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Fueling the fire: predicting cogongrass (*Imperata cylindrica*) impacts on fire behavior across environmental and seasonal gradients

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Abstract

Invasive species can fundamentally alter fire regimes by modifying fuel characteristics, yet predicting their impacts on fire behavior remains challenging. Cogongrass (*Imperata cylindrica*), a highly invasive grass spreading across the southeastern US, has been associated with increased fuel loads and fire intensity, but it is unclear how its impacts on fuel load and fire behavior vary across environmental and seasonal gradients. We measured fuel characteristics across 159 cogongrass invaded and non-invaded plots spanning from central Florida to southern Mississippi across multiple seasons. Using these data, we developed custom fuel models in BehavePlus to predict cogongrass effects on surface fire behavior and tree torching across spatial and temporal gradients. Cogongrass invasion increased live fuel loads by up to 1.96 t/ha, with effects strongest in summer and at lower latitudes, and dead fuel loads by up to 1.88 t/ha across all sites. Latitude × invasion interactions indicated that fuel load differences between invaded and non-invaded plots diminished toward northern sites. Cogongrass-driven fuel load alterations elevated surface fire rate of spread (median + 0.75 m/min), and flame length (+ 0.16 m), with the largest increases observed in spring (rate of spread: + 2.60 m/min; flame length: + 0.80 m). Invasion also consistently increased the crown fire transition probability, with magnitudes mirroring those of surface fire effects. Our findings highlight the potential for cogongrass to substantially alter fire behavior across a range of environmental conditions, although the magnitude of these effects varies geographically and tends to be strongest at lower latitudes. These results underscore the importance of targeted management in regional fire planning of invaded landscapes.

Keywords Invasion, Modeling, Fire behavior, Spatial–temporal gradients, Surface, Torching

Introduction

Invasive plant species can transform fire regimes by altering fuel characteristics and creating novel dynamics that challenge fire prediction and management. These invaders modify the quantity, continuity, and flammability of fuels across landscapes (Brooks et al. 2004; Kerns et al. 2020). By doing so, invasion can substantially alter fuelbed characteristics and predicted fire behavior (D'Antonio and Vitousek 1992). In many instances, invasive plants introduce feedback loops that reinforce invasion and fire activity, fundamentally transforming ecosystem fire dynamics. A classic example is cheatgrass (*Bromus tectorum*) invasion of the Great Basin of North

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America, which increases fine fuel loads and continuity, leading to more frequent and larger fires that perpetuate its dominance and suppress native vegetation (D'Antonio and Vitousek 1992; Pilliod et al. 2017; Bradley et al. 2018). Similar grass-fire cycles have been documented in other regions, including African lovegrass (*Eragrostis curvula*) in Australian temperate grasslands and buffelgrass (*Pennisetum ciliare*) in Sonoran Desert ecosystems, where invasion increases fire frequency in systems that historically experienced infrequent fire regimes (Clarke et al. 2005; McDonald and McPherson 2011).

Invasive plants can exhibit asynchronous phenology relative to native vegetation, altering the timing and moisture status of fine fuels, thereby complicating predictions of fire behavior. When invasive grasses cure earlier than surrounding native species, they can introduce dry fuels during periods that historically experienced low fire activity, increasing flammability and extending the effective fire season (Barbour and Billings 2000; Brooks et al. 2004; Coffman et al. 2010; Kerns et al. 2020). Early-season fuel drying can increase the likelihood of ignition and promote faster rates of spread (Balch et al. 2013). Fuel moisture dynamics are further conditioned by soil moisture availability, which regulates plant water status, delays or accelerates curing, and influences the flammability of both live and dead fuels across seasons (DeBano 2000; Keeley 2009). Conversely, invasive species that retain moisture later into the growing season can dampen fire spread by maintaining higher fuel moisture during periods when surrounding fuels are otherwise flammable (Bowles et al. 2003; Stevens and Beckage 2010). These phenology-driven shifts in fuel conditions influence fire intensity and rate of spread, key determinants of fire controllability and ecological outcomes (Byram 1959; Andrews and Rothermel 1982; Scott and Burgan 2005), and can, under certain phenological configurations, shift historically manageable fire regimes toward more fire-prone conditions that challenge both management and ecosystem recovery (Brooks et al. 2004).

