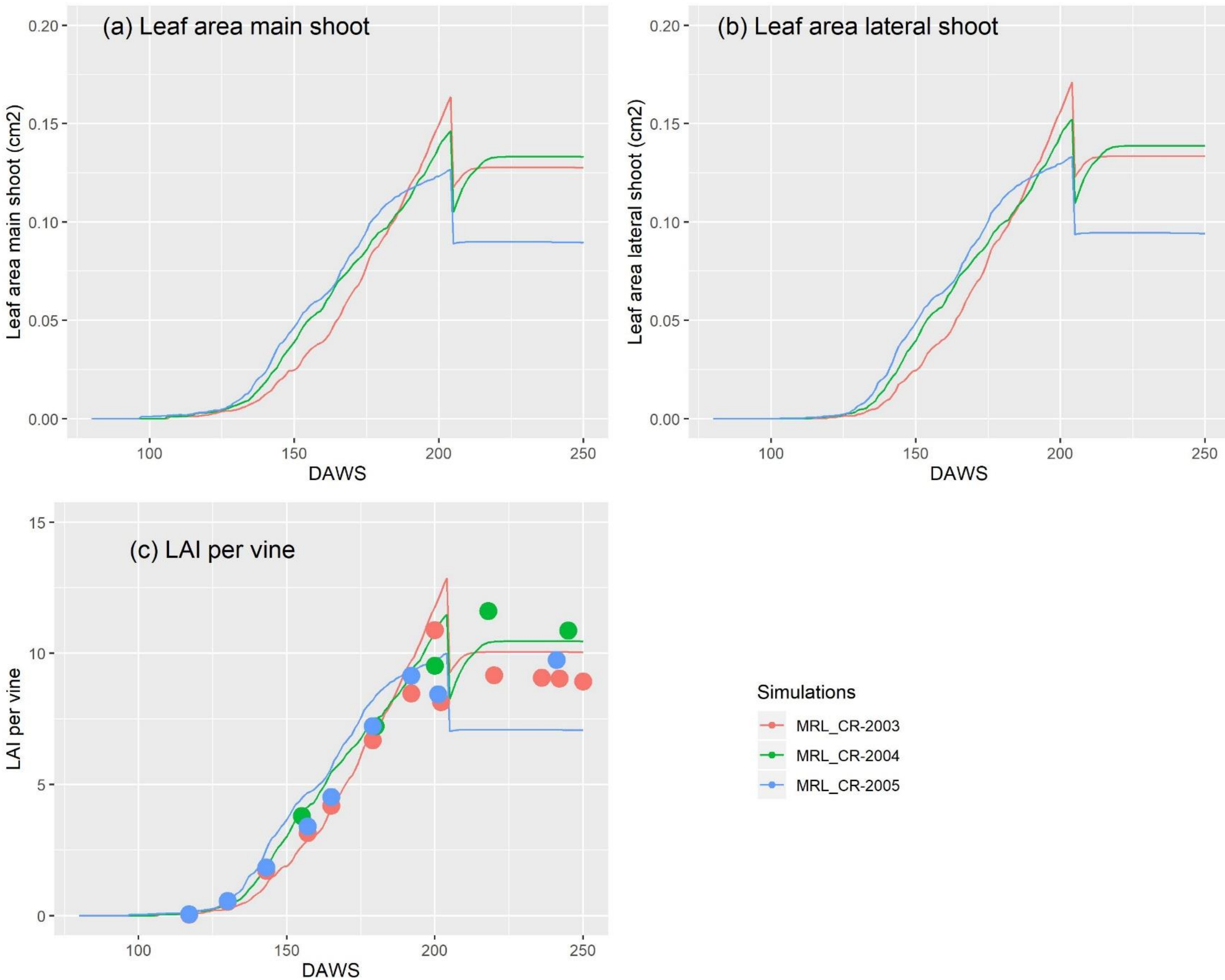
Phenology prediction for other varieties



