

Insights into forest mortality and management of agricultural ecosystems via wavelet-based statistical inference

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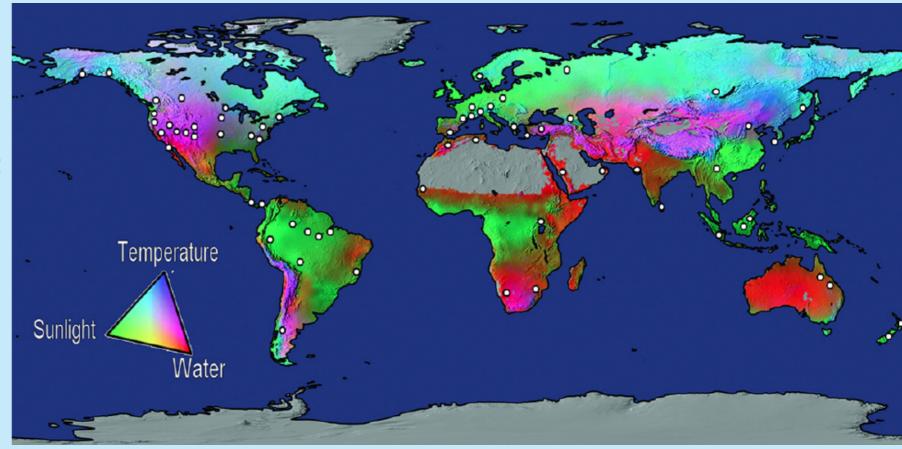
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Global forest mortality

Widespread Mortality attributed to temperature, light or water stress



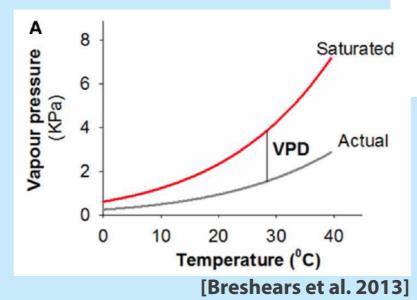
[Allen et al. 2010]

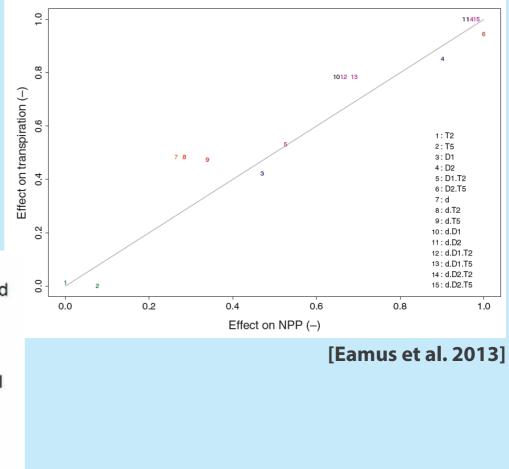


Interaction: drought and heat stress

Modelling study: high *D* alone or in combination with high *T* leads to larger restrictions on productivity and transpiration than heat stress alone [Eamus et al. 2013]

Increase in temperature results in nonlinear increase in vapour pressure deficit [Breshears et al. 2013]





Ecosystem-scale studies of mortality

Mortality without forest die-back



Mulga mortality 2013, AU-ASM

Forest die-back



Piñon mortality, New Mexico USA [Allen et al. 2015]

"long-term field observations of plant water stress prior to, and culminating in, mortality are essentially non-existent" [Breshears et al. 2009]

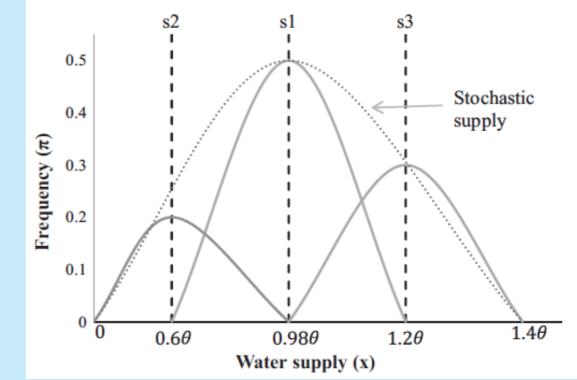


Agriculture and drought

Role of water reform policy for future drought is crucial for building resilience into agricultural systems