Cogongrass (*Imperata cylindrica*) is widely considered a highly flammable invasive grass in the southeastern US that alters key components of surface fire behavior through changes in fine-fuel characteristics (Platt and Gottschalk 2001; Estrada and Flory 2015). Studies have documented that cogongrass invasion substantially increases fine fuel loads, often exceeding those of non-invaded sites by more than 100% (Lippincott 2000; Tomat-Kelly et al. 2021). Such increases in fuel loads can result in higher fireline intensity, increased soil heating, and reduced native herbaceous seedling emergence following fires that burn through cogongrass-dominated fuels (Lippincott 2000; Hagan et al. 2013; Tomat-Kelly et al. 2021). These altered fuel characteristics, combined with cogongrass's capacity for rapid post-fire regeneration, facilitate its spread and compound ecological and economic costs (Dozier et al. 1998; Adhikari et al. 2025). Despite this evidence, important gaps remain in our understanding of how cogongrass alters the specific fuel properties that directly govern fire behavior, including fuel and soil moisture, fuel bed structure, and the extent to which increases in surface fuel loading are sufficient to modify fire behavior beyond surface fire intensity (Lippincott 2000; Holzmueller and Jose 2011; Dillon et al. 2021; Tomat-Kelly et al. 2021). In particular, existing studies of cogongrass-fire interactions have largely been conducted at limited spatial and temporal scales (Lippincott 2000; Platt and Gottschalk 2001; Daneshgar et al. 2008), and no research has examined how cogongrass fuel characteristics and their effects on fire behavior vary across seasons or across the broader range of environmental conditions present in the southeastern US. As a result, the degree to which cogongrass-driven fuel dynamics produce predictable, seasonally and regionally contingent fire behavior remains poorly understood.

We determined how cogongrass impacts fuel dynamics and modeled fire behavior across environmental and seasonal gradients in the southeastern US. Specifically, we sought to (1) quantify the influence of cogongrass presence and its phenology on fuel characteristics, (2) develop fuel models and use them to simulate fire behavior in cogongrass-invaded versus non-invaded conditions, and (3) estimate how cogongrass phenology influences modeled fire behavior. We collected native vegetation and cogongrass fuel data across a latitudinal gradient in the southeastern US, ranging from central Florida to southern Mississippi, to capture environmental variability in fuel dynamics. In addition, we collected seasonal fuel data within a subset of sample regions to determine how phenology influences fuel dynamics. Fuel data were then used to generate fuel models to simulate fire behavior under varying cogongrass conditions. Specifically, we assessed fireline intensity, flame length, rate of spread, and crown fire transition ratio—key fire behavior metrics that influence fire management decisions and ecological outcomes. We hypothesized that (1) cogongrass presence would increase fuel loading and generate altered fuel moisture dynamics relative to non-invaded sites and that these effects would vary seasonally; (2) reduced live and dead fuel moistures in cogongrass-invaded fuels would result in higher fireline intensity and flame length; (3) the influence of cogongrass on fire behavior would vary seasonally, with the early green-up growth stage producing

the highest fireline intensity due to the combination of dry, cured fuels from the previous season and new fine fuels. We also anticipate that fuel characteristics and resulting fire behavior will vary across the latitudinal gradient because climate conditions that co-vary with latitude are expected to influence cogongrass productivity and fuel-curing rates.

Methods

Study design

We sampled fuels across a southeastern US latitudinal gradient, from central Florida through southern Mississippi (Fig. 1; Fig. S1). Our study ranged between 28.5°N and 31.6°N latitude and 89.8°W and 81.9°W longitude. This gradient includes five state and national forests, and three privately owned forests across central Florida, north Florida/southern Alabama, hereafter referred to as north Florida, and southern Mississippi. Central Florida's sampling locations consist of Withlacoochee State Forest and Ocala National Forest. North Florida's sampling locations include three private lands, Blackwater River State Forest, and Escambia Experimental Forest. Southern Mississippi sampling was conducted at Bogue Chitto National Wildlife Refuge. Collecting samples from private and publicly managed forests, and across a latitudinal range, aids in understanding general trends in cogongrass fuel dynamics.

