A minimal soil moisture model fit to environmental data from multiple pasture locations in Taranaki, New Zealand

Jennifer L. Knopp*

**Department of Mechanical Engineering, University of Canterbury, Christchurch, New Zealand*

Abstract: The application of models and precision technology to optimize productivity and sustainability is increasingly common in agriculture. Soil moisture (SM) modelling is an important component of pasture growth modelling, or for runoff/catchment modelling. This paper examines a minimal modelling approach for SM modelling using soil moisture data from 10 locations in the Taranaki region, New Zealand. Several simple compartment-based models are tested with/without daylight and temperature effects on terms relating to SM loss, and gain from rainfall. It was found that SM dynamics differed from site to site, with a simple loss dynamic proportional to current SM level dominating in soils with moisture levels above field capacity. A SM loss term modified by temperature and day length described sites where SM was below field capacity. Thus, a simple model was able to fit locational data, and distinguished between differing dynamics based on SM level relative to field capacity. This is model is a first step towards a model-predictive approach to soil moisture modelling requiring a minimum of measured inputs.

Keywords: Soil Moisture, Modelling and control of agriculture, Modelling and identification of environmental systems, Environmental decision support systems

1. INTRODUCTION

Agriculture practices are increasingly turning to technology to optimise productivity and environmental sustainability. Such approaches often combine measurements and models to offer greater insight and inform on-farm practices. An area with significant potential impact for model-driven precision approaches concerns pasture or crop growth, where hydrology and nutrient models have implications for productivity, fertiliser use, and management of nitrogen leaching (Bryant and Snow, 2008).

Soil moisture (SM) models are particularly important for modelling plant growth, and have implications for runoff or catchment modelling. SM models are found within agricultural programs or frameworks for crops, pasture growth, and water quality assessment. Many model frameworks have been developed for use in Australian (Ranatunga et al., 2008) and New Zealand contexts (Bryant and Snow, 2008, Woodward et al., 2008). Model structures range along a continuum from empirical to mechanistic models, with differing degrees of complexity depending on model purpose and applications.

'Simple' models often utilise a 'tipping bucket' process, whereby a soil layer is filled to saturation and excess water leaves the system as runoff or filtration to another soil level. Such models can be single or multi-layer, and may include interactions with the groundwater table. Layers are assumed internally homogenous, and multi-layer models often require greater inputs in terms of water and soil characteristics (Ranatunga et al., 2008). More complex models treat soil structures and moisture dynamics as a continuums, and hydrologic flows are based off fundamental equations and mechanisms (Ranatunga et al., 2008).

Models are structured differently, and require different inputs, depending on their intended use and degree of resolution. The accuracy and usefulness of empirical models is usually tied to the context or location from which data was derived. Other models, particularly those requiring less input data to tailor or inform the model to a particular context, can be reliable on average across geography or time, but less able to predict specific instances (Ranatunga et al., 2008). The fundamental trade off in any sort of modelling is the complexity of the model, as well as the structural and practical identifiably (Docherty et al., 2011), related to the amount of data required to make such models identifiable and informative.

This paper presents a simple model of soil moisture based on a lumped compartment modelling approach. The model broadly replicates mechanistic trends by relating soil moisture gain and loss to daylight hours, soil temperature. The aim is to parameterise a model using a minimum of environmental data inputs, where model parameters thus represent overall soil characteristics at a particular location. This model is fit to environmental data from a regional council database in New Zealand, providing field/farm scale models of soil moisture suitable for forward simulation and prediction of pasture growth or inclusion in farm-scale modelling.

2. METHODS

2.1 Soil Moisture Models

The SM models developed are based on compartment model principles, and intentionally kept minimal to model soil moisture against a minimum of measured inputs. The first (Model 1) modelled SM gain as proportional to direct conversion/infiltration of rainfall (P, mm), and SM loss as proportional to current soil moisture level (S):

$$\frac{dS}{dt} = -\alpha_1 S + \alpha_2 P \tag{1}$$

Where parameters α_1 and α_2 describe loss and gain respectively. Models 2, 3, and 4 modified Model 1 (Equation 1) to include the influence of soil temperature (°C) and/or day length on the moisture loss:

$$\frac{dS}{dt} = -\alpha_1 S\left(\frac{T_s}{20}\right) + \alpha_2 P \quad (2)$$

$$\frac{dS}{dt} = -\alpha_1 S\left(\frac{D_L}{12}\right) + \alpha_2 P \quad (3)$$

$$\frac{dS}{dt} = -\alpha_1 S\left(\frac{T_s}{20}\right)\left(\frac{D_L}{12}\right) + \alpha_2 P \quad (4)$$

In Equations 2 – 4 soil temperature T_s was divided by 20°C, and D_L by 12 hours, to scale these terms relative to an approximately optimum pasture growth temperature and half of a 24 hour period, respectively. This scaling allows some degree of consistency in magnitude between similar parameters in different model formulations.