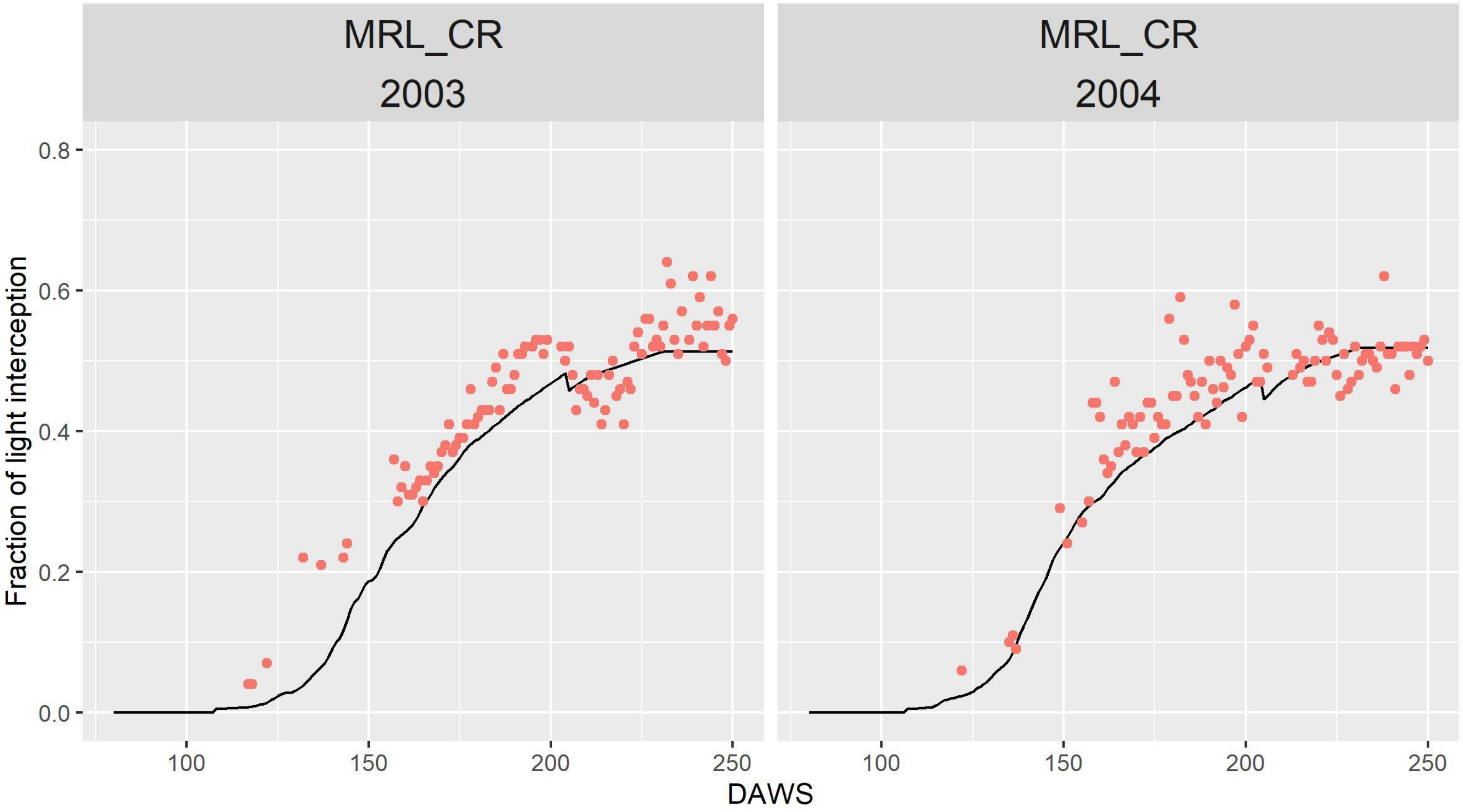
Leaf number per shoot



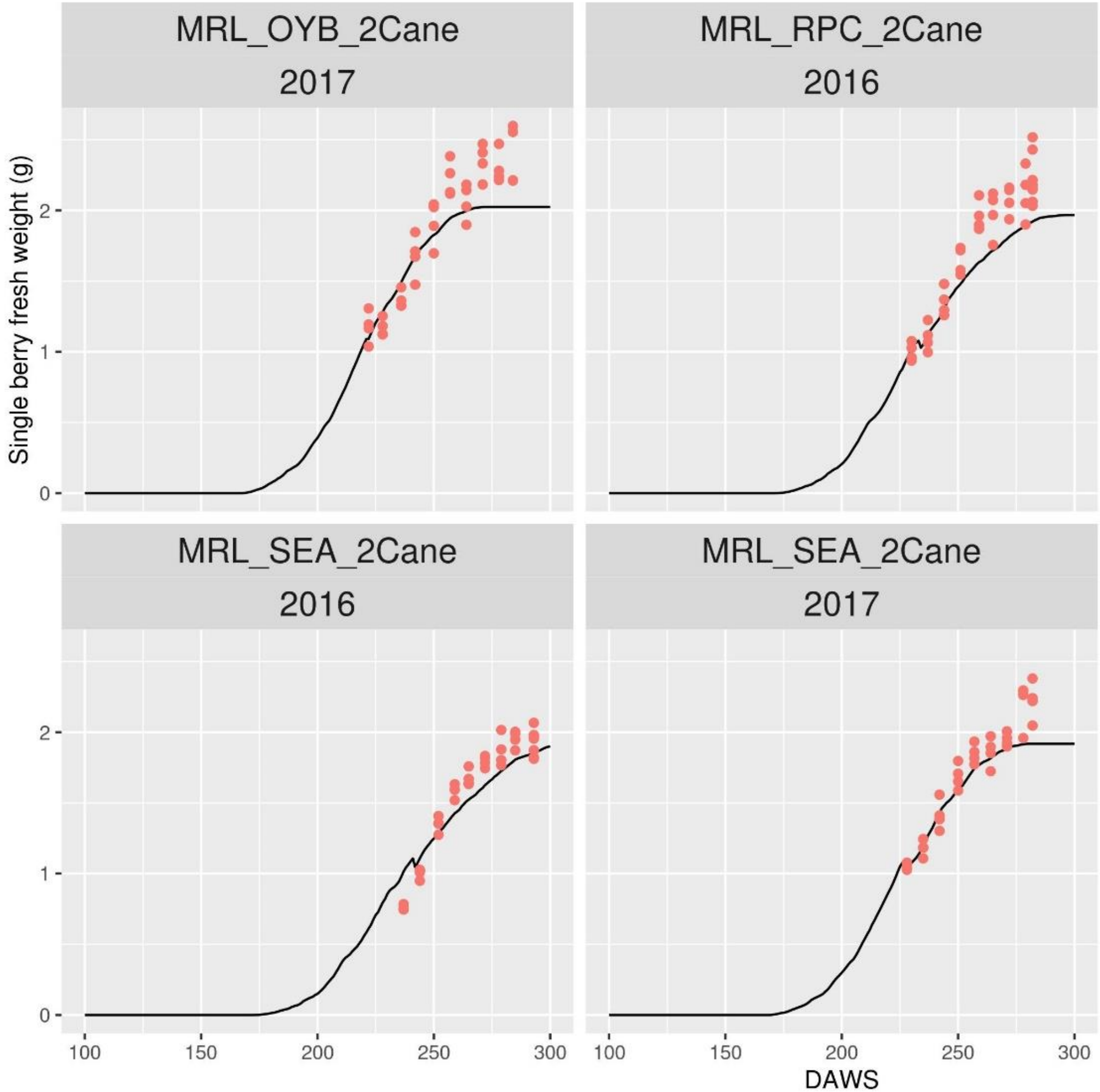
Leaf area


(a) Leaf area main shoot
Leaf area main shoot (cm2)
0.00
0.05
0.10
0.15
0.20
100
150
200
250
DAWS
(b) Leaf area lateral shoot
Leaf area lateral shoot (cm2)
0.00
0.05
0.10
0.15
0.20
100
150
200
250
DAWS
(c) LAI per vine
LAI per vine
0
5
10
15
100
150
200
250
DAWS
Simulations
MRL_CR-2003
MRL_CR-2004
MRL_CR-2005