We established 30 m by 30 m plots across our sampling extent ($N = 159$; 78 invaded plots and 81 non-invaded plots). We collected data from 52 plots in central Florida, 75 in north Florida, and 32 in southern Mississippi. Within each region, we identified cogongrass locations through collaboration with forest managers, citizen science programs (iNaturalist 2024; EDDMaps 2024), and ground truthing. From identified cogongrass, we selected cogongrass-invaded plots, hereafter, invaded plots, for sampling based on two criteria. First, plots had to contain at least one cogongrass patch. We defined a cogongrass patch as a relatively contiguous area of cogongrass measuring a minimum of 1 m by 0.5 m. Second, plots were required to be located at least 5 m from roadsides to minimize the influence of roadside disturbances. Any plot meeting these criteria was classified as invaded, regardless of the proportion of the 30-m plot occupied by cogongrass. Multiple invaded plots could be located within a continuous cogongrass patch, given that plots remained 45 m apart from each other. For each invaded

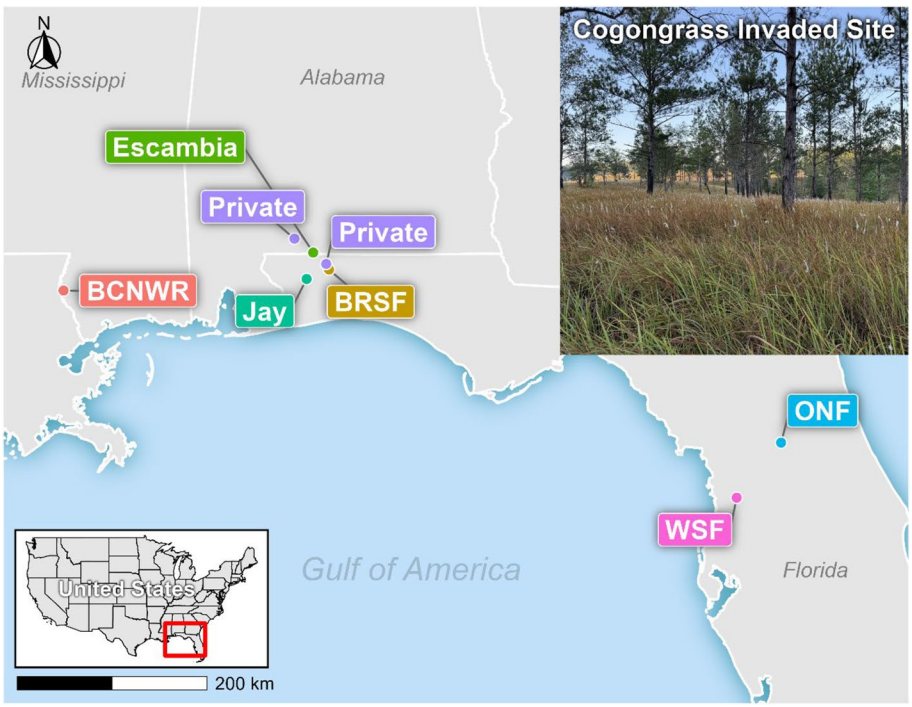

Fig. 1 Locations of fuel sampling plots across the southeastern U.S. Points are color-coded by site: coral—Bogue Chitto National Wildlife Refuge (BCNWR), gold—Blackwater River State Forest (BRSF), green—Escambia Experimental Forest, teal—Jay Research Forest, purple—two private properties in the western Florida panhandle, pink—Withlacoochee State Forest (WSF), cyan—Ocala National Forest (ONF). The inset map shows the study region (red box) within the USA. The photo depicts a cogongrass invaded forest stand in the Withlacoochee State Forest. Inset photo credit: Alan Ivory, UF/IFAS

plot, we randomly selected a nearby location without cogongrass that acted as a non-invaded plot. We selected non-invaded plots using randomly generated points at least 45 m away from the nearest invaded or non-invaded plot within the same forest stand or, if no plots were available within the same stand, then in a neighboring stand with the same stand conditions (e.g., similar burn history and forest structure). All plots were located in forested areas, with the majority in upland sandhill ecosystems, as well as a few additional plots within pine flatwoods and hardwood hammock forests.