Models 5 and 6 account for two different pathways of moisture loss, where a loss proportional to S might reflect drainage, and a loss proportional to S and T_s and/or D_L might include/reflect a loss to transpiration or evaporation:

$$\frac{dS}{dt} = -\alpha_1 S - \alpha_{1b} S\left(\frac{T_s}{20}\right) + \alpha_2 P \quad (5)$$

$$\frac{dS}{dt} = -\alpha_1 S - \alpha_{1b} S\left(\frac{T_s}{20}\right)\left(\frac{D_L}{12}\right) + \alpha_2 P \quad (6)$$

Models 7 and 8 adjusted the conversion of precipitation P to soil moisture S in two ways:

$$\frac{dS}{dt} = -\alpha_1 S - \alpha_{1b} S\left(\frac{T_s}{20}\right) + \alpha_2 P\left(\frac{30}{S}\right) \quad (7)$$

$$\frac{dS}{dt} = -\alpha_1 S - \alpha_{1b} S\left(\frac{T_s}{20}\right)\left(\frac{D_L}{12}\right) + \alpha_2 P + \alpha_{2b} P\left(\frac{30}{S}\right) \quad (8)$$

In Equations 7 and 8, at higher SM levels the conversion of rainfall to SM is reduced, as would be expected in saturated or near-saturated soil. A scaling factor of 30% is chosen as an approximate average SM across the data sets used, to keep the 30/S term near 1 for average soil moisture levels.

Models are fitted to environmental data using integral-based fitting (Docherty et al., 2012) and least squares methods. For Model 8 the least squares fitting function was:

$$Ax = \mathbf{b}$$

$$A = \left[-\int_{t_0}^{t} S\,dt\,, -\int_{t_0}^{t} S\left(\frac{T_s}{20}\right)\left(\frac{D_L}{12}\right)dt\,, \int_{t_0}^{t} P dt,\ \int_{t_0}^{t} P\left(\frac{30}{S}\right)dt\right] \quad (9)$$

$$\mathbf{b} = [S|_t - S|_{t0}\,]$$

In Equation 9, integrals are calculated using the trapezium rule on measured data.

Day length represented the number of hours of daylight in a day, which was calculated from day of year and latitude using a function written for the Matlab (gubertoli, 2016).

2.2 Soil Moisture Data

Soil moisture data spanning 365 days was pulled from the Taranaki Regional Council (TRC) website (Taranaki Regional Council, 2019a). The TRC monitors a number of environmental factors at locations around the Taranaki Region. Environmental monitoring points were filtered to those which measured daily averages for SM (%), soil temperature (°C), and precipitation (mm). Where available, daily average ambient temperature (°C) and wind speed (km/hr) were also downloaded.

Data meeting this criteria was found for 11 rural locations around Taranaki, shown in Figure 1. Data from one location, Waitotara at Rimunui Station, was discarded because data only spanned 2-3 months, not a full year. Latitude was determined to 2 decimal places using Google maps. Broad soil types for each location were also determined from the TRC website (Taranaki Regional Council, 2019b). Soil Moisture sensor type and depth was not specified, and is assumed here to be similar across all locations, and representative of SM in the root zone.

Figure 1: Locations of Soil Moisture monitors around Taranaki, with current soil moisture. Modified from image accessed 18/10/2019 (Taranaki Regional Council, 2019a)

2.3 Analysis

Model error was calculated as the percent absolute difference between the measured and modelled SM.

$$Fitting\ error = 100 \times \frac{abs(S - S_{meas})}{S_{meas}} \quad (10)$$

Fitting error here is the relative percentage error, not difference in the SM % units recorded.