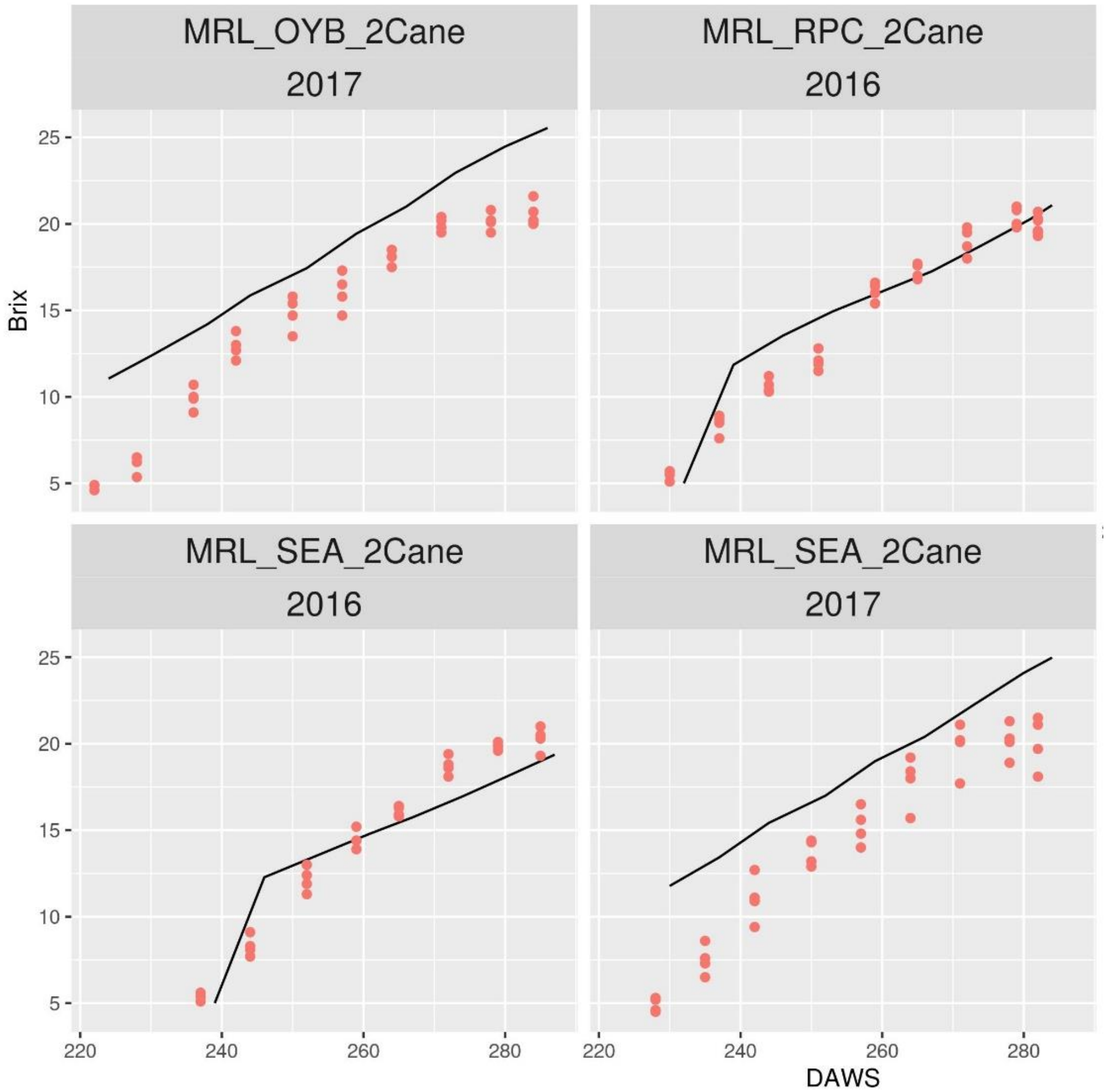
Radiation interception



Berry fresh weight

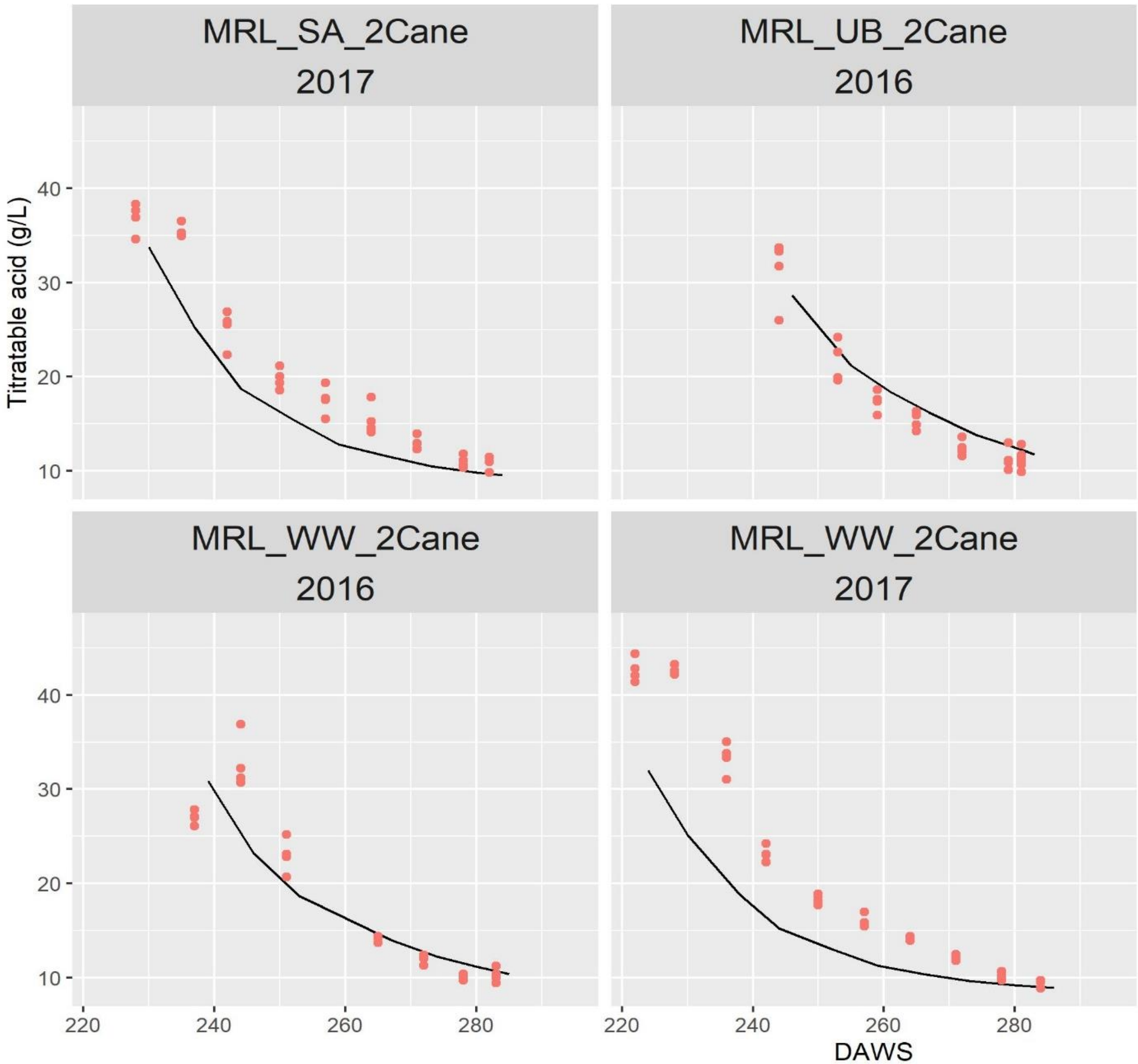


Berry brix



MRL_OYB_2Cane
2017
MRL_RPC_2Cane
2016
MRL_SEA_2Cane
2016
MRL_SEA_2Cane
2017
Brix
25
20
15
10
5
220
240
260
280
DAWS