Limited by our ability to attribute productivity and yield to climate

Crop failure due to drought or due to unseasonable rainfall (climate variability) is of particular concern [Ellis and Albecht 2017]



[[]Adamson et al. 2017]



Attribution: lags and auto-correlation

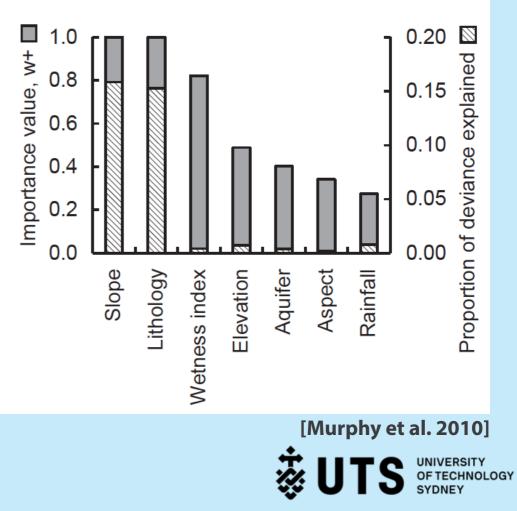
"The relative influence of specific climate parameters on forest decline is poorly understood" [Williams et al. 2013]

"Temporal psuedoreplication is committed if measurements taken through time are used as replicates" [Hargrove and Pickering 1992]

> Using generalized autoregressive error models to understand fire-vegetationsoil feedbacks in a mulga-spinifex landscape mosaic

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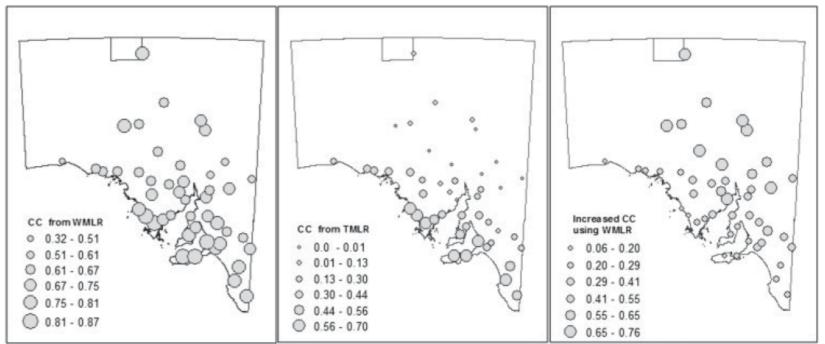
^(a) Mulga cover



Wavelet multiple linear regression

Much improved correlation using WMLR relative to traditional MLR [He and Guan 2014]

Interaction of ENSO, IOD and SAM explained 99% of variability in rainfall for SA met stations [He and Guan 2013]





