**Methods**

*Data selection and curve-fitting*

All grasses (exotic, native, annual, perennial) were at first combined into a separate variable which we call 'total grass cover'. The set of variables consisting of small, medium and large Eucalyptus seedlings as well as Eucalyptus canopy cover, we call 'Eucalyptus growth'. To proceed with our analysis, we first tested whether a) Eucalyptus growth would differ after almost two years (Winter 2006 to Autumn 2007) and b) if there was a general relationship between grasses and Eucalyptus presence (Fig. 1). When both showed to be true, we generated a dataset that included the grasses data from Winter 2006 as well as the Eucalyptus growth data from Autumn 2007 because we were interested how initial grass cover would affect Eucalyptus growth later on. Since, on plot-level, there was often zero Eucalyptus, we decided to group and summarize the data on property level. In this data set, we also split up exotic (annual and perennial) and native (annual and perennial) grass cover. Next, we visually explored all combinations of grass cover (total, exotic, native) with all combinations of Eucalyptus growth (canopy, small, medium and large seedlings). Since only exotic grasses showed a consistent effect on Eucalyptus growth and all seedling sizes behaved comparably, we went on with detailed analysis and curve fitting for Eucalyptus canopy and all seedlings vs. exotic grass cover (depicted in Fig. 2). For curve fitting with the non-linear least square method (nls() function in R), we chose an exponential decay equation of the shape a \* *e*(-b \* x). Pearson correlation was used to assess the relationship of fitted vs. observed values. Analysis was done in R, version 3.5.1 (R Core Team, 2019) and the packages *tidyverse* (Wickham et al., 2019), *gridExtra* (Auguie 2017) and *ggpubr* (Kassambara 2020).

Confounding effects

After testing the effects of exotic grass cover on eucalyptus seedling establishment, we tested influence factors on exotic grass (sum of annual and perennial exotic grass). Therefore, first a linear model stepwise regression (both directions) was conducted on exotic grass to select the best model predictors based on the lowest AIC. Prior to conducting the stepwise regression all, variables regarding sampling design (SurveyID, Property, Quadrat no., Date) and geographic information (Easting, Northing, Aspect, Landscape position) were excluded as predictors, because being non-numeric. The remaining variables were checked for auto-correlation using pearsons correlation (with cut-off pearsons-R² > 0.7) and linear dependency. As predictor variables for the full model we used bare ground, litter, moss & lichen, and, rock cover, distance to eucalyptus canopy, PET, Valley-bottom flatness index, K, Th and, U concentration, solar radiation in January and, July, and shrub and, exotic grass cover without any interaction term. As null model we used response ~ 1. The selected variables of the stepwise regression were bare ground, litter, moss & lichen, and, rock cover, PET, solar radiation in July, Valley-bottom flatness index and U concentration. These parameters have then been used to build a linear mixed effect model with Season as additional fixed effect and Quadrat number nested in Property as random effect (~1 | Property / Quadrat number). Due to violation of variance homoscedasticity an exponential variance structure was added for bare ground, litter, moss & lichen, and, rock cover as these parameters include numerous zero-observations and inflated variance. Analysis was done using R, version 3.6.2(R Core Team, 2019) and the packages *tidyverse* (Wickham et al., 2019), *Hmisc* (Harrell et al., 2008), *plm* (Croissant & Millo, 2008), *caret* (Kuhn et al., 2020), *MASS* (Venables & Ripley, 1999), *lmtest* (Zeileis & Hothorn, 2002), *nlme* (Pinheiro et al., 2019), *predictmeans* (Luo et al., 2014) and *MuMIn* (Bartoń, 2020).

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