Berry Ta



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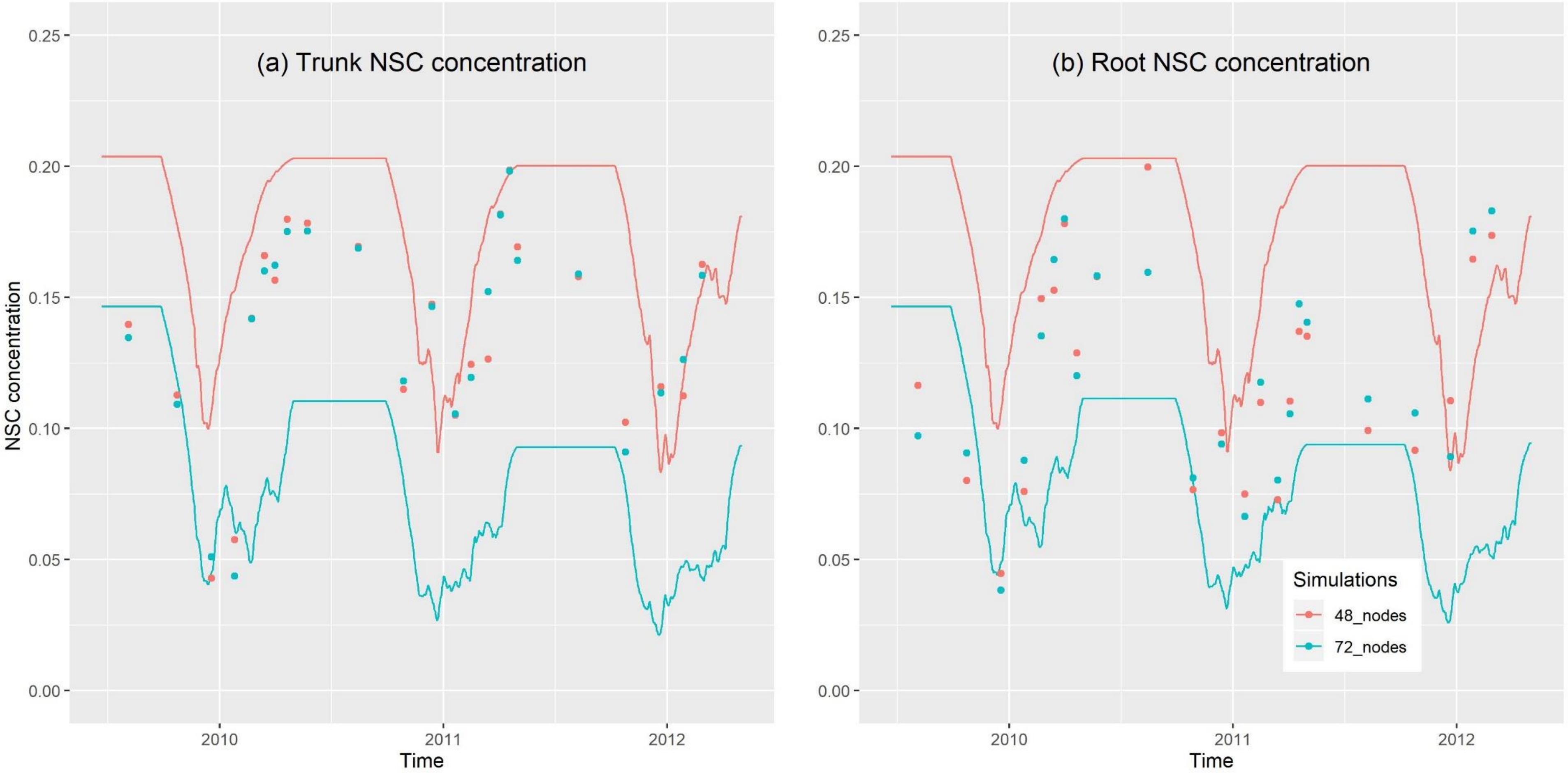
Carbon reserves