Once the model with lowest overall error was established, model-fit parameters were analysed in the following ways:

- The model was fit to all 365 days of data, and model parameters compared by location and soil type
- Model 1 fit to data on 7-day and 30-day intervals, and changes in parameters plotted over time.

A model is considered viable if it maximally fits data, while also attempting to minimise the environmental measurements required to inform the model. Only model 1 was used in the second analyses as the shorter time frames did not in some cases provide sufficient variation in temperature, day length, or rainfall to identify all model parameters in Models 5-9.

Table 1: Location details. Superscripts on soil type reflect drainage class, as per the NZ Soil Classification system (Milne et al., 1995)

Location	Lat	Soil type	Topography	Rainfall (mm)	Ambient Temp. (°C)	Soil Temp. (°C)	Wind Speed (km/hr)
Hilsborough	-39.06	Brown loam[5]	Flat/rolling	0 [0 – 4.5]	14.1 [11.9-18.0]	14.4 [11.6 – 18.6]	12.5 [9.3 – 16.9]
Kapoaiaia	-39.27	Coarse sand[5]	Coastal flat	0 [0 – 3]	14.6 [12.7 – 17.4]	15.6 [12.7 – 15.8]	18.0 [12.8 – 24.7]
Kaupokoni	-39.54	Loam[5]	Coastal flat	0 [0 – 3]	13.7 [11.6 – 17.1]	15.6 [12.0 – 20.5]	n/a
Mangatete Bridge	-39.22	Fine sandy loam[5]	Flat	0.5 [0 – 5.5]	13.2 [11.0 – 15.6]	14.2 [11.3 – 19.4]	n/a
Motunui	-39.00	Black loam[5]	Coastal flat	0 [0 – 3.4]	13.8 [11.6 – 17.3]	14.0 [11.4 – 18.7]	n/a
Patea	-39.74	Loamy sand[3]	Coastal flat	0.2 [0 – 3.0]	13.7 [11.5 – 17.0]	15.1 [11.9 – 19.4]	18.5 [12.5 – 25.2]
Pohokura Saddle	-39.16	Brown loam[5]	River valley	0.5 [0 – 5.0]	n/a	14.4 [11.0 – 18.7]	n/a
Taungatara	-39.43	Loam[5or 2]	flat	0.5 [0 – 5.0]	13.1 [10.7 – 16.3]	14.3 [11.2 – 18.5]	15.3 [12.3 – 20.5]
Uruti	-39.03	Brown loam[5]	Hill country	0.5 [0 – 5.5]	n/a	14.8 [11.6 – 18.7]	9.5 [7/5 – 13.0]
Waitotara – Hawken's Rd	-39.83	Silt loam/clay loam[5]	River flat	0.2 [0 – 3.2]	13.4 [11.1 – 16.7]	14.3 [11.7 – 19.2]	n/a

Table 2: Parameter values and error from model-fit to all 365 days of data for each location. Values are median [IQR].

	Model Parameters				Abs. Err. (%)
	α_1	α_{1b}	α_2	α_{2b}	
Model 1	0.0116 [0.0091-0.0170]		0.0888 [0.0559-0.1143]		3.9 [8.5 - 16.2]
Model 2	0.0112 [0.0051-0.0140]		0.0387 [0.0361-0.0731]		4.3 [9.5 - 15.6]
Model 3	0.0073 [0.0053-0.0123]		0.0477 [0.0384-0.0736]		4.5 [8.3 - 14.2]
Model 4	0.0068 [0.0035-0.0096]		0.0294 [0.0265-0.0505]		4.4 [9.0 - 15.6]
Model 5	0.0103 [0.0041-0.0126]	0.0021 [0.0000-0.0109]	0.0968 [0.0559-0.1356]		3.8 [7.6 - 13.8]
Model 6	0.0099 [0.0046-0.0121]	0.0020 [0.0000-0.0065]	0.0940 [0.0496-0.1356]		3.8 [7.3 - 12.9]
Model 7	0.0012 [0.0000-0.0091]	0.0082 [0.0022-0.0125]	0.0751 [0.0551-0.0874]		3.2 [6.9 - 12.6]
Model 8	**0.0097 [0.0007-0.0121]**	**0.0045 [0.0013-0.0127]**	**0.0173 [0.0001-0.1139]**	**0.0466 [0.0132 0.0761]**	**2.9 [6.2 - 10.8]**

SM model parameters were compared by location and soil type. Median (IQR) SM for a location was compared to the field capacity and wilting point (WP) typical of broad soil type, where these thresholds were drawn from (O'Geen, 2013).

