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Use of seasonal forecasting to manage weather risk in ecological restoration

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Abstract. Ecological restoration has widely variable outcomes from successes to partial or complete failures, and there are diverse perspectives on the factors that influence the likelihood of success. However, not much is known about how these factors are perceived, and whether people's perceptions match realities. We surveyed 307 people involved in the restoration of native vegetation across Australia to identify their perceptions on the factors influencing the success of restoration projects. We found that weather (particularly drought and flooding) has realized impacts on the success of restoration projects, but is not perceived to be an important risk when planning new projects. This highlights the need for better recognition and management of weather risk in restoration and a potential role of seasonal forecasting. We used restoration case studies across Australia to assess the ability of seasonal forecasts provided by the Predictive Ocean Atmosphere Model for Australia, version M24 (POAMA-2) to detect unfavorable weather with sufficient skill and lead time to be useful for restoration projects. We found that rainfall and temperature variables in POAMA-2 predicted 88% of the weather issues encountered in restoration case studies apart from strong winds and cyclones. Of those restoration case studies with predictable weather issues, POAMA-2 had the forecast skill to predict the dominant or first-encountered issue in 67% of cases. We explored the challenges associated with uptake of forecast products through consultation with restoration practitioners and developed a prototype forecast product using a local case study. Integrating seasonal forecasting into decision making through (1) identifying risk management strategies during restoration planning, (2) accessing the forecast a month prior to revegetation activities, and (3) adapting decisions if extreme weather is forecasted, is expected to improve the establishment success of restoration.

Key words: climate; decision support tool; restoration planning; revegetation; risk management; seasonal forecasting; weather.

Introduction

Recognition of the need to restore the world's ecosystems and landscapes to maintain biodiversity and the provision of ecosystem services has resulted in significant international commitments to large-scale restoration, such as the recent 2014 New York Declaration on Forests (Bullock et al. 2011, Suding et al. 2015, Chazdon et al. 2017). Governments and nongovernmental organizations worldwide are now looking for options to scale up restoration efforts and improve the return on restoration investments (Menz et al. 2013). Nevertheless, restoration outcomes have been variable and it remains uncertain whether ecosystem recovery will be delivered (Suding et al. 2015).

The outcomes of restoration projects are influenced by a range of ecological, financial, and social factors (Miller and Hobbs 2007, Suding 2011), and there are diverse perspectives on which factors most limit success. Invasive plant species and animals that consume or displace native plant species are traditionally key risks that, if unmanaged, can slow or suppress recovery (Standish et al. 2001, Dodd et al. 2011). The extent that site conditions are altered by previous land uses such as cropping indicate the level of intervention required to restore ecosystems (Cramer et al. 2008, Jones and Schmitz 2009) with greater intervention likely to be more costly and risky to the point that restoration of novel ecosystems may be considered (Hobbs et al. 2009). Limited funding, logistical constraints (i.e., shortage of skilled staff), and short timeframes can constrain what can realistically be restored, and lack of long-term funding for ongoing management can affect the success of restoration (Miller and Hobbs 2007, Kanowski 2010). Social engagement is also recognized to be critical to successful restoration and lack of public acceptance and support can impact on restoration efforts and ongoing stewardship (Miller and Hobbs 2007, Brooks et al. 2013, Shackelford et al. 2013, Standards Reference Group SERA 2017).

The weather also impacts the recovery of ecosystems. Young restoration plantings in previously cleared areas are particularly vulnerable to frost (Scowcroft and Jeffrey 1999, Curran et al. 2010). Seedling establishment and survival are also determined by climate, specifically rainfall and temperature (Commander et al. 2013, Standish et al. 2015). Drought can trigger mortality of adult trees in natural systems (Anderegg et al. 2012), such as drought-induced death of savanna eucalypts in northeast Australia (Fensham et al. 2015), sub-boreal Scots pine (*Pinus sylvestris*) in the alpine forests of Switzerland (Rigling et al. 2013), and coniferous forests in southeastern and southwestern United States

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(Klos et al. 2009, Ganey and Vojta 2011), as well as damage seedlings in restoration plantings (Maestre et al. 2006, Smallbone et al. 2007). Conversely, too much rainfall can result in flooding of riparian zones and floodplains, inducing tree mortality in riparian and floodplain forests (Hawkins et al. 1997, Acker et al. 2003, Damasceno-Junior et al. 2004, Reid and Bhattacharjee 2014). Severe weather events can also affect the recovery of ecosystems, such as hurricanes (Jones and Schmitz 2009) and cyclones (Kanowski et al. 2008). The scale of restoration can vary among projects, which is an additional factor that might influence the likelihood and consequence of weather events.

Resilience planning is advocated in restoration to mitigate the potential adverse effects of weather, such as planting frost-tolerant species (Curran et al. 2010), and adapting to predicted long-term climate change through selecting drought-tolerant provenances (Sgrò et al. 2011, Booth et al. 2012, Breed et al. 2016). Historical weather observations for the site of interest are sometimes assessed to inform restoration design and priorities (Hardegree et al. 2012, Bollenbacher et al. 2014). However, merely coping with climate variability represents a reactive management approach, whereas proactive management would entail integrating information about future conditions into planning to reduce potential negative impacts (Hodgkinson et al. 2014, Hobday et al. 2016). Likewise, while uncertainty (i.e., risk of failure) from climate variability can be explicitly integrated into restoration planning to determine optimal revegetation actions (McCarthy and Possingham 2007, Dorrough et al. 2008), actively reducing uncertainty will likely further improve management decisions.

While long-term climate changes are a concern for the future resilience of forest restoration (Millar et al. 2007, Newton and Cantarello 2015), climatic conditions in the near term directly affect the short- and long-term outcomes of restoration projects. Ecological resilience planning (Newton and Cantarello 2015) and risk diversification (Crowe and Parker 2008) can help to future-proof restoration projects against climate change; however, as the climate changes and the seasons become more unpredictable, seasonal forecasting can assist in decision making by adapting management decisions during the crucial initial stages of active restoration.

Seasonal forecasts provide insight into future weather and have the potential to be integrated into restoration planning to improve decision making and risk management. Forecasts based on dynamic coupled ocean and atmospheric models, such as the Predictive Ocean Atmosphere Model for Australia, version M24 (POAMA-2), offer improved performance relative to statistical methods (Hudson et al. 2013). Forecast variables include rainfall and air temperature, and are considered accurate up to approximately four months into the future, depending on the region and season of interest (Spillman et al. 2015, Hobday et al. 2016). Seasonal forecasting is being used in marine farming and fishing operations in Australia to reduce uncertainty and manage risks on production (Spillman et al. 2015, Hobday et al. 2016), and for management of the Australian Great Barrier Reef to minimize damage to reef ecosystems from coral bleaching events (Spillman 2015). The value of seasonal thermal stress forecasts to manage coral bleaching risk is also being recognized across the Pacific region (Griesser and Spillman 2016). Development and utilization of seasonal forecast technology has been suggested to enhance establishment success in rangeland restoration efforts in the United States (Hardegree et al. 2012) and to guide decisions on which phase of restoration to conduct in Californian grassland depending on rainfall variability (Kimball et al. 2015). Seasonal forecasting has also been shown to be reliable and skillful to inform optimum crop designs to increase farmer's profits and reduce risks in dryland cropping (Rodriguez et al. 2018).