Assessment Tool for Landscape-scale Agricultural Systems

- Cross-CRI tool

ATLAS

Spatial Framework

Slides from Edmar Teixeira

https://atlas.powerplant.dev.pfr.co.nz/

universitätbonn

Landcare Research
Manaaki Whenua

NIWA
Taihoro Nukurangi

CSIRO

zalf

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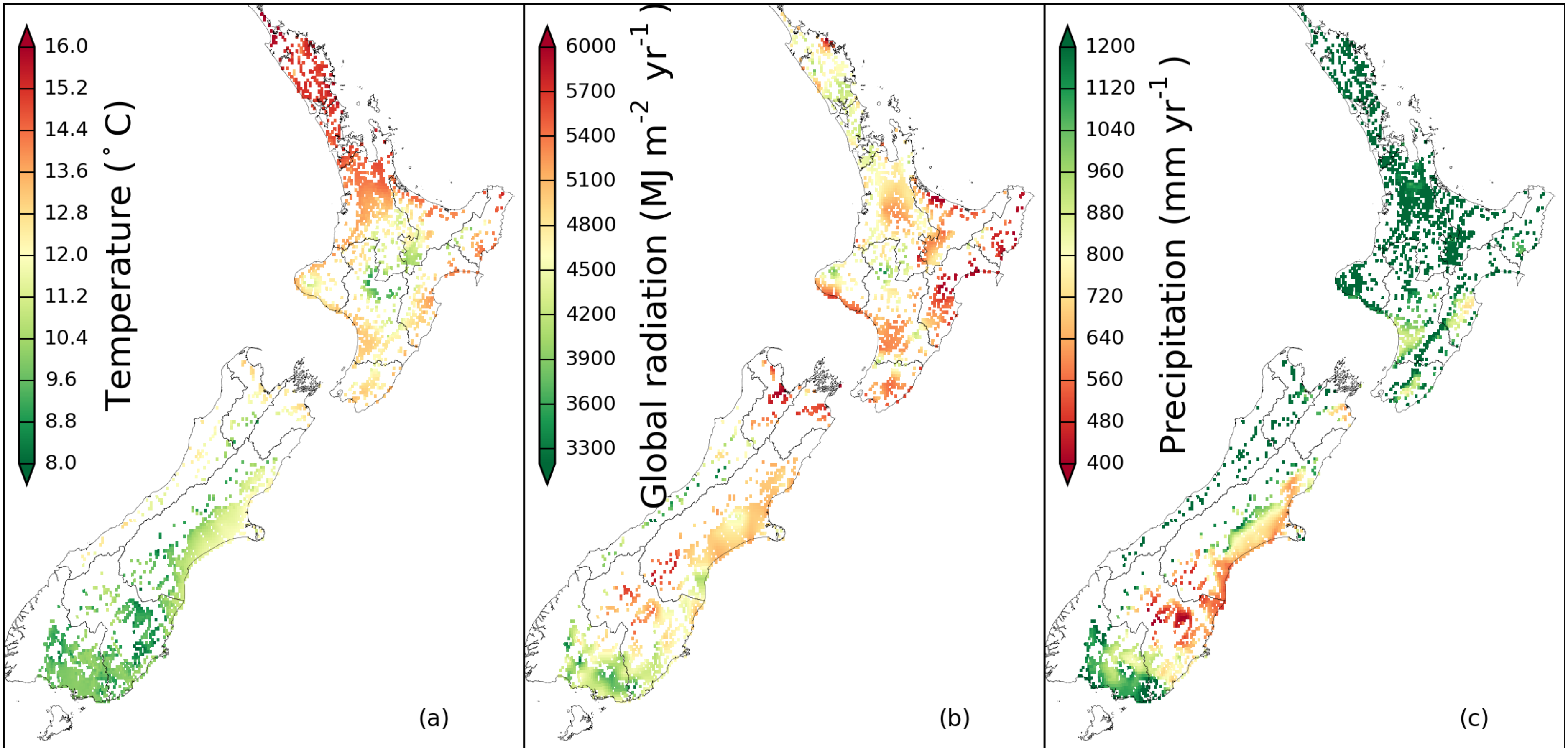
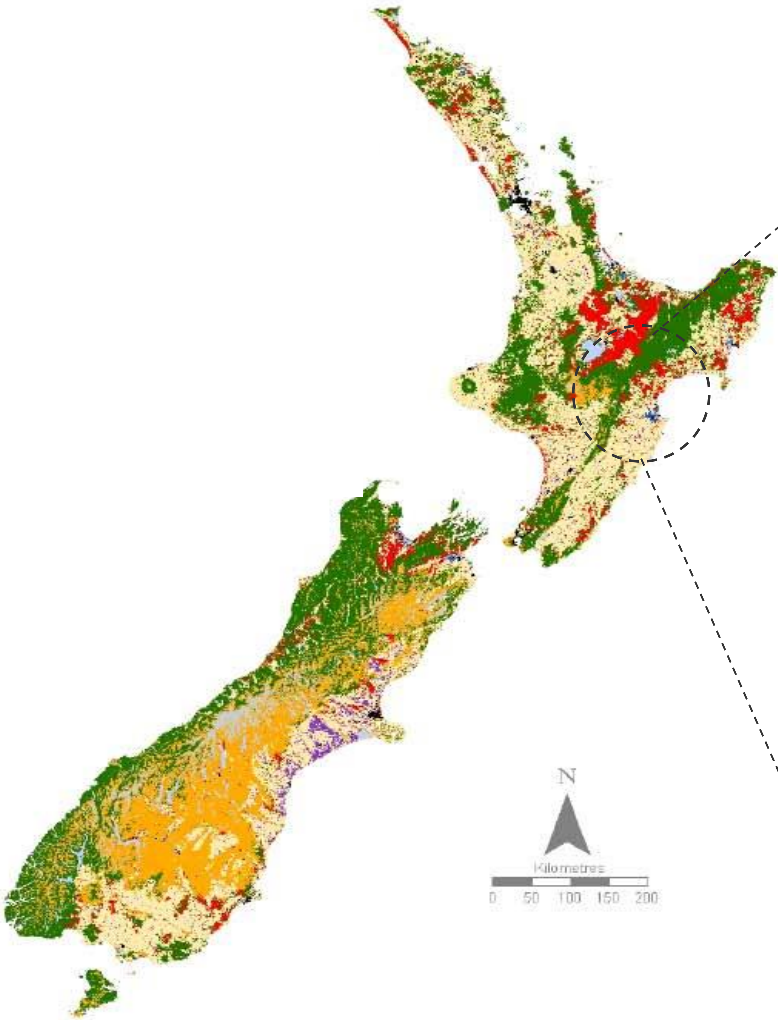
From point- to landscape-scale simulations …

NZ climate + climate change data (NIWA, ~5 km)