3. RESULTS

Model-fit parameters for Models 1-8 are shown in Table 2, and the forward simulation for selected models in Figure 2. The basic model (Model 1) was able to capture trends and some response to individual precipitation events well in all locations but one (Figure 2,Kaupokoni). Including temperature and/or day length effects (Models 2–4) improved model-fit for some locations and worsened it for others. Including SM saturation effects in models 7 and 8 reduced model error. Model 8 performed best (med. [IQR]: 2.9 [6.2 – 10.8)% error), as it included terms from Models 1-4, allowing stronger fits to some terms on a location by location basis (Table 3), thus bringing together the location-specific benefits of each model.

Figure 3 shows parameter changes on a weekly and monthly basis, where selected locational results are representative of overall trends/results across all sites. Model fit to data is extremely good when model parameters are allowed to vary. Figure 2 shows these changes in the rate of soil moisture gain and loss are not directly functions of daylight, or ambient temperature. Seasonal trends are apparent, where rainfall uptake is most often minimised in winter, even if overall moisture and rainfall levels are similar to autumn.

Delineating parameters on a weekly basis shows more parameter variability for no appreciable gain in model fit accuracy across most sites. At this time-resolution the parameters are likely susceptible to noise directly related to rainfall events, particularly in the case of large rainfalls.

Location-specific parameters in Table 3 show SM-proportional SM loss ($\boldsymbol{\alpha_1}$-type) is higher in non-coastal loam sites, compared to a loss with temperature and daylight effects. Four out of five of these $\boldsymbol{\alpha_1}$-type dominated losses occurred in where average SM was higher than the typical field capacity (Table 3), and vice versa. The $\boldsymbol{\alpha_{1b}}$-type losses were strongest where SM was lower than the field capacity. No trends were apparent in precipitation infiltration.

4. DISCUSSION

4.1 Model performance

A simple model relating rainfall to SM in pasture was fit to 365 days of SM data. It was found that a model accounting for temperature, SM, and day length effects on rainfall infiltration and SM loss (Model 8) was able to capture overall trends very well in all 10 data sets, with median [IQR] error of 2.9 [6.2-10.8] %. In 6 data sets the largest discrepancy between model and SM measurements occurred in late summer when SM was at its lowest. In some locations, the model was also unable to capture the extent of day-day variability in SM levels, likely due to changing seasonal effects. For example, the Uruti site in Figures 2 and 3 shows improved infiltration of rainfall in late spring and early autumn, compared to mid-summer and winter. Overall results suggest this simple model can estimate SM levels at 8 sites around Taranaki.

Model fit was improved when parameters were fit across 30 days. Shorter fitting periods resulted in parametric noise related to insufficient variation in environmental data to successfully delineate terms. Monthly parameter variation highlights seasonal changes in soil characteristics and climate