Seasonal weather forecasts could support restoration decisions when there is a need to avoid or mitigate weather-related impacts that can be predicted and for which management options are available in response to the forecasts (Hobday et al. 2016). Seasonal forecasting could potentially be aligned with restoration planning and budgeting to inform site preparation, planting or seeding and/or site maintenance to minimize the risk associated with weather-related impacts. However, for seasonal forecasting to be useful in restoration, it would need to forecast appropriate variables and have adequate accuracy and lead time for critical decisions to be changed or adapted to reduce the risk. Quantitative and qualitative information on the potential benefits and utility of seasonal weather forecasts is also paramount to informing future product design (Sivakumar 2006, Everingham et al. 2012).

Here, we explore the need, potential benefit, and utility of seasonal weather forecasts for managing the risks associated with weather-related impacts on terrestrial restoration. To determine the need, we report on a national survey of restoration stakeholders across Australia and identify whether the perceived risks match those that are realized on the ground. We then evaluate the potential benefit via retrospective analysis of 18 restoration projects to identify specific weather issues encountered, how and when these affected restoration outcomes, and whether seasonal weather forecasts could have reduced risk by predicting unfavorable weather with sufficient skill and lead time. We explore the potential utility of seasonal weather forecasts through a focus group discussion with restoration stakeholders. Finally, we develop a prototype POAMA-based forecast product and discuss how it could be incorporated in restoration planning.

Methods

National survey of restoration stakeholders to identify the need for seasonal weather forecasting

We surveyed individuals and organizations across Australia involved in the restoration of terrestrial native vegetation (hereafter referred to as stakeholders) to identify (1) the perceived risks to restoration projects and the restoration approaches perceived to be most effective in improving success, and (2) the realized risks to restoration projects after implementation. Restoration was defined as any method of reinstating native vegetation on previously cleared lands, including by plantings, seeding, assisted natural regeneration, or a combination of these methods. The aims of the broader survey were to identify the motivations for restoration of different stakeholder types and across different regions, to ascertain their perceptions on the factors influencing restoration success and elicit data on restoration methods, costs and outcomes for Australia's major terrestrial vegetation types. The methods used to design the survey and undertake sampling, and a copy of the full survey are provided in Hagger et al. (2017).

In total, we received 307 completed responses, corresponding to a response rate of 28%. Responses were representative of various states (Victoria, Queensland, New South Wales, Western Australia, and South Australia) and a range of stakeholder types (community groups, state government agencies, local government agencies, not-for-profit (NFP) organizations, private organizations, natural resource management (NRM) bodies, and landholders). A total of 220 of the 307 respondents provided an example of a restoration project as a case study. The restoration projects varied in size from 1300 to 0.0002 km^2 but with a median size of 0.08 km^2.

To inform the survey design, we identified through review of the literature factors that have been previously reported to limit the success of restoration projects (risks; Table 1). We asked the survey respondents to rate how strongly they agree that success is limited by each risk (on a five-point scale from strongly agree to strongly disagree). We then coded these responses as binary variables. For the risk variable, a 1 indicated that the respondent "strongly agreed" or "agreed" that the risk could potentially limit success. These binary responses were analyzed to assess differences in how risks were perceived to limit success. We used generalized linear models with binomial errors and logit link function followed by post hoc pairwise comparisons between risks using the glht function in the multcomp package (Hothorn et al. 2017). All statistical analyses were performed in R version 3.3.3 (R Core Team 2017).

To determine realized risks, we asked survey respondents who reported the general risks to provide a case study of a specific restoration project for which they have been involved. We asked them which risks (using the categories from Table 1), if any, limited success in that project and asked them to rank those that apply. We then calculated the proportion of responses that selected each risk as their primary factor. To account for the possibility that respondents would report on projects that performed well and thereby bias the results toward successful case studies, or toward risks that only became apparent after implementation, we asked respondents to report on a restoration project that had failed to deliver desired outcomes. Responses were categorized by the investigator into the categories from Table 1 and the proportion of responses that identified each risk as a failure reason was calculated.

Table 1. Survey response categorizations for risks.

Number	Risks
1	*Financial* constraints (e.g., short-term, variable, and/or limited funding/budget).
2	*Land use* conflicts (e.g., other proposed land uses for revegetation site).
3	*Local climate* (e.g., frost, dry, and/or cold winters, hot and dry summers).
4	*Logistical* constraints (e.g., site access, limited availability of nursery stock, shortage of skilled staff).
5	*Natural events* (e.g., cyclones, flood, drought, fire).
6	*Pest* animals (e.g., herbivory and site disturbance).
7	Depleted *seed sources.*
8	*Social* constraints (e.g., lack of stakeholder/community support, challenges with engaging private landholders).
9	Altered *site conditions* (e.g., soil, hydrology) from previous land use.
10	*Time* constraints (e.g., short time frames to deliver projects, lack of long-term commitment for maintenance/monitoring).
11	*Weed* invasion.
12	*Other.*

Note: Abbreviated categories displayed in the figures are shown in italic typeface.

Retrospective analysis of case studies to identify the potential benefit of seasonal weather forecasting

Out of the 220 case studies from the national survey, 45 reported local climate or natural events as a primary or secondary constraint to restoration success and used ecological plantings or seeding as their revegetation method. We were able to contact the survey participants of 38 of those case studies planted or seeded between 2002 and 2017 and sought information on the location of the restoration site, the date of revegetation, what the weather issues were and when they occurred, and how restoration outcomes were affected. We were able to obtain all required information for 16 case studies, comprising seven from Queensland, two from New South Wales, four from Victoria, and three from Western Australia. We also undertook a literature review using Web of Science (Core Collection) and Wiley Online (to capture the journal *Ecological Management and Restoration*) to locate peer-reviewed articles describing case studies in Australia that reported the effects of weather or climate-related perturbations on restoration of native vegetation. The literature search terms were "(drought OR frost OR cyclone OR flood* OR heat*) AND (restoration OR revegetation OR rehabilitation) AND Australia." From this review, an additional two case studies (Kanowski et al. 2008, Curran et al. 2010) were identified from north Queensland (Fig. 1).