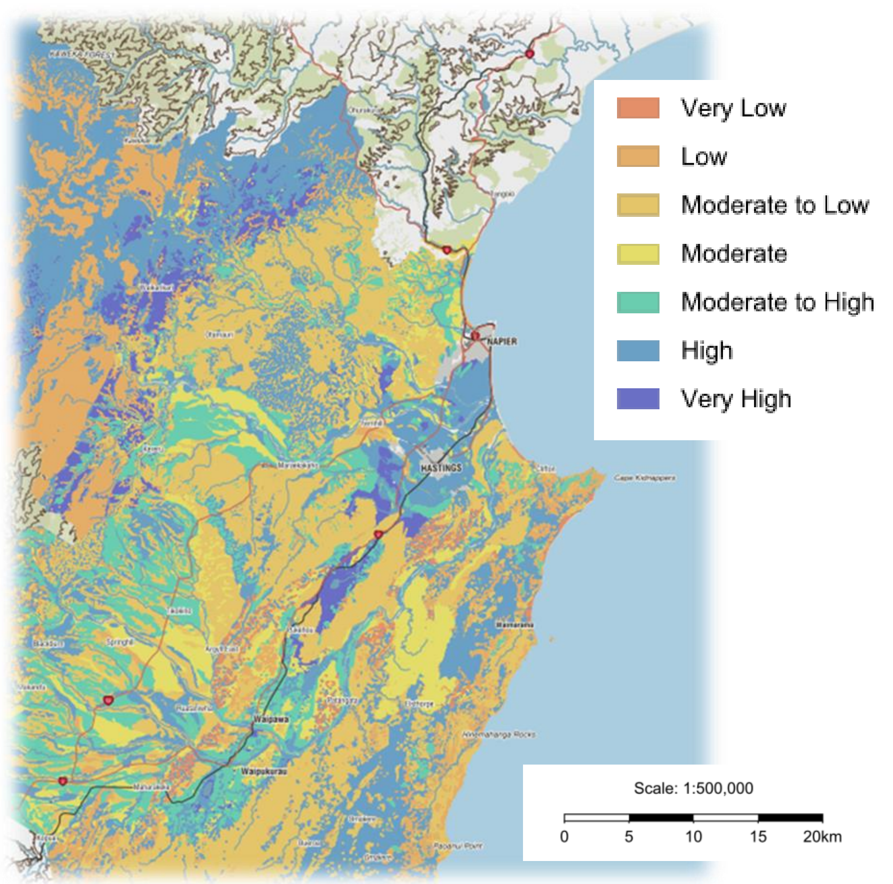


Source: ERA dataset NIWA VCSN (www.niwa.co.nz)
Filtered by arable lands ~1.5 k 5 km grid-cells (https://lris.scinfo.org.nz/)

NZ soil dataset (MW-Landcare S-map)