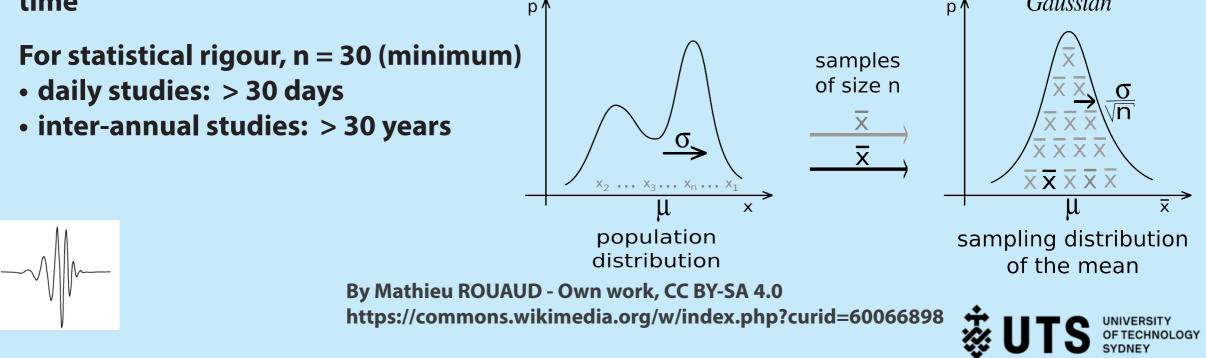




Central Limit Theorem

For non-independent samples (which thus violate statistical assumptions like normality), summary statistics (mean, variance) of the samples will tend to comply with probability theory

Wavelet transformation: linear function which summarizes variance/co-variance overtimep↑Gaussian



Aim and hypotheses

Aim

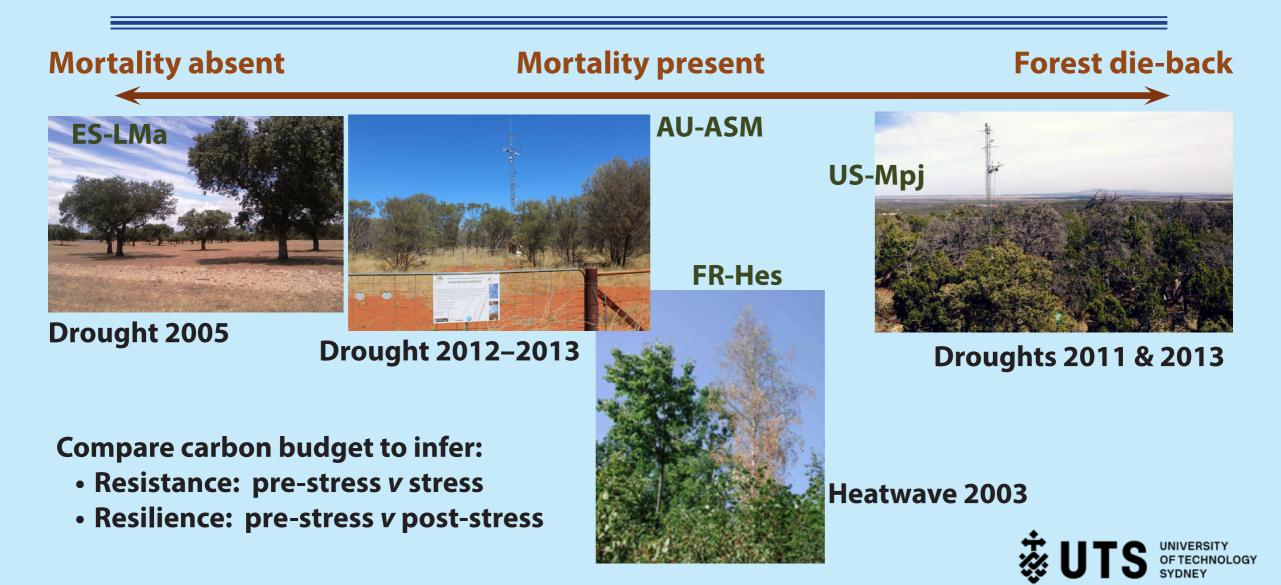
 To identify the drivers of variations in growing-season surface fluxes (i) of natural ecosystems undergoing stress and (ii) in agricultural landscapes