We evaluated the case studies to determine (1) if the weather issues that have led to suboptimal outcomes can be predicted by available seasonal forecasting variables and (2) whether the issues occurred on an appropriate timescale for seasonal weather forecasting to be accurate, defined as within four months of the model start date as suggested by Hobday et al. (2016). Weather issues were categorized into six groups (dryness, heat, flooding, frost, strong winds, and cyclones), with six case studies experiencing more than one issue. For case studies that experienced more than one issue, we used the dominant or first-encountered issue. First, we identified which weather issues relate to the seasonal forecasting variables available in POAMA-2. For applicable case studies, we then generated retrospective seasonal weather forecasts to assess whether the issue would have been predicted within the acceptable forecast period. Seasonal forecasts were generated by POAMA-2. This is the Australian Government Bureau of Meteorology's (BOM) current operational seasonal prediction system, comprising a coupled ocean and atmosphere–land surface climate model and data

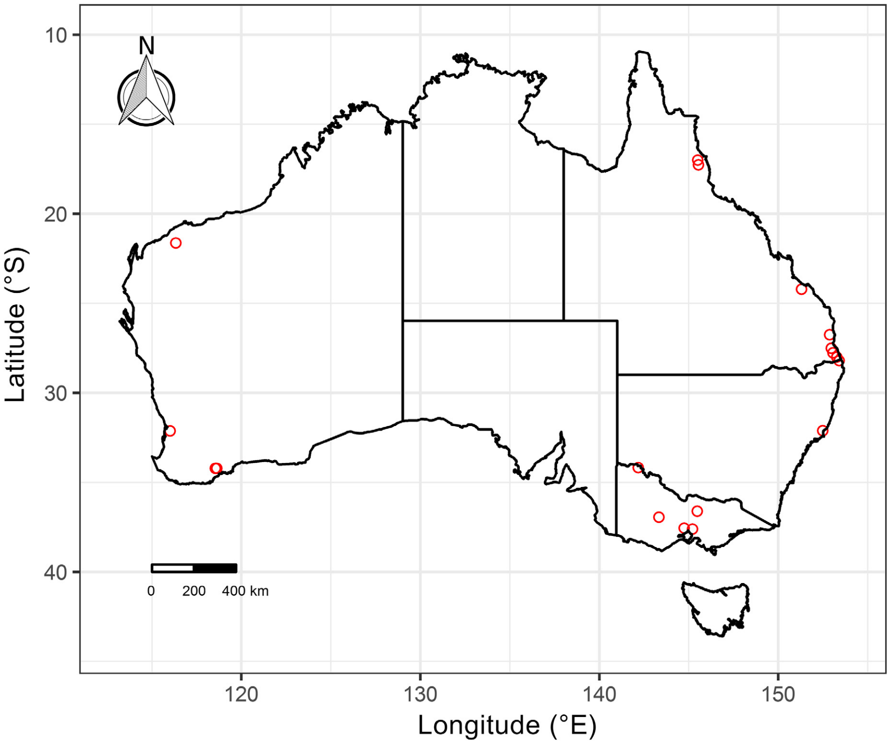

FIG. 1. Location of the 18 restoration case studies (sites marked in red on map).

assimilation systems (see Hudson et al. [2013] and Appendix S1 for details). Anomaly and tercile probability forecasts (see Appendix S2) were created for applicable case study locations for the relevant weather variable (i.e., daily precipitation [rainfall], daily minimum surface temperature [T_{min}], and/or daily maximum surface temperature [T_{max}]). These forecasts were generated for four lead times that are considered to have sufficient accuracy (first fortnight, second fortnight, first calendar month, and first season [average of first three calendar months]). The forecast start date was set as one month prior to the planting or seeding date to allow time for adapting decisions. For example, for a forecast beginning on 18 March, the first fortnight is 18–31 March, the second fortnight 1–14 April, the first calendar month 1–30 April, and the first season 1 April–30 June.

To quantify the benefit of seasonal forecasting, we took case studies that experienced weather issues within the acceptable forecast period and identified if the anomaly or tercile probability forecasts correctly predicted the weather event within the timeframe reported. For example, if dryness at the site was reported by the stakeholder to occur one month after implementation (which is two months after the model start date), the forecasted anomaly for rainfall for the first season would be negative and the forecasted tercile would be lower. The proportion of case studies that had correct forecasts for both anomalies and terciles were calculated.

Focus group discussion to determine the potential utility of seasonal weather forecasting

We undertook a focus group discussion to investigate the potential use of seasonal forecasting in restoration practice, bringing together 12 stakeholders across southeast Queensland, including practitioners from private organizations, planners, and managers from local government, natural resource management (NRM) bodies and private restoration organizations, and university scientists who research restoration or forecasting in the agricultural industry. The purpose of the focus group was to (1) confirm weather issues, impacts, and timescales experienced in restoration projects to identify forecast variables and lead times, (2) identify management options and decision lead times in response to unfavorable conditions, and (3) explore the challenges associated with implementing a seasonal weather forecast product.

Prototype forecast product development

To illustrate application of seasonal forecasts in restoration, we developed forecast products at local and national scales for a case study (Greenvale Park environmental offsets, Chambers Flat, Queensland, Australia) that experienced three significant weather events (dryness, frost, and flooding). The model start date was set as one month prior to the planting date (18 March 2013). Probabilistic tercile forecasts for rainfall, T_{max}, and T_{min} were generated using POAMA-2 for the following lead times: first fortnight, second fortnight, first calendar month, and first season.

RESULTS

Risks identified from the national survey

The risk factors perceived by respondents to most strongly limit the success of restoration projects were financial constraints (Probability [*P*] = 0.9), weed invasion and time constraints (both *P* = 0.85), and pest animals (*P* = 0.82) (Fig. 2a). Sixty-five percent of the restoration case studies (*n* = 220) reported factors that limited the success of the project. Risks commonly identified as most important were financial constraints (22%), local climate (16%), natural events (15%), and weeds (13%; Fig. 2a). A total of 136 respondents reported being involved in a restoration project that failed to deliver the expected outcomes. The main reasons reported were local climate (32%), weeds (17%), and natural events (15%; Fig. 2c). Other reasons reported were lack of maintenance (29%) and low plant survival rates (15%).

We found a mismatch between realized risks and perceived risks. Despite local climate and natural events (particularly drought and flooding) recognized as main risks limiting the success of restoration projects, neither are important perceived risks.

Prediction of weather issues from case studies

Weather events found to effect case studies (*n* = 18) were (1) rainfall surplus resulting in flooding and soil erosion of riparian areas or waterlogging of soils in gully areas, (2) rainfall deficit causing dryness, delayed commencement of seasonal rains, or drought over longer periods, (3) extreme