Fuel sampling

We collected fuel samples from each identified sampling plot between May 2024 and June 2025. Our fuel sampling consisted of two components: (1) a primary growing season sampling effort conducted across all study regions to capture latitudinal and environmental variation in fuel characteristics, and (2) a seasonal sampling effort conducted at a subset of sites in north Florida and central Florida to capture phenological variation in cogongrass fuel dynamics.

To determine the appropriate timing for sampling, we analyzed five-year trends in the Normalized Difference Vegetation Index (NDVI) as a proxy for photosynthetic activity and vegetation greenness to identify key phenological shifts in the dominant vegetation. We timed growing season fuel collection at the point where the 5-year trend in NDVI began to plateau. As such, we started our sampling in central Florida in May 2024, followed by north Florida in June and July of 2024. We conducted additional fuel sampling in southern Mississippi in May and June of 2025. Further, for our subset of seasonal sampling sites, we identified two additional distinct fuel stages: a senesced stage (sampled from January to February 2025) and a transitional early green-up stage (sampled in April 2025).

Growing season fuel sampling

At invaded and non-invaded sampling plots alike, we collected fuels from three 0.25 m by 0.25 m quadrats spaced equally along a 30 m transect (Fig. S2). In instances where the cogongrass patch was too small to collect fuels from three quadrats, we collected as many as possible from within the cogongrass patch while leaving at least three meters between quadrats. Within each quadrat, we measured live vegetation and litter height, as well as soil moisture using a 10 cm soil moisture probe (Fieldscout TDR 150, Spectrum Technologies ®, Aurora, IL). We then clipped all live and dead herbaceous vegetation rooted within the quadrat to within 2.54 cm above soil level and collected all litter within the quadrat, excluding all woody debris. As we are primarily interested in cogongrass's influence on herbaceous fuel characteristics, we did not include woody vegetation in our fuel sampling efforts. We separated live vegetation, dead vegetation, and litter samples into different bags, weighed them in the field, and then oven-dried them at 60 °C, weighing them daily until they reached a constant mass. We determined the final dry weight for each sample by subtracting the weight of the empty collection bag from the total oven-dried mass. We calculated fuel moisture content from each sampling using the gravimetric method (Eq. 1; Pollet & Brown 2007). Wet weight refers to the mass of the fuel samples as collected in the field, including their water content, whereas dry weight represents the mass of the same samples after oven drying, when all moisture has been removed.

$$\text{MoistureContent}(\%) = \frac{(\text{WetWeight} - \text{DryWeight})}{\text{DryWeight}} x100 \quad (1)$$

To parameterize overstory inputs for fire behavior modeling (e.g., canopy height and canopy base height), we quantified tree density and diameter at breast height (DBH) at each plot using the point-centered quarter method (Cottam and Curtis 1956; Pollard 1971). At each plot center, we recorded distances to the nearest tree in each of four quadrants, and we measured DBH for each selected tree. We then used tree density estimates and DBH distributions to characterize stand structure and inform canopy-related inputs for the fire model. Additionally, we estimated shrub cover at each plot using a 1-by-30-m belt transect. We estimated cover by documenting the length of the transect overlapping a shrub species.

Seasonal fuel sampling

To address the influence of seasonal differences in fuel dynamics, we conducted additional fuel sampling at a subset of the north Florida and central Florida sites. We scheduled sampling periods to correspond with key seasonal stages of cogongrass phenology. We followed the same sampling procedures used for growing season sampling to collect live, dead, and litter samples, soil moisture, and vegetation height from invaded and non-invaded plots (Fig. S2). Sampling was conducted within the same invaded and non-invaded plots used during the growing season survey; however, new transects were established during each sampling period. We collected up to three fuel samples, with a minimum of three meters of space between samples. An additional three fuel samples were collected in a nearby non-invaded area. We collected 48 (24 invaded and 24 non-invaded) fuel samples (22 in north Florida, and 26 in central Florida) during

the senesced fuel stage and 42 (21 invaded and 21 non-invaded) fuel samples (22 in north Florida, and 20 in central Florida) during the green-up period.

Fire behavior modeling

To compare fire behavior in cogongrass-invaded versus non-invaded forest stands, we simulated fire behavior (e.g., rate of spread and fireline intensity) using the Rothermel (1972, 1991) surface and crown fire spread models in BehavePlus software (v. 6.0.0; Heinsch and Andrews 2010; Andrews 2013). Rothermel's models predict fire behavior based on fuel characteristics (loading, moisture, bed depth, and heat content) and environmental conditions (wind speed and slope) and are often parameterized using standardized fuel models to characterize the fuel complex.

