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Calibration and evaluation of APSIM Next Generation for grapevine growth and water use in Australia

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Abstract: Crop models are valuable tools for improving crop management and resource use efficiency. In this study, we calibrated and evaluated a model for *Vitis vinifera* L. cv. Cabernet Sauvignon under Australian conditions, building on the first perennial crop model within the Agricultural Production Systems sIMulator (APSIM) framework that was originally developed for New Zealand conditions and grape varieties. Calibration aimed to minimise simulation error in Leaf Area Index (LAI), phenological stages onset, and Soil Water Content (SWC) through iterative, manual adjustment of the model's parameters while preserving the default values. The Normalised Root Mean Squared Error (NRMSE) was used as the calibration's primary metric for its scale independence, interpretability, and cross-variable comparability. To provide further insight into residual errors after calibration, the Mean Squared Error (MSE) was also decomposed into three additive interpretable components. The model performed well across all metrics ($0.02 \leq$ NRMSE ≤ 0.10; $0.78 \leq$ NSE ≤ 1.00; $-1.07 \leq$ PBIAS ≤ 0.65). MSE decomposition indicated that the predominant source of error came from the inability to simulate the timing and sequence of measured trends, followed by the inability to simulate the spread of measured data. Also, overall systematic bias contributed minimally to the observed MSEs across all calibrated parameters. These results provide insights for further model improvements and indicate APSIM's potential for effectively supporting sustainable and climate-resilient viticulture in Australia.

Keywords: *APSIM Next Generation, Grapevine, Crop Modelling, Water Use, Calibration.*

1. INTRODUCTION

The Murray–Darling Basin produces about 80% of Australia's grapes, using nearly 9% of its irrigation water, with almost half of the vineyard area located in the Lower Murray catchment, where water supply is highly regulated, particularly during droughts (Australian Bureau of Agricultural and Resource Economics and Sciences, n.d.). Given that vineyards are long-term investments with productive lifespans of 20–30 years, consistent irrigation is essential, and climate change poses significant risks that require careful long-term planning. Crop simulation models, such as the Agricultural Production Systems sIMulator (APSIM; Holzworth et al. 2014), can help represent interactions between climate, soil, management, and crop physiology to support climate-resilient decision-making. APSIM Next Generation has extended this capability to perennial crops, including a grapevine model developed for New Zealand conditions (Zhu et al. 2021). However, differences in management, climate, soils, and cultivars require calibration for Australian conditions. This study calibrates and then evaluates the calibrated APSIM Next Generation grapevine model in simulating phenological stages, soil water content (SWC), and leaf area index (LAI) of *Vitis vinifera* L. cv. Cabernet Sauvignon in Langhorne Creek, South Australia.

2. METHODOLOGY

Site descriptions and measured data are available in Phogat et al. (2023). For calibration, SWC, LAI, and the onset of phenological stages were collected. Twelve SWC observations (one per month) and ten LAI measurements from budburst to harvest at ~20-day intervals were used. Phenological data were obtained from a phenology model (Thomas et al., in preparation) and local expert knowledge. Calibration aimed to minimise simulation error in estimating LAI, the onset of phenological stages, and SWC. This was carried out through an iterative, manual adjustment of the model's parameters—following the parameter group sequence proposed by Zhu et al. (2021) and selecting, within each group, those considered by experts to be most influential on the target outputs—while preserving the model's original structure, physiological logic, and default values as much as possible. Initial values were taken from the default model configuration, and site-specific parameters were introduced with minimal disruption to maintain biological realism. The process continued until further adjustments no longer resulted in meaningful improvements in model performance, with the Normalised Root Mean Squared Error (NRMSE) used as the primary calibration metric for its scale independence, interpretability, and suitability for cross-variable, cross-study, and multi-parameter calibration. Other statistical metrics to evaluate the performance of the model were Mean Squared Error (MSE), Nash–Sutcliffe Efficiency (NSE), Percent Bias (PBIAS), and Pearson Correlation Coefficient (r). The performance thresholds were interpreted according to widely accepted agronomic modelling benchmarks (e.g., NRMSE ≤ 0.1 = very good; NSE ≥ 0.75 = good). The mean squared error (MSE) was decomposed into three interpretable additive components, following Kobayashi and Salam (2000), to determine whether residual errors arose from systematic bias (overall under- or overestimation), variability mismatch (inability to simulate the spread of measured data), or temporal pattern misalignment (inability to simulate the timing and sequence of measured trends). This approach helps distinguish the source of the remaining error and provides insights regarding further model improvement and calibration.