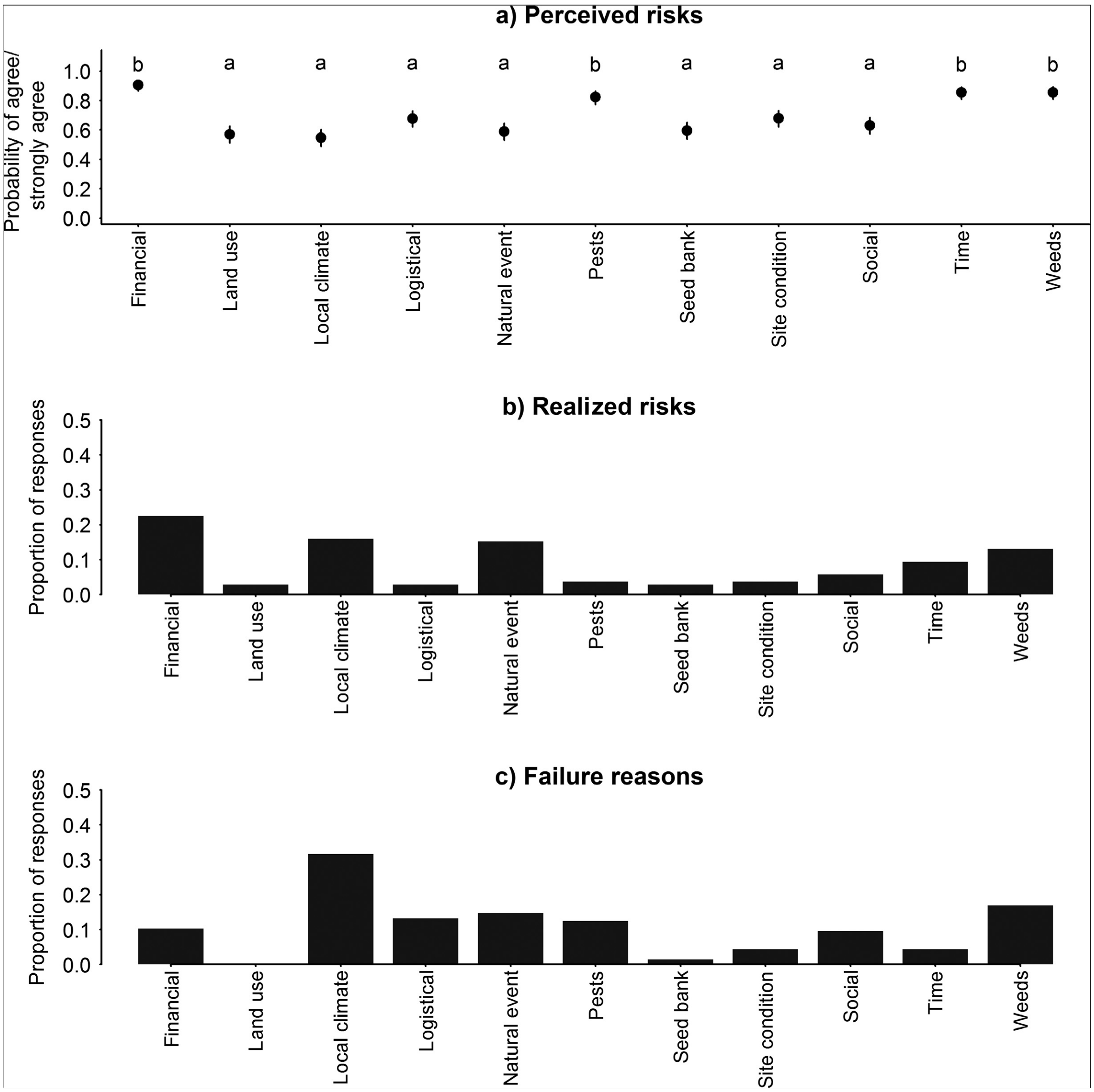

Fig. 2. Perceived and realized risks to restoration projects showing (a) probability of "strongly agree" or "agree" response for risk factors perceived to limit the success of restoration projects (*n* = 283 [financial], 279 [land use], 280 [local climate], 281 [logistical], 280 [natural event], 282 [pest animals], 279 [seed source], 276 [site condition], 279 [social], 281 [time], 283 [weeds]). Letters above each risk factor refer to the post hoc pairwise comparisons and indicate which perceived risks differ significantly ($P < 0.05$). Error bars show 95% upper and lower confidence intervals. (b) Realized (primary) risks to restoration case studies (*n* = 138) and (c) failure reasons of restoration projects that did not progress as planned (*n* = 136). For failure reasons, respondents could identify more than one reason; therefore, total proportion does not equal one.

heat, (4) extreme cold causing frost, (5) strong winds, and (6) cyclones. Rainfall immediately prior to implementation was also found to be important (for soil moisture availability for seed germination or plant establishment). For the case studies, more than one weather issue was experienced for most projects, and the most common issues were dryness (38%), flooding/waterlogging (23%), and frost (19%). Impacts on revegetation included delayed commencement of works, and mortality of new plantings and young seedlings (ranging from minimal to significant losses) from flooding/waterlogging, dryness and heat. Frost, strong winds, and cyclones caused extensive damage to restoration plantings and loss of a large patch of newly seeded area.

POAMA-2 forecast variables predicted 88% of issues encountered in the 18 case studies (dryness, flooding, heat, and frost). Cyclones and strong winds were not predicted. Sixty-seven percent of the 18 case studies had the dominant or first-encountered issue occur within the forecast skill of POAMA-2 (i.e., within 4 months of the model start date, which was three months after the implementation date). Of these case studies, anomaly forecasts (83%) were more accurate in predicting the dominant or first-encountered issue than the tercile forecasts (75%). Anomalies indicate forecast conditions above or below the historical mean, whereas terciles indicate forecast probabilities for three categories (above normal, near normal, and below normal). Terciles are therefore more sensitive to identifying extremes (e.g., surplus and deficit rainfall) than anomalies, so this decline in skill is expected. For example, to predict dry weather for a particular lead time, the anomaly forecast would have to be negative, whereas the forecasted tercile would have to be in the lowest 33%. For those case studies (n = 4) that reported additional climatic issues that can be predicted (frost, flooding, dryness, heat), the weather events generally occurred more than four months after implementation of the restoration project, and beyond the forecast skill of POAMA-2.

Insights from the focus group

Weather issues discussed by stakeholders in the focus group were similar to those identified in the case studies. Similarly, ecological impacts ranged from small to widespread damage or loss of plantings/seeding. Financial and landscape impacts were also reported due to additional costs and time delays associated with mitigation (e.g., replacement plantings) and soil erosion (see Appendix S3). The timescales over which this affected revegetation ranged from immediately after implementation, within 3–6 months, to 1–5 yr after implementation.

A number of management strategies were identified that could be implemented in sufficient timescales to respond to weather forecasts (Table 2). Timing of the site preparation activities can be adjusted to maximize effectiveness of soil preparation and weed control, for example, plow when dry and undertake weed treatment after rain. Increasing the number of frost or heat tolerant species in the planned species mix or increasing the overall density of planting or seeding can be done to enhance resilience in the restoration or account for expected losses over time. Adaptions to the restoration treatments can also be done, such as using mulch or weed matting to suppress weed growth and increase moisture retention in the soil. Improved scheduling of revegetation can help to avoid weather issues (e.g., delay planting) and planting in stages may provide more flexibility in response to weather over time (see Appendix S3 for further detail).

Prototype forecast product

Forecast variables in POAMA-2 that have the ability to predict weather issues identified in both the case studies and focus group include rainfall, T_{max}, and T_{min}. Lead times of the first and second fortnight, first calendar month, and first season (next three months) were determined to be most useful for decision making (first four weeks to provide indication of soil moisture prior to planting, one month ahead to provide indication of weather during planting, and one season ahead to provide indication of weather after planting when the seedlings are most vulnerable) as well as sufficiently skillful.

To serve as an example of how forecasts could be used, we show a national probability forecast product for one case study (Fig. 3), issued on 18 March 2013. For the case study location, drier than average rainfall was indicated for April and the upcoming season (April–June) and cooler than average T_{max} and T_{min} values were indicated for the next two fortnights, which continued into April for T_{min}. Forecasted terciles for rainfall corresponded well to the conditions reported for June–August 2013 (dry winter causing ground to crack open). The forecast did not predict the weather events that occurred in subsequent years (severe frost in May 2014 and flooding April 2017).