Hawke's Bay example



ATLAS development in Plant and Food Discovery Science (2017 – 2019)

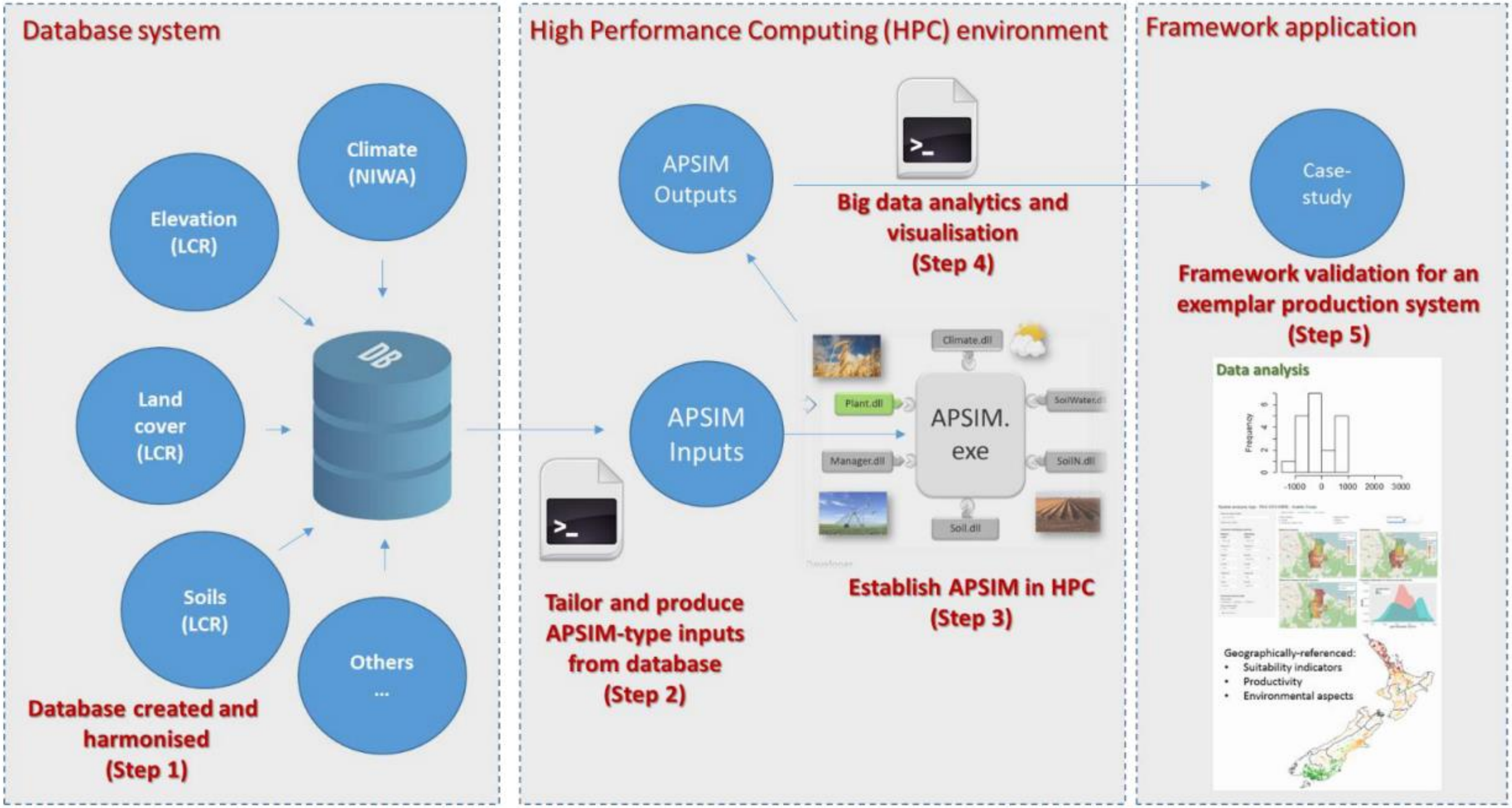
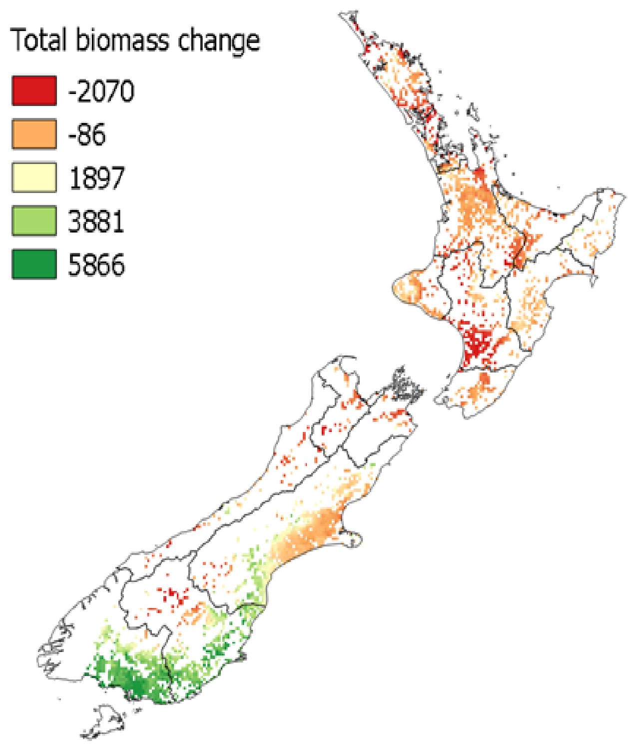