3. RESULTS AND CONCLUSION

The results demonstrated the robustness of APSIM Next Generation in simulating grapevine growth and water use under Australian conditions. Among the evaluated variables, phenology achieved the highest accuracy, with the lowest absolute errors across all metrics (NRMSE = 0.02, NSE = 1.00, PBIAS = –0.48, r = 1.00), indicating a perfect match between simulated and observed developmental stages. While SWC showed comparatively higher error values, performance remained strong (NRMSE = 0.10, NSE = 0.78, PBIAS = –1.07, r = 0.93), reflecting good agreement with measured water dynamics. The model also reproduced LAI effectively (NRMSE = 0.10, NSE = 0.97, PBIAS = 0.65, r = 0.99), capturing both growth and senescence patterns with high precision. The MSE decomposition revealed temporal pattern misalignment (explained in Methodology) as the dominant error source for all variables, contributing 59–90% of the total MSE. Variability mismatch was the second largest contributor, most notably in phenology (35%), indicating differences in the variability spread between observed and simulated datasets. Systematic bias accounted for less than 7% of total error in all cases.

These findings indicate that further improvements in APSIM grapevine model performance could potentially be achieved through enhanced representation of temporal dynamics, although the model was able to capture the overall trends of both underground and aboveground measured data and does not suffer from overall over- or underestimation, showing its robustness in the simulation of the soil-plant-atmosphere continuum. However, the minimal bias could be related to calibration that eliminated the majority of the model's bias. Although MSE decomposition alone cannot separate the effects of calibration from inherent model limitations, the calibrated model provides a strong foundation for further research and also for applications in vineyard water management, climate adaptation planning, and the development of sustainable viticulture in the Murray–Darling Basin and other irrigated grape-growing regions.

4. REFERENCES

Australian Bureau of Agricultural and Resource Economics and Sciences (n.d.) Irrigated grapes in the Murray–Darling Basin. Department of Agriculture, Fisheries and Forestry, Australian Government. Available at: https://www.agriculture.gov.au/abares/research-topics/surveys/irrigation/grapes (accessed 12 August 2025)

Holzworth DP, Huth NI, deVoil PG, Zurcher EJ, Herrmann NI, McLean G, Chenu K, van Oosterom EJ, Snow V, Murphy C, Moore AD, Brown H, Whish JPM, Verrall S, Fainges J, Bell LW, Peake AS, Poulton PL, Hochman Z, Thorburn PJ, Gaydon DS, Dalgliesh NP, Rodriguez D, Cox H, Chapman S, Doherty A, Teixeira E, Sharp J, Cichota R, Vogeler I, Li FY, Wang E, Hammer GL, Robertson MJ, Dimes JP, Whitbread AM, Hunt J, van Rees H, McClelland T, Carberry PS, Hargreaves JNG, MacLeod N, McDonald C, Harsdorf J, Wedgwood S and Keating BA (2014) APSIM – Evolution towards a new generation of agricultural systems simulation. Environmental Modelling & Software 62, 327-350.

Phogat V, Pitt T, Petrie P, Šimůnek J and Cutting M (2023) Optimization of Irrigation of Wine Grapes with Brackish Water for Managing Soil Salinization. Land 12(10), 1947.

Thomas DS, Cameron W, Hayman PT, Bonada M, Sadras VO, Gambetta JM, Jolley JYC and Petrie PR (in preparation) Developing and testing of winegrape phenology models for Australian conditions.

Zhu J, Parker A, Gou F, Agnew R, Yang L, Greven M, Raw V, Neal S, Martin D, Trought MCT, Huth N and Brown HE (2021) Developing perennial fruit crop models in APSIM Next Generation using grapevine as an example. in silico Plants 3(2).