We also present a tailored local probability forecast product for the case study (Fig. 4), which shows the probability of rainfall, T_{min} and T_{max} falling in the lower (driest/coolest 33%), middle (neutral 33%), or upper (wettest/warmest 33%) terciles at the case study location for the first and second fortnights, first calendar month, and first season. For reference, the anomaly ensemble mean (deviation from the long-term mean) is provided for each lead time.

Discussion

Need for better management of climate risks

Our survey results reveal that restoration managers and practitioners recognize certain risks to successful restoration (financial and time constraints, weeds, and pest animals). It is these perceptions that are likely to influence how people invest in the implementation and initial maintenance of restoration projects. However, the survey revealed discrepancies between perceived risks to restoration projects in general (Fig. 2a) and realized risks from specific case studies after implementation (Fig. 2b). For example, local climate and natural events were not considered as important perceived risks, but both were recognized as major reasons limiting the success of specific case studies. Furthermore, local climate was the main cause cited for the failure of restoration projects (Fig. 2c).

Given that investment in different implementation actions is based in part on people's perceptions of factors influencing the success of restoration, better understanding and

Table 2. Possible management strategies to respond to seasonal weather forecasts and associated lead times and constraints to implementation.

Management strategies	Decision lead times	Constraints
Timing of site preparation (e.g., plow, weed control)	weeks	weather, weed type, site access, staff availability
Species selection	weeks (existing stock), 3 months (order pregrown), 8–12 months (growing tubestock from collected seed)	target ecosystem, season of planting, availability of seed and nursery stock, regional nursery capacity, provenance restrictions
Restoration treatments (e.g., mulch, weed and erosion matting, tree guards, water crystals)	weeks to 2 months	availability of resources (staff and materials), site access, additional cost
Supplementary watering	days to weeks	availability of resources (staff and materials), site access, additional cost
Scheduling and sequencing of planting (e.g., delay or stages)	days to weeks	management constraints, short project life cycles, financial year budgets, staff availability, holding stock at nurseries, lose access to or quality of stock

realization of climate risk is needed. Our case studies revealed that active restoration efforts (planting and seeding) in temperate and tropical regions are affected by diverse climatic conditions including low or high rainfall, extreme heat, cold temperatures, strong winds, and cyclones, and that interactions between conditions (e.g., hot and dry or windy and hot) can exacerbate effects. Restoration planning should therefore have a larger emphasis on managing the risk of weather-related impacts to improve restoration outcomes. Although we focus on restoration using planting or seeding, there would also be benefits to assisted natural regeneration, such as timing of weed control or pest management to encourage regeneration of native species.

Incorporating seasonal forecasting in decision making

Seasonal weather forecasting could be used as a decision support tool to mitigate risks to restoration from dryness, flooding, heat, and frost. This captures the main causes of weather-related impacts on restoration efforts; it cannot, however, capture the risk of cyclones (or hurricanes) and strong winds. To manage the risk of cyclones, the tropical cyclone forecast issued by the BOM every season could be used. Seasonal forecasting could increase establishment success if implementation is timed to coincide with favorable conditions for seeding and planting, or if timing is not flexible, to better plan for predicted unfavorable conditions (Hardegree et al. 2012, Hobday et al. 2016). Our focus group revealed several management options with acceptable lead times to manage climate risks. Improved timing or scheduling of site preparation or revegetation activities can reduce the likelihood of extreme weather coinciding with planting. It may also be possible to sequence planting in stages to spread risk across a range of conditions. Problems may arise if scheduling adjustments involve delaying planting, as seedlings can become root bound if held too long and nurseries may be forced to sell on stock to other projects if delays are substantial. In addition, delays may not be possible due to project contracts, funding cycles, and other administrative and political constraints. In these cases, it may be more feasible to adjust restoration approaches to mitigate impacts. Funds could also be allocated to maintenance to mitigate expected weather issues, such as supplementary watering or replacement plantings. However, adjusting restoration approaches and spending more on initial maintenance will divert limited funds from other management actions such as weed or pest animal control. Alternatively, it may be possible to adjust species mixtures to include higher relative abundances of species that are tolerant of the expected extreme conditions, depending on what species are available at short notice and how prescriptive the project is about species and provenances.

Given the range of management options available, alternative strategies for specific projects could be incorporated into contingency planning during the planning process to identify what management decisions could be made to manage weather risk. Seasonal forecasts could then be sought three to four months prior to implementation and decisions adapted if required. An updated forecast after implementation may also inform intervention options for maintenance, such as supplementary watering. Integrating seasonal forecasting into decision making is expected to reduce reactive management to short-range weather forecasts based on rushed decisions. It can inform better decisions through consideration of climatic conditions early in the project life cycle, which is likely to lead to improved outcomes in restoration both ecologically and financially. Ongoing research should quantify the economic benefit of seasonal forecasting for restoration, but should be undertaken over long enough timeframes to capture the probabilistic nature of forecasts (Hobday et al. 2016).

Development and implementation of a forecast product

Rainfall and temperature seasonal forecasts have considerable potential to improve restoration outcomes. We created two possible forecast products based on data extracted from Australia's current forecast system, POAMA-2: national scale probability forecast maps for rainfall, $T_{\max}$, and $T_{\min}$ (Fig. 3), and a location-specific summary combining the probability forecasts for all three variables (Fig. 4). Forecasts are provided on a scale of 250 km^2, which more than covers the scale of typical restoration projects. Lead times (first and second fortnight, first calendar month, and first season) were determined to be both the most useful to restoration managers and practitioners for decision making as well as sufficiently