Research hypotheses

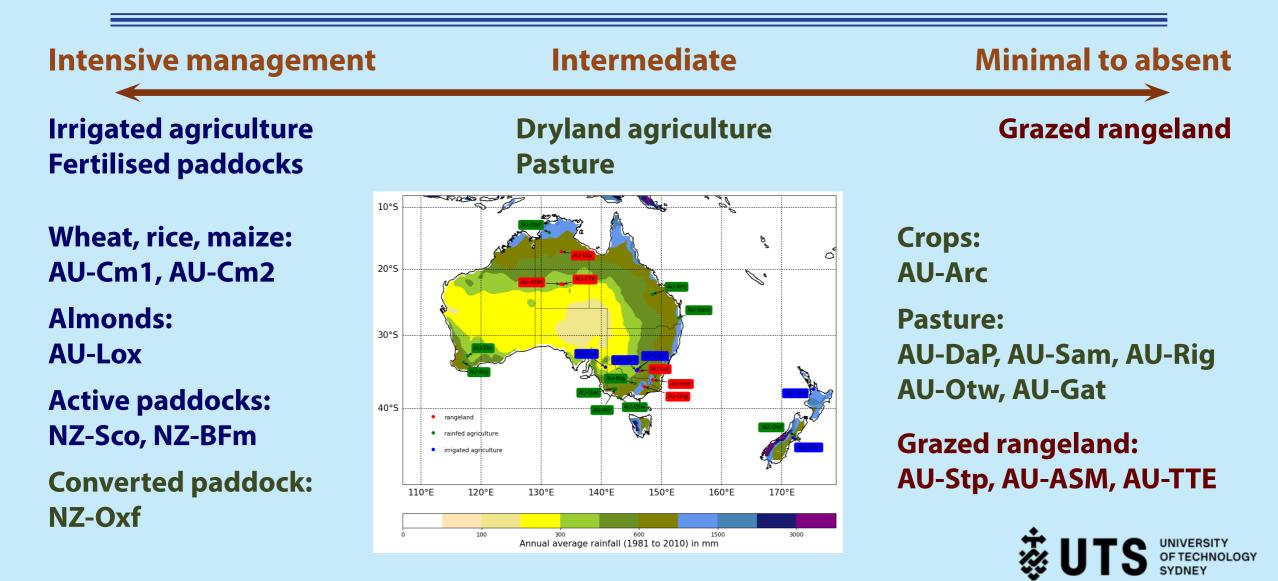
- Carbon fluxes are expected to lose sensitivity to vapour pressure deficit following drought/heatwave in ecosystems which are susceptible to forest die-back
- Meteorological drivers of fluxes are expected to group by management intensity and climate



Sites — mortality



Sites — agricultural ecosystems

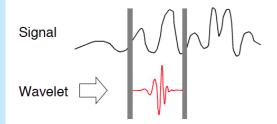


Wavelet-based statistics

Direct functional response — fluctuation in dependent variable \rightarrow fluctuation in independent variable

Mortality study: {*NEE*, *GPP*, *ER*}_{L6} ~ {*T_a*, *D*, *T_a*×*D*} *Y*: univariate (multivariate Y: singular matrix) *T_a*×*D* interaction: bi-nomial *post-hoc*: compare hot-wet *v* hot-dry *v* cold-wet *v* cold-dry

Agricultural study: $\{PC_{NEE, E, FH}\}_{L5} \sim \{T_{a'}, D, F_{n'}, q, T_{s'}, \theta, F_{g'} \text{ interactions}\}; wavelet PCA [Cleverly et al. 2016]$ Y: bi- or tri-nomial*post-hoc*for significant PCs [Cleverly et al. 2016]X interaction terms: PCs for variables which contribute to PC, additional straight interaction for variables which do not contribution substantively to PCs



Daily timescale (59–62 days), growing season

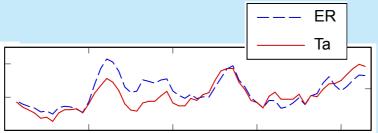
Requires: Gap-free data



Ecosystem respiration

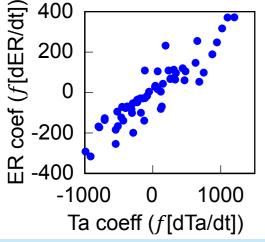
Significantly, positively related to T_a alone in all comparisons except:

- also related to D (independently without $T_a \times D$) at:
 - Piñon–Juniper (pre-drought)
 - Alice Mulga (drought)
- related to neither T_a nor D at:
 - Piñon–Juniper (drought and post-drought)