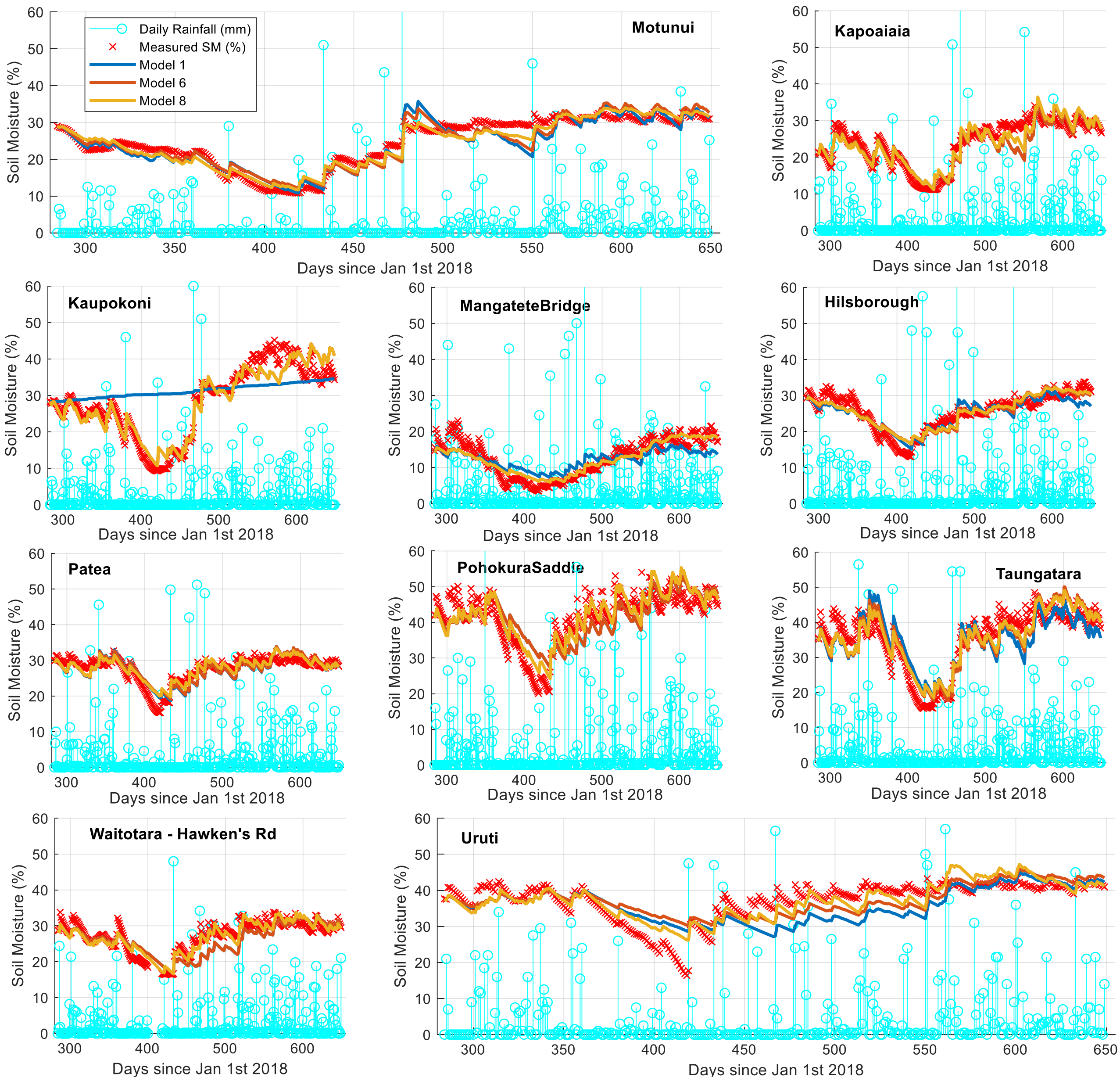

Figure 2: Model solution (S in Equations 1 – 9) fitted to measured soil moisture (SM), temperature and rainfall data at 10 locations in Taranaki. The first data point occurs at October 10th (day 284 of year), and data spans 365 days. Cyan bars denote daily rainfall in mm. The Motouni and Uruti sites are presented on a longer x-axis scale to clarify interesting model features.

aspects not currently modelled. Such aspects might include the effect of frosts, or light rainfall extended over longer periods, compared to the more singular rainfall patterns seen in summer, which can effect surface SM and overall rainfall runoff or infiltration. Winds likely also contribute, and future work will consider modifying Model 8 by wind speed to account for this. However, overall wind speeds do not appear to significantly differ month to month (not shown here), and thus do not directly account for seasonal changes.. An example of underlying seasonal changes can be seen in Uruti in Figure 2 and 3, where a one-off mid-summer rainfall does not seem to affect SM levels significantly, but rainfall over several days less than a month later has a more effect on SM.

Models were constructed to capture SM gain by different processes. The simple linear dependence on SM levels in Model 1 was thought to capture drainage or diffusive-type mechanisms ($\boldsymbol{\alpha_1}$-type), while inclusion of a temperature and/or day length dependant terms captures evaporative or transpiratory losses ($\boldsymbol{\alpha_{1b}}$-type).