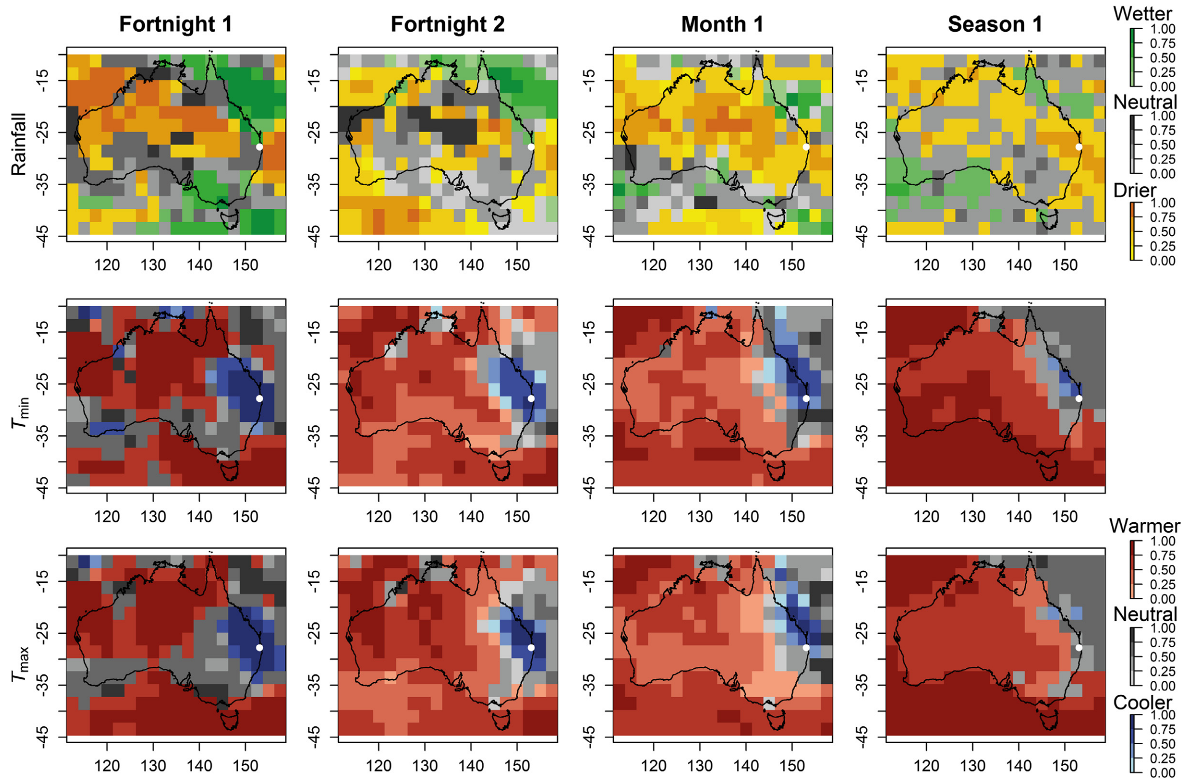

FIG. 3. National seasonal forecasts for Greenvale Park restoration project (site marked in white on map) showing tercile probability forecasts for rainfall, daily minimum surface temperature T_{min}, and daily maximum surface temperature T_{max} over Australia for lower (drier/cooler), middle (neutral), and upper (wetter/warmer) for the first fortnight (18 March–1 April 2013), second fortnight (2–16 April 2013), first calendar month (1–30 April 2013), and first season (1 April–30 June 2013).

accurate. The national forecast product could be provided on an industry-specific webpage, updated weekly or fortnightly, and accessed at any time; however, end users may have difficulty with interpretation at that scale. Regional-scale maps, or tailored local probability forecasts with the addition of the anomaly and climatology (historic long-term average) values for that forecast period, may be more favorably received (Spillman et al. 2015, Hobday et al. 2016). To assist with interpretation and enhance implementation, the webpage could also contain descriptions of forecast accuracy and explanations of probabilistic forecasts and lead times, together with links to other forecast information to provide easy access to all available information for use in decision making (Spillman et al. 2015). Such a website has been developed for forecasting southern bluefin tuna habitat in the Great Australian Bight for the fisheries industry (Eveson et al. 2015). Participatory product development with restoration practitioners and managers would refine the most useful scale of forecasts, and the platform on which they are delivered.

Users need to have confidence in the forecasts to use them to inform decision making (Spillman and Hobday 2014). Therefore, uptake will also be governed by how well the forecast predicts the observed conditions. Forecast accuracy will vary with the forecast model, region, time of year, climate variable, and lead time. Generally, forecast accuracy decreases as the lead time increases and is better for temperature than rainfall (Hendon et al. 2015, Hudson et al. 2017). Although POAMA-2 skillfully predicts some components of

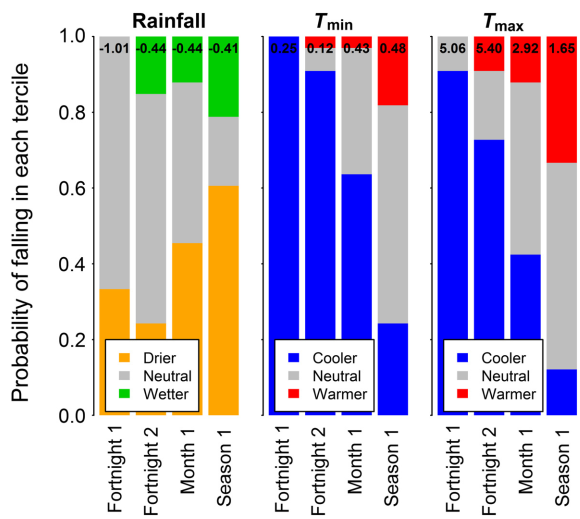

FIG. 4. Local seasonal forecasts for Greenvale Park restoration project showing tercile probability forecasts for rainfall, daily minimum surface temperature T_{min}, and daily maximum surface temperature T_{max} for the first fortnight (18 March – 1 April 2013), second fortnight (2–16 April 2013), first calendar month (1–30 April 2013), and first season (1 April–30 June 2013). For reference, the ensemble mean anomaly (emn) is shown for each forecast at the top of the bar.

regional climate in Australia from weeks to seasons in advance (Langford and Hendon 2013, Hendon et al. 2015), the United Kingdom Met Office's GloSea5-GC2 (Global

Seasonal Forecast System version 5 with Global Coupled 2.0 science configuration) provides forecasts that are generally more skillful than POAMA-2 across Australia (Shi et al. 2016) and throughout the central and eastern Pacific (Hendon et al. 2015). Australia is basing its next seasonal forecast system on GloSea5-GC2 (known as ACCESS-S1, Australian Community Climate and Earth System Simulator version 1) and is likely updating the land surface initialization strategy with realistic initial conditions in the next version of the model (ACCESS-S2) to improve performance for Australia (Zhao et al. 2017). Therefore, creating a forecast product with the best available forecast model for the country of interest would be most beneficial to integrate seasonal forecasting into decision making. For example, in Australia, using ACCESS-S2 would offer improvements in forecast accuracy and also address concerns with model resolution and applicability to local context. The spatial resolution will be 60 km^2 and will provide better differentiation of regional climates and important large-scale climate drivers (Shi et al. 2016).

Extensive validation of the forecast model chosen would be critical in gaining user confidence, and enhancing its acceptance in implementation (Spillman and Hobday 2014). Assessment of forecast accuracy should comprise historical validation of the forecasts with observations for regions of interest and each season, variable and lead time to determine the skills of the model predicting the conditions in the upper tercile for T_{max} (heat), lower tercile for T_{min} (frost), upper tercile for rainfall (flooding), and lower tercile for rainfall (dryness) as these events are of greatest concern to restoration managers and practitioners. This information can also be used to explain how to interpret uncertainty and to discuss realistic expectations about forecast accuracy (Hobday et al. 2016).

Here, we demonstrate how available forecast models can be used to extract potentially useful information about future climatic conditions influencing successful restoration. We create a potential forecast product using Australia and POAMA-2 as a case study, and demonstrate how it can be incorporated as part of a decision support tool to inform better decisions in restoration to improve outcomes, and discuss constraints with its implementation. Although we focus on Australia, there is application for this in restoration worldwide, using reliable seasonal forecast systems for other countries, such as the IRI's Probabilistic Seasonal Climate Forecasts (Kirtman et al. 2014) for North America. It is expected that seasonal forecasting will continue to advance, such as a new multiyear dynamical prediction system that exhibits a high degree of skill in forecasting wildfire probabilities and drought for 10–23 and 10–45 months lead time for southwestern North America, which extends far beyond the current prediction activities (Chikamoto et al. 2017).