Fuel model development

We developed custom cogongrass fuel models by altering the SH4 fuel model (Scott and Burgan 2005), which represents low- to moderate-load shrub and litter fuels that commonly occur beneath a pine (*Pinus* sp.) overstory in humid climates. Using field-measured fuel characteristics from our study sites, we parameterized our cogongrass fuel model with invasion-specific values for 1-h fuel load (based on the combined mass of dead herbaceous and litter fuels), live herbaceous fuel load, fuel bed depth, and dead and live herbaceous fuel moisture. As BehavePlus does not have an input category for litter moisture, the dead herbaceous moisture values used in modeling were calculated as the averages of the 25th–25th, 50th–50th, and 75th–75th percentile values for dead and litter moisture, respectively. To provide a baseline for comparison, we parameterized an additional fuel model for non-invaded sites using the same suite of field-measured values applied to the cogongrass-invaded sites.

As fuel bed depth (FBD) is highly correlated with live biomass load (Scott and Burgan 2005; Hood and Wu 2006), we scaled FBD accordingly. We calculated FBD by first grouping plots based on invasion status and average shrub vegetation cover. Because cogongrass growth is substantially reduced under canopy shade (Patterson 1980), we assumed that non-shrub cover within a plot was composed primarily of herbaceous material, and estimated herbaceous cover as 1 − shrub cover proportion (SCP). We then averaged SCP within each group and applied the following equation to estimate fuel bed depth for each quantile.

$$\mathrm{FBD} = (\mathrm{SCP} * \mathrm{SH4FBD}) + ((1 - \mathrm{SCP}) * (\mathrm{SH4FBD} + (\mathrm{INVht} - \mathrm{NIVht}))) \quad (2)$$

The terms INV ht and NIV ht represent the herbaceous material height in invaded and non-invaded sites, respectively. By using SCP, we were able to provide an estimate for shrub and herbaceous cover at each herbaceous height quantile. We left all other variables, including 10-h and 100-h fuel loads, live woody fuel loads, surface area-to-volume ratios (1-h, live herbaceous, and live woody), dead and live fuel heat content, and foliar moisture, at the SH4 fuel model default values.

To better represent the forest stands in which our fuel sampling was conducted within our fuel models, we also included a number of stand-specific measurements of trees and shrubs. We estimated tree height from field-collected DBH measurements, applying a species-specific DBH-to-tree-height model (Gonzalez-Benecke et al. 2014). We also used the canopy bulk density for longleaf pine (*Pinus palustris*) savanna reported by Rocha et al. (2023), due to the spatial proximity of their study to ours, and calculated canopy base height using the canopy base height ratio (42.35%) identified in their study.

To evaluate changes in fire behavior in relation to cogongrass invasion, we used the SURFACE and CROWN modules within BehavePlus (Wagner 1977; Scott and Reinhardt 2001). The fire behavior metrics produced by these modules include the surface fire rate of spread, flame length, and fireline intensity from the SURFACE module, as well as the transition ratio from the CROWN module. The transition ratio is particularly crucial for evaluating crown fire potential, as when it is greater than or equal to one, the surface fireline intensity is sufficient to initiate a crown fire (Rothermel 1991). To limit unnecessary variability in our models, we set the terrain to flat (0% slope steepness) and the wind speeds to the average annual wind speeds in Jay, FL, USA (6 km/h), where the majority of our fuel samples were collected (National Centers for Environmental Information 2023). To align with the SH4 fuel model default value, a wind adjustment factor of 0.5 was applied. We set our dead fuel moisture of extinction higher than the largest dead or litter moisture percentage (60%) to ensure BehavePlus allowed our simulation to run.

Cogongrass impacts on fire behavior

To evaluate the potential impacts of cogongrass invasion on fire behavior, we compared invaded and non-invaded forest plots during the summer season. To capture variability in stand structure and fuel conditions, we ran fuel models under a range of scenarios where each measured fuel parameter (live, litter, and dead fuel moisture, live, litter, and dead fuel load, and tree height) was input at the 25th, 50th, and 75th percentiles of their observed distributions. We fixed foliar moisture content at 100%,

following Scott & Reinhardt (2001). A full factorial combination of invasion status (invaded vs. non-invaded), five fuel characteristics, and three canopy height levels resulted in a total of 1458 individual fire behavior simulations. For each scenario, we calculated four key fire behavior metrics: surface fire rate of spread, surface fire flame length, surface fireline intensity, and crown fire transition ratio.