A location-by location comparison of model parameter values, (Table 3), showed strong trends with soil type. Of the $\boldsymbol{\alpha_1}$-type dominated losses, 4/5 occurred in soils that were had higher average SM than the typical field capacity for that soil type, and vice versa. The Waitotara and Patea sites were the exception, where at Waitotara median [IQR] SM was lower than field capacity. At the Patea site, SM levels were much greater than the typical soil field capacity, but $\boldsymbol{\alpha_1}$-type and $\boldsymbol{\alpha_{1b}}$-type losses were near-evenly matched, at approximately the same magnitude as the $\boldsymbol{\alpha_1}$-type dominated losses. Overall, a $\boldsymbol{\alpha_1}$-type (potentially drainage) loss is associated with SM greater than the field capacity, while $\boldsymbol{\alpha_{1b}}$-type losses are associated with SM levels within the plant-available water (PAW) region.

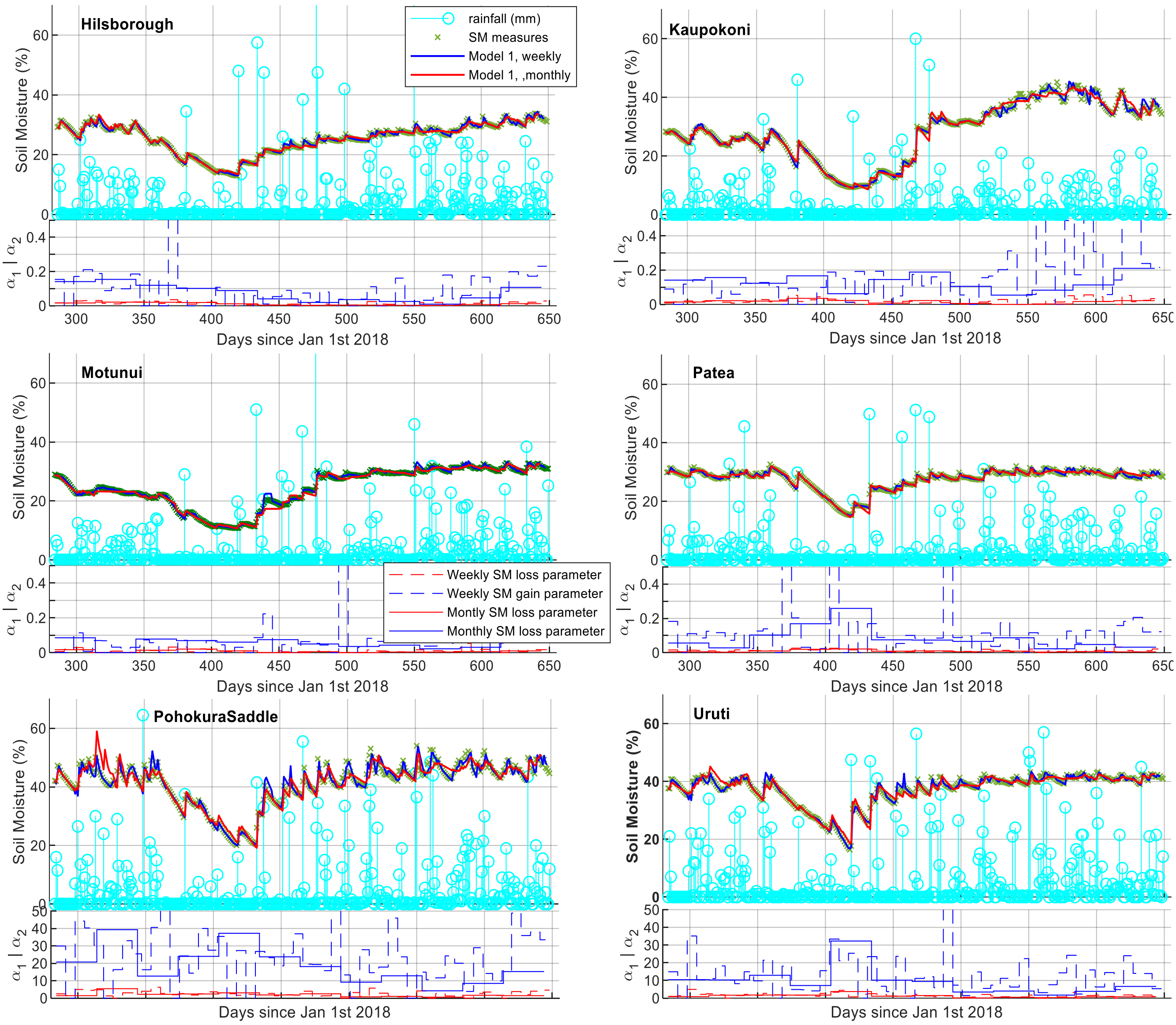

Figure 3: Model solution (S in Equations 1 – 9) fitted to measured soil moisture (SM), temperature and rainfall data at 10 locations in Taranaki. The first data point occurs at October 10th (day 284 of year), and data spans 365 days. Vertical lines denote seasons.