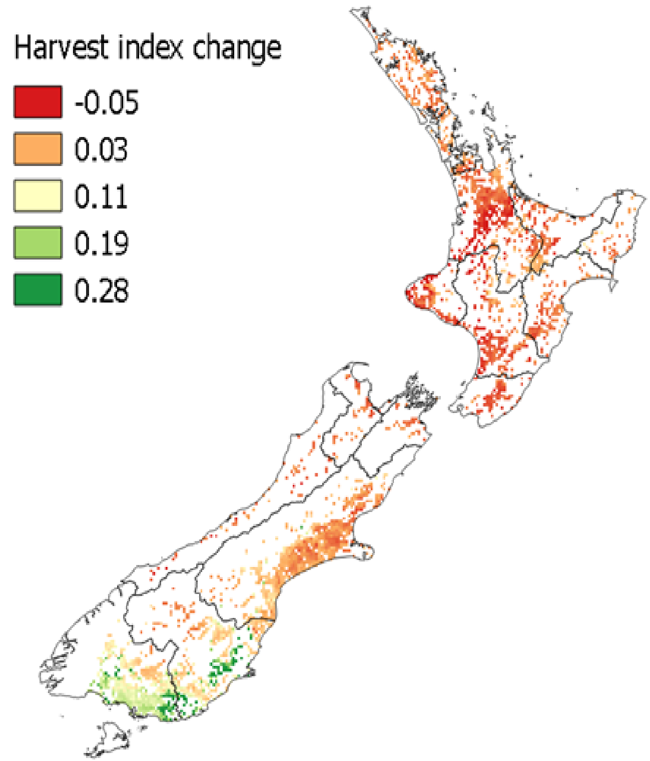
Figure 1 Schematic representation of components to be developed at each critical step (CS).

Impact of climate change scenarios

Silage biomass (kg/ha)



Harvest Index (fractional)

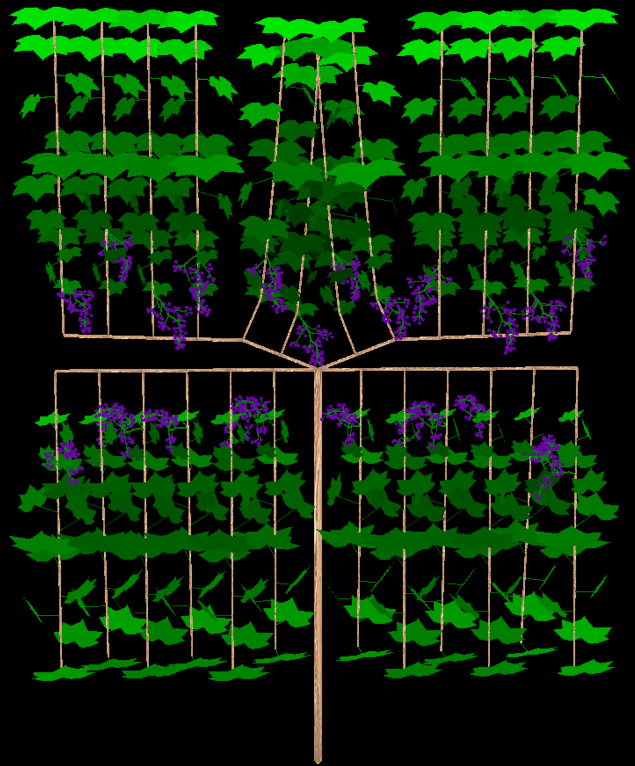


New opportunities for this area of research

- Integrating disease risk models with phenology and yield predictions
- Develop predictions of yield, and risk under climate change scenarios
- Identify future suitability for grapevine production in NZ
- Quantifying effects of carbon and water status on yield formation (whole-vine structural functional model)
- Quantifying effects of yield and phenology on ripening dynamics (berry growth model)

Geneva double curtain

Scott Henry



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PFR SSIF funding

Thank you

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