0.83		3	55 95		.4 8.810e-22*	
)		Coef	StdErr	t	р	
	Int	0.038	9.67	0.0040	0.997	
_	D		0.018	0.06	0.951	
	T	0.26	0.021	12.4	1.245e-17*	
-	T _a ×D	7.34e-06	0.021 2.76e-05	0.3	0.791	

р



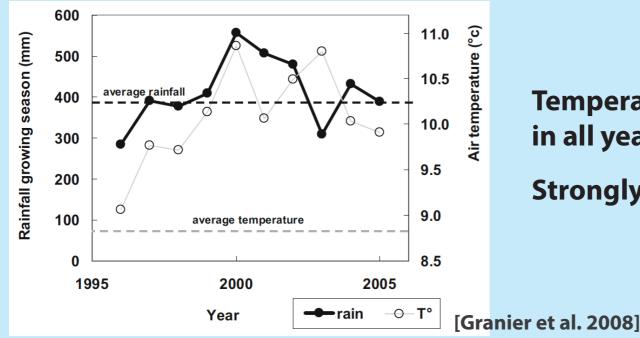
Caution: might reproduce results built-in by respiration model, **but:** timing of fluctuations are not represented in respiration model (thus not as susceptible to model errors as straight regression)

ER (ES-LMa, pre-drought):

adj-R² df_treatment df_error F

Resistance and resilience





Temperature higher than the long-term average in all years of the EC era

Strongly driven by D



Mortality: summary

Site	Mortality	Resistant	Resilient	Forest die-back
AU-ASM	+	+	+	_
US-Mpj	+	-	-	+
FR-Hes	+	-	+	— (high risk)
ES-LMa	-	+ (partial)	+	— (low risk)

Photosynthetic resistance and resilience to drought protects against forest die-back, regardless of the presence of tree mortality (e.g., AU-ASM)

Piñon-Juniper ecosystems very susceptible to worsening global-change-type drought

More severe/frequent European drought + heatwave suggests resilience at FR-Hes is likely to fail in the future

Partial resistance at ES-LMa suggests low but present future risk of mortality and forest die-back



What about other drivers?

Revised experimental design of canonical correlation analysis for agricultural study (new design completed last Monday to include all main and interaction effects)

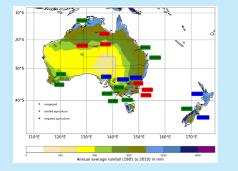
Results from AU-ASM:

Fluxes wavelet-PCA: explains 78.4% of variability in fluxes: $-0.42 \text{ NEE} + 0.71 \text{ E} + 0.57 \text{ F}_{h}$

Drivers wavelet-PCA: PC1 and PC2 together include all drivers as interaction effects (85.4% of variability)

1, 62.1% of variability: 0.42 F_n + 0.42 T_a - 0.31 θ + 0.45 D - 0.39 q + 0.41 T_s + 0.18 F_a

2, 23.4% of variability: $-0.71 F_n - 0.01 T_a - 0.43 \theta + 0.11 D - 0.38 q + 0.09 T_s - 0.39 F_a$

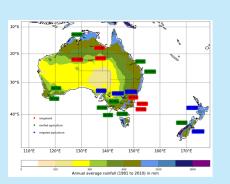




Preliminary results/conclusions

To be confirmed or revised

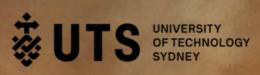
- Irrigation released NEE and E in agriculture from dependence upon environmental drivers, except
 - in extreme conditions like flooding (rice) or high heat (Loxton almonds)
- Close coupling between fluxes and meteorological/edaphic drivers in:
 - dryland agriculture
 - pasture
 - energy-limited environments of New Zealand



 Grazed rangelands are most strongly coupled to the large fluctuations in available energy and atmospheric humidity which characterise the summer wet season of northern and central Australia



Thank you **Questions?**



Chris Tangey / SWNS.com