Seasonal impacts of cogongrass on fire behavior

To evaluate how cogongrass invasion affects fire behavior seasonally, we simulated fire behavior under varying seasonal fuel conditions. Specifically, we used our custom fuel models to predict surface fire rate of spread, flame length, fireline intensity, and the crown fire transition ratio. We used data on live, dead, and litter fuel load, moisture content, and vegetation height sampled from a subset of our north and central Florida research plots to parameterize fuel models across three seasonal phases of growth: green-up, established, and senesced. We calculated fire behavior metrics across a range of scenarios using the 25th, 50th, and 75th percentiles for each fuel metric during each season (Table S1). We set all fuel variables (e.g., 10-h, 100-h, and live woody fuel loads, and surface area-to-volume ratios) to default values provided by the SH4 fuel model. We conducted a full-factorial analysis of all possible combinations of fuel metrics across the three phenological stages, yielding 4,374 unique fire behavior simulations.

Data analysis

Objective 1: cogongrass relationship with fuel dynamics

To evaluate how cogongrass invasion influences fuel dynamics, we analyzed the effects of invasion status (invaded vs. non-invaded), seasonality (summer, winter, spring), and latitude on key fuel characteristics, including live, dead, and litter fuel loads, fuel moisture content, soil moisture, and vegetation height. These fuel characteristics represent critical components of fire behavior, influencing the potential rate of spread and intensity. We treated each of these fuel metrics as a dependent variable in separate Bayesian generalized linear mixed-effects models (GLMMs; Zhao et al. 2006). We estimated all models in a Bayesian framework using the 'brms' package in R with a Student-t error distribution (Bürkner 2017; R Core Team 2025; RStudio Team 2025). We included an interaction term between invasion status and season to test whether the effect of cogongrass differs across seasons. Interaction terms were removed from models in which the credible interval for the interaction effect overlapped zero, indicating insufficient evidence for a credible interaction. Due to the paired design of our sampling, we included site identity as a random intercept (e.g., Withlacoochee State Forest, Blackwater River State Forest, Jay Research Forest). We evaluated model assumptions using residual diagnostics (Schielzeth 2010; Schielzeth et al. 2020). To better investigate the interaction between invasion status and season, we calculated estimated marginal means for each season and then computed the pairwise difference between invaded and non-invaded plots using the 'emmeans' R package (Lenth 2016). We also report the highest posterior density (HPD) intervals, as they provide the narrowest possible interval that contains 95% of the probability mass.

Objective 2: custom fuel models to determine cogongrass impacts on fire behavior

To determine whether cogongrass invasion increases fire risk, we used Bayesian generalized linear models (GLMs; Schmidt & Makalic 2020; Zhao et al. 2006) to model each fire behavior metric (surface rate of spread, flame length, fireline intensity, and crown transition ratio) as a function of invasion status. We specified weakly informative normal priors for regression coefficients with mean 0 and standard deviation 1, and Student-t priors for the variance with 3 degrees of freedom, centered at 0 and with scale 2. Models were fit using a Student-$\underline{t}$ likelihood to reduce sensitivity to outliers in the simulated fire behavior data, with 4 chains of 4000 iterations each (including 1000 warmup iterations). We assessed model convergence using a potential scale reduction factor ($\hat{r}$) and effective sample sizes. We considered cogongrass invasion to meaningfully affect fire behavior when the 95% credible interval (CrI) for the invasion status effect excluded zero. We summarized posterior distributions using medians and 95% CrIs.