Table 3: Site-specific parameter values for Model 8. Values that are relatively higher within the gain/loss parameter pairs (α_1 and α_2 respectively) are highlighted. Superscripts on soil type reflect soil drainage class, as per the NZ Soil Classification system. Fld Cap is field capacity, and WP is wilting point, drawing from (O'Geen, 2013) for broad soil types.

Location	**Soil type**	**Topography**	$\boldsymbol{\alpha_1}$	$\boldsymbol{\alpha_{1b}}$	$\boldsymbol{\alpha_2}$	$\boldsymbol{\alpha_{2b}}$	**Avg. SM (%)**	**Fld cap. (%)**	**WP (%)**
Hilsborough	Brown loam^{5}	Flat/rolling	0.0007	0.0065	0.0081	0.0207	26.9 [22.6-29.3]	25 – 33%	10-15%
Kapoaiaia	Coarse sand^{5}	Coastal flat	0.0178	0.0018	0.1171	0.0132	25.6 [19.6-28.9]	6 - 10%	3-6%
Kaupokoni	Loam^{5}	Coastal flat	0.0026	0.0173	0.1597	0.0000	28.9 [22.5-36.2]	25 – 33%	10-15%
MangateteBridge	Fine sandy loam^{5}	flat	0.0000	0.0127	0.0265	0.0000	13.7 [7.0-17.2]	15-25%	6-11%
Motunui	Black loam^{5}	Coastal flat	0.0003	0.0141	0.0021	0.0540	25.8 [20.8-30.2]	25 – 33%	10-15%
Patea	Loamy sand^{3}	Coastal flat	0.0091	0.0012	0.0001	0.0761	28.9 [27.4-29.9]	12 - 15%	5-7%
PohokuraSaddle	Brown loam^{5}	River valley	0.0139	0.0025	0.0000	0.1962	43.2 [38.6 46.5]	25 – 33%	10-15%
Taungatara	Loam$^{5or\ 2}$	flat	0.0121	0.0077	0.1139	0.0392	38.2 [33.6-41.1]	25 – 33%	10-15%
Uruti	Brown loam^{5}	Hill country	0.0104	0.0013	0.0000	0.1049	39.3 [35.8-41.0]	25 – 33%	10-15%
WaitotaraHawken	Silt /clay loam^{5}	River flat	0.0118	0.0001	0.0434	0.0589	28.4 [25.5-30.4]	30-37%	15-23%

Association of $\boldsymbol{\alpha_1}$-type losses with SM above field capacity could be explained by 'free-drainage' through gravity effects when SM is greater than field capacity. In contrast, within the PAW region daylight and temperature dependant pasture transpiration effects are expected to dominate, which was typical of SM less than field capacity in Table 3. Thus, the proposed model is able to distinguish between SM behaviours above and below field capacity. Future work will explore and validate these explanations for observed behaviours.

4.4 Limitations & Future work

The parameters α_2 and α_{2b} are used to describe conversion of precipitation to SM levels. Future work will explore alternative parameterisations to more explicitly quantify runoff and the effect of soil moisture saturation. Conservation of mass should also be considered, as per the approach of (Walker et al., 2004), to compare SM increases to precipitation volumes. Where the soil moisture increases by more than theoretically possible, results suggest either sensor error, or geographic considerations such as runoff pooling or subterranean flow.

The proposed model often overestimated SM levels at the end of summer, when SM levels are at their lowest. In this low SM region values are nearer wilting point, so it is likely non-linear dynamics are required in this region. Future work could consider parametric identification of a location-specific estimate of field capacity using available data and carefully formulated models. An anticipated potential issue is lack of identifiability at locations where peak SM levels do not exceed field capacity - SM dynamics not measured cannot be captured in model-based methods.