We found industry support for developing and implementing a restoration-specific forecast product. Should a forecast product be developed it must be continually reviewed and updated in line with new advances in forecast modeling to enhance its implementation. However, its successful implementation depends on how well it is integrated in planning of the restoration project. Specifying when the product will be used and how decisions will be adapted in response to unfavorable forecasts will be critical to allow better decisions for site preparation, revegetation, and maintenance. Used in this manner, it has potential to reduce uncertainty in decision making and improve the success and cost-efficiency of restoration projects.

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Literature Cited

Acker, S. A., S. V. Gregory, G. Lienkaemper, W. A. McKee, F. J. Swanson, and S. D. Miller. 2003. Composition, complexity, and tree mortality in riparian forests in the central Western Cascades of Oregon. Forest Ecology and Management 173:293–308.

Anderegg, W. R. L., J. M. Kane, and L. D. L. Anderegg. 2012. Consequences of widespread tree mortality triggered by drought and temperature stress. Nature Climate Change 3:30.

Bollenbacher, B. L., R. T. Graham, and K. M. Reynolds. 2014. Regional forest landscape restoration priorities: integrating historical conditions and an uncertain future in the Northern Rocky Mountains. Journal of Forestry 112:474–483.

Booth, T. H., K. J. Williams, and L. Belbin. 2012. Developing biodiverse plantings suitable for changing climatic conditions 2: using the Atlas of living Australia. Ecological Management & Restoration 13:274–281.

Breed, M. F., N. J. C. Gellie, and A. J. Lowe. 2016. Height differences in two eucalypt provenances with contrasting levels of aridity. Restoration Ecology 24:471–478.

Brooks, J., K. A. Waylen, and M. B. Mulder. 2013. Assessing community-based conservation projects: a systematic review and multilevel analysis of attitudinal, behavioral, ecological, and economic outcomes. Environmental Evidence 2:2.

Bullock, J. M., J. Aronson, A. C. Newton, R. F. Pywell, and J. M. Rey-Benayas. 2011. Restoration of ecosystem services and biodiversity: conflicts and opportunities. Trends in Ecology & Evolution 26:541–549.

Chazdon, R. L., P. H. S. Brancalion, D. Lamb, L. Laestadius, M. Calmon, and C. Kumar. 2017. A policy-driven knowledge agenda for global forest and landscape restoration. Conservation Letters 10:125–132.

Chikamoto, Y., A. Timmermann, M. J. Widlansky, M. A. Balmaseda, and L. Stott. 2017. Multi-year predictability of climate, drought, and wildfire in southwestern North America. Scientific Reports 7:6568.

Commander, L. E., D. P. Rokich, M. Renton, K. W. Dixon, and D. J. Merritt. 2013. Optimising seed broadcasting and greenstock planting for restoration in the Australian arid zone. Journal of Arid Environments 88:226–235.

Cramer, V. A., R. J. Hobbs, and R. J. Standish. 2008. What's new about old fields? Land abandonment and ecosystem assembly. Trends in Ecology & Evolution 23:104–112.

Crowe, K. A., and W. H. Parker. 2008. Using portfolio theory to guide reforestation and restoration under climate change scenarios. Climatic Change 89:355–370.

Curran, T. J., E. M. Reid, and C. Skorik. 2010. Effects of a severe frost on riparian rainforest restoration in the Australian wet tropics: foliage retention by species and the role of forest shelter. Restoration Ecology 18:408–413.

Damasceno-Junior, G. A., J. Semir, F. A. M. D. Santos, and H. d. F. Leitão-Filho. 2004. Tree mortality in a riparian forest at Rio Paraguai, Pantanal, Brazil, after an extreme flooding. Acta Botanica Brasilica 18:839–846.

Dodd, M., G. Barker, B. Burns, R. Didham, J. Innes, C. King, M. Smale, and C. Watts. 2011. Resilience of New Zealand indigenous forest fragments to impacts of livestock and pest mammals. New Zealand Journal of Ecology 35:83–95.

Dorrough, J., P. A. Vesk, and J. Moll. 2008. Integrating ecological uncertainty and farm-scale economics when planning restoration. Journal of Applied Ecology 45:288–295.

Everingham, Y. L., N. E. Stoeckl, J. Cusack, and J. A. Osborne. 2012. Quantifying the benefits of a long-lead ENSO prediction model to enhance harvest management—A case study for the Herbert sugarcane growing region, Australia. International Journal of Climatology 32:1069–1076.

Eveson, J. P., A. J. Hobday, J. R. Hartog, C. M. Spillman, and K. M. Rough. 2015. Seasonal forecasting of tuna habitat in the Great Australian Bight. Fisheries Research 170:39–49.

Fensham, R. J., J. Fraser, H. J. MacDermott, and J. Firn. 2015. Dominant tree species are at risk from exaggerated drought under climate change. Global Change Biology 21:3777–3785.

Ganey, J. L., and S. C. Vojta. 2011. Tree mortality in drought-stressed mixed-conifer and ponderosa pine forests, Arizona, USA. Forest Ecology and Management 261:162–168.

Griesser, A. G., and C. M. Spillman. 2016. Assessing the skill and value of seasonal thermal stress forecasts for coral bleaching risk in the western pacific. Journal of Applied Meteorology and Climatology 55:1565–1578.

Hagger, V., J. Dwyer, and K. Wilson. 2017. What motivates ecological restoration? Restoration Ecology 25:832–843.

Hardegree, S. P., J. Cho, and J. M. Schneider. 2012. Weather variability, ecological processes, and optimization of soil micro-environment for rangeland restoration. Pages 107–121 *in* T. A. Monaco and R. L. Sheley, editors. Invasive plant ecology and management: linking processes to practice. CABI, Wallingford, Oxfordshire, UK.

Hawkins, C. P., K. L. Bartz, and C. M. U. Neale. 1997. Vulnerability of riparian vegetation to catastrophic flooding: implications for riparian restoration. Restoration Ecology 5:75–84.

Hendon, H. H., M. Zhao, A. Marshall, E.-p. Lim, J.-J. Luo, O. Alves, and C. MacLachlan. 2015. Comparison of GLOSEA5 and POAMA2.4 Hindcasts 1996-2009. Bureau Research Report - 011. Australian Government Bureau of Meterology, Melbourne, Victoria, Australia.

Hobbs, R. J., E. Higgs, and J. A. Harris. 2009. Novel ecosystems: implications for conservation and restoration. Trends in Ecology & Evolution 24:599–605.

Hobday, A. J., C. M. Spillman, J. Paige Eveson, and J. R. Hartog. 2016. Seasonal forecasting for decision support in marine fisheries and aquaculture. Fisheries Oceanography 25:45–56.

Hodgkinson, J. H., A. J. Hobday, and E. A. Pinkard. 2014. Climate adaptation in Australia's resource-extraction industries: ready or not? Regional Environmental Change 14:1663–1678.

Hothorn, T., F. Bretz, P. Westfall, R. M. Heiberger, A. Schuetzenmeister and S. Scheibe. 2017. Package 'multcomp'. Simultaneous inference in general parametric models. Version 1.4-8. http://multcomp.R-forge.R-project.org

Hudson, D., A. Marshall, Y. Yin, O. Alves, and H. Hendon. 2013. Improving intraseasonal prediction with a new ensemble generation strategy. Monthly Weather Review 141:4429–4449.