The model developed here is only tested on SM measurements across 10 locations, and future work should expand its application. However, this model has been tested on a variety of differing locations, topographies, and soil types within the Taranaki region, a promising first result. The data provided did not detail SM sensor type or methodology, which could vary with site. One study of SM measurement techniques under field conditions shows general consistency of measurements between different sensors, with differing tendencies to exaggerate or undercut peaks/troughs resulting from rainfall events (Walker et al., 2004).

In addition, it was not clear at what depth SM measurements were taken. It is assumed all measurements are taken from around the root-zone. Deeper measurements may blunt or delay the magnitude of response to rainfall, or introduce new dynamics. Future work can examine the effect of SM sensor depth on measured and modelled SM.

The current model is fit to a full 365 days of SM data. Future work will look at the minimum amount of SM data required to inform the model for accurate forward prediction extrapolations using precipitation. Where a simple model to fully describe SM across all four seasons is not possible, monthly parameter fitting can create 'virtual soils,' similar to a 'virtual patient' approach (Chase et al., 2018), where seasonal and site-specific effects can be lumped and imposed under forward simulation. Such 'virtual soils' could be used to guide water management.

This study is a first step towards a larger scale dairy modelling system, where SM levels are important for pasture growth modelling. The aim is to model phenomenon in a manner as simple as possible, making use of readily available data, without tying model-systems to empirically derived and thus highly localised models.

5. CONCLUSIONS

A simple minimal compartment model to describe soil moisture levels was developed and fit to soil moisture data from 10 sites in the Taranaki region. Model fit to data was good, and soil moisture dynamics in response to rainfall differed from site to site. A simple loss proportional to current soil moisture level was dominant in soils with moisture levels above field capacity, and terms modified by temperature and day length described sites where soil moisture was below field capacity. This is model is a first step towards soil moisture modelling requiring a minimum of measured inputs.

REFERENCES

Bryant, J. R. & Snow, V. 2008. Modelling pastoral farm agro-ecosystems: a review. *New Zealand Journal of Agricultural Research,* 51**,** 349-363.

Chase, J. G., Preiser, J. C., Dickson, J. L., Pironet, A., Chiew, Y. S., Pretty, C. G., Shaw, G. M., Benyo, B., Moeller, K., Safaei, S., Tawhai, M., Hunter, P. & Desaive, T. 2018. Next-generation, personalised, model-based critical care medicine: a state-of-the art review of in silico virtual patient models, methods, and cohorts, and how to validation them. *Biomedical Engineering Online,* 17.

Docherty, P. D., Chase, J. G. & David, T. 2012. Characterisation of the iterative integral parameter identification method. *Medical and Biological Engineering and Computing***,** 1-8.

Docherty, P. D., Chase, J. G., Lotz, T. F. & Desaive, T. 2011. A graphical method for practical and informative identifiability analyses of physiological models: A case study of insulin kinetics and sensitivity. *Biomedical Engineering Online,* 10.

Gubertoli. 2016. *Daylength Function* [Online]. Available: https://au.mathworks.com/matlabcentral/fileexchange/55702-daylength-function [Accessed 31/10/2019].

Milne, J. D. G., Clayden, B., Singleton, P. L. & Wilson, A. D. 1995. *Soil description handbook,* Lincoln, New Zealand, Manaaki Whenua Press

O'geen, A. T. 2013. Soil Water Dynamics. *Nature Education Knowledge,* 4**,** 9.

Ranatunga, K., Nation, E. R. & Barratt, D. G. 2008. Review of soil water models and their applications in Australia. *Environmental Modelling & Software,* 23**,** 1182-1206.

Taranaki Regional Council. 2019a. *Environmental Data* [Online]. Available: https://www.trc.govt.nz/environment/maps-and-data/regional-overview/?measureID=5 [Accessed 10/10/19].

Taranaki Regional Council. 2019b. *Land cover and soil* [Online]. Available: https://maps.trc.govt.nz/LocalMapsViewer/?map=0824911d3f58406dbab44cfb8dde6ae6 [Accessed 10/10/2019].

Walker, J. P., Willgoose, G. R. & Kalma, J. D. 2004. In situ measurement of soil moisture: a comparison of techniques. *Journal of Hydrology,* 293**,** 85-99.

Woodward, S. J. R., Romera, A. J., Beskow, W. B. & Lovatt, S. J. 2008. Better simulation modelling to support farming systems innovation: review and synthesis. *New Zealand Journal of Agricultural Research,* 51**,** 235-252.