Hudson, D., L. Shi, O. Alves, M. Zhao, H. H. Hendon and, G. Young. 2017. Performance of ACCESS-S1 for key horticultural regions. Bureau Research Report - 020. Australian Government Bureau of Meterology, Melbourne, Victorial, Australia.

Jones, H. P., and O. J. Schmitz. 2009. Rapid recovery of damaged ecosystems (rapid ecosystem recovery). PLoS ONE 4:e5653.

Kanowski, J. 2010. What have we learnt about rainforest restoration in the past two decades? Ecological Management and Restoration 11:2–3.

Kanowski, J., C. P. Catterall, S. G. McKenna, and R. Jensen. 2008. Impacts of cyclone Larry on the vegetation structure of timber plantations, restoration plantings and rainforest on the Atherton Tableland, Australia. Austral Ecology 33:485–494.

Kimball, S., M. Lulow, Q. Sorenson, K. Balazs, Y. C. Fang, S. J. Davis, M. Connell, and T. E. Huxman. 2015. Cost-effective ecological restoration. Restoration Ecology 23:800–810.

Kirtman, B. P., et al. 2014. The North American multimodel ensemble: phase-1 seasonal-to-interannual prediction; phase-2 toward developing intraseasonal prediction: the North American Multimodel Ensemble prediction experiment is described, and forecast quality and methods for accessing digital and graphical data from the model are discussed. Bulletin of the American Meteorological Society 95:585.

Klos, R. J., G. G. Wang, W. L. Bauerle, and J. R. Rieck. 2009. Drought impact on forest growth and mortality in the southeast USA: an analysis using Forest Health and Monitoring data. Ecological Applications 19:699–708.

Langford, S., and H. Hendon. 2013. Improving reliability of coupled model forecasts of Australian seasonal rainfall. Monthly Weather Review 141:728–741.

Maestre, F. T., J. Cortina, and R. Vallejo. 2006. Are ecosystem composition, structure, and functional status related to restoration success? A test from semiarid Mediterranean steppes. Restoration Ecology 14:258–266.

McCarthy, M. A., and H. P. Possingham. 2007. Active adaptive management for conservation. Conservation Biology 21:956–963.

Menz, M. H. M., K. W. Dixon, and R. J. Hobbs. 2013. Hurdles and opportunities for landscape-scale restoration. Science 339:526–527.

Millar, C. I., N. L. Stephenson, and S. L. Stephens. 2007. Climate change and forests of the future: managing in the face of uncertainty. Ecological Applications 17:2145–2151.

Miller, J. R., and R. J. Hobbs. 2007. Habitat restoration—Do we know what we're doing? Restoration Ecology 15:382–390.

Newton, A. C., and E. Cantarello. 2015. Restoration of forest resilience: an achievable goal? New Forests 46:645–668.

R Core Team. 2017. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. www.R-project.org

Reid, M. L., and J. Bhattacharjee. 2014. Episodic flooding of the Ouachita river: levee-mediated mortality of trees and saplings in a bottomland hardwood restoration area. Southeastern Naturalist 13:493–505.

Rigling, A., et al. 2013. Driving factors of a vegetation shift from Scots pine to pubescent oak in dry Alpine forests. Global Change Biology 19:229–240.

Rodriguez, D., P. de Voil, D. Hudson, J. Brown, P. Hayman, H. Marrou, and H. Meinke. 2018. Predicting optimum crop designs using crop models and seasonal climate forecasts. Scientific Reports 8:2231.

Scowcroft, P. G., and J. Jeffrey. 1999. Potential significance of frost, topographic relief, and Acacia koa stands to restoration of mesic Hawaiian forests on abandoned rangeland. Forest Ecology and Management 114:447–458.

Sgrò, C. M., A. J. Lowe, and A. A. Hoffmann. 2011. Building evolutionary resilience for conserving biodiversity under climate change. Evolutionary Applications 4:326.

Shackelford, N., R. J. Hobbs, J. M. Burgar, T. E. Erickson, J. B. Fontaine, E. Libert'e, C. E. Ramalho, M. P. Perring, and R. J. Standish. 2013. Primed for change: developing ecological restoration for the 21st century. Restoration Ecology 21:297–304.

Shi, L., D. Hudson, O. Alves, G. Young, and C. MacLachlan. 2016. Comparison of GloSea5-GC2 skill with POAMA-2 for key horticultural regions. Bureau Research Report - 013. Australian Government Bureau of Meterology, Melbourne, Victoria, Australia.

Sivakumar, M. V. K. 2006. Climate prediction and agriculture: current status and future challenges. Climate Research 33:3–17.

Smallbone, L. T., S. M. Prober, and I. D. Lunt. 2007. Restoration treatments enhance early establishment of native forbs in a degraded temperate grassy woodland. Australian Journal of Botany 55:818–830.

Spillman, C. M. 2011. Operational real-time seasonal forecasts for coral reef management. Journal of Operational Oceanography 4: 13–22.

Spillman, C. M., and A. J. Hobday. 2014. Dynamical seasonal ocean forecasts to aid salmon farm management in a climate hotspot. Climate Risk Management 1:25–38.

Spillman, C. M., J. R. Hartog, A. Hobday, and D. Hudson. 2015. Predicting environmental drivers for prawn aquaculture production to aid improved farm management. Aquaculture 447:56.

Standards Reference Group SERA. 2017. National Standards for the Practice of Ecological Restoration in Australia. Second Edition. Society for Ecological Restoration Australasia. www.seraustralasia.com.

Standish, R. J., A. W. Robertson, and P. A. Williams. 2001. The impact of an invasive weed *Tradescantia fluminensis* on native forest regeneration. Journal of Applied Ecology 38:1253–1263.

Standish, R. J., M. I. Daws, A. D. Gove, R. K. Didham, A. H. Grigg, J. M. Koch, and R. J. Hobbs. 2015. Long-term data suggest jarrah-forest establishment at restored mine sites is resistant to climate variability. Journal of Ecology 103:78–89.

Suding, K. N. 2011. Toward an era of restoration in ecology: successes, failures, and opportunities ahead. Annual Review of Ecology, Evolution, and Systematics 42:465–487.

Suding, K., et al. 2015. Committing to ecological restoration. Science 348:638–640.

Zhao, M., H.-Q. Zhang and I. Dharssi. 2017. Impact of land-surface initialization on ACCESS-S1 and comparison with POAMA. Bureau Research Report – BRR 023. Australia Government Bureau of Meterology, Melbourne, Victoria, Australia.

Supporting Information

Additional supporting information may be found online at: http://onlinelibrary.wiley.com/doi/10.1002/eap.1769/full

Data Availability

Data available from the UQ eSpace and the Australian Government Bureau of Meteorology OpenDap server; Seasonal forecast results for restoration case studies: https://doi.org/10.14264/uql.2018.308.

Seasonal forecast files (real-time forecasts and hindcasts): http://opendap.bom.gov.au:8080/thredds/catalogs/bmrc-poama-catalog.html.