To determine if the fuel characteristics that most strongly influence fire behavior differ between invaded and non-invaded plots, we conducted a secondary regression analysis (Bessie and Johnson 1995). In this analysis, fire behavior metrics (e.g., surface rate of spread, fireline intensity) were modeled as a function of observed fuel predictors, including live, dead, and litter fuel load (t/ha), live and dead fuel moisture, and base canopy height (m), where appropriate (e.g., transition ratio). We standardized predictors (mean = 0, SD = 1) to facilitate direct comparison of effect sizes across variables. Because predictors were standardized, regression coefficients (β) can be interpreted as directly comparable effect sizes, indicating the relative influence of each fuel parameter on fire behavior. This approach allows the models to estimate differences in fire behavior metrics across categories. Models were fit separately for invaded and non-invaded sites to assess whether the relative contributions of fuel parameters differed between invasion conditions. We

summarized posterior distributions of regression coefficients using medians and 95% CrI, which represent the range of values within which the parameters fall with 95% posterior probability (PP). This approach allowed us to identify the fuel characteristics most responsible for variation in fire behavior within invaded and non-invaded systems.

Objective 3: seasonal cogongrass invasion influence on fire behavior

To evaluate how invasion status and seasonal fuel changes influence fire behavior, we fitted Bayesian GLMs for each fire behavior variable using invasion status, phenological stage, and fuel parameters (live, dead, litter fuel load, and fuel moisture) relevant to each fire behavior equation (Rothermel 1991) as predictor variables. We calculated estimated marginal means for each season and recorded the pairwise difference between invaded and non-invaded plots to better understand the interaction between invasion status and season on fire behavior metrics.

We specified weakly informative priors to minimize their influence on the posterior distribution. Specifically, we used a normal prior with mean 0 and standard deviation 1 for all regression coefficients, and a Student-*t* prior with 3 degrees of freedom, centered at 0, and scale 2 for the residual standard deviation. We assessed model convergence and stability by confirming all parameters had a potential scale reduction factor ($\hat{r}$) within ± 0.1 of 1.0 and an effective sample size (ESS) of at least 400. For all model results, we report the posterior median estimate to summarize the central tendency of the posterior distribution. To quantify uncertainty, we report 95% CrIs. Specifically, we calculated the HPD interval, as it provides the narrowest possible interval containing 95% of the PP mass and thus represents the most credible set of values for a parameter. To assess the strength of the evidence for each parameter, we calculated the probability of direction (Pd), which represents the certainty with which an effect is strictly positive or negative. Pd ranges from 0.5 to 1.0, where 0.5 indicates maximum uncertainty (a 50/50 split of the posterior distribution) and 1.0 indicates total certainty that the effect exists in a specific direction. We interpreted Pd ≥ 0.95 as strong evidence of a directional effect.

Results

Objective 1: cogongrass relationship with fuel characteristics

Cogongrass invasion strongly influenced live fuel load, and these effects varied seasonally and geographically (Fig. 2A; Table S2). Cogongrass invasion increases live fuel load across all seasons, but its effect is most pronounced during summer. Invaded plots had a median of 1.96 t/ha more live fuel (Pd > 0.99) than non-invaded plots during summer, with a 95% credible interval (CrI) of 1.62 to 2.30 t/ha (Fig. 2A). The effect, while still credible (i.e., the 95% CrI does not overlap zero), was smaller in the spring (median difference = 1.26 t/ha, 95% CrI: [0.76, 1.78]) and winter (median difference = 0.96 t/ha, 95% CrI: [0.51, 1.43]; Table S3). We found a high-certainty interaction between invasion and latitude (median estimate = − 0.57 t/ha, 95% CrI [− 0.81, − 0.34]). Because the 95% CrI excludes zero, we consider this interaction to be a reliable predictor of fuel load patterns (Pd > 0.99). Non-invaded plots have 0.35 t/ha more fuels per unit increase in latitude, while fuels in invaded plots decreased by 0.22 t/ha per unit increase in latitude (Fig. S3), suggesting that the effect of cogongrass invasion on fuel load differences between invaded and non-invaded plots diminishes at more northern sites.

Dead fuel loads show consistent, substantial increases in invaded sites across all conditions (median difference = 1.88 t/ha, 95% CrI: [1.53, 2.25], Pd > 0.99; Fig. S4; Table S4). Seasonal effects were comparatively small: spring showed a positive shift relative to summer, though the 95% CrI overlapped zero (median difference = 0.32 t/ha, 95% CrI: [− 0.07, 0.73]), indicating uncertainty in this effect, while winter exhibited a credible increase (median difference = 0.43 t/ha, 95% CrI: [0.01, 0.93], Pd > 0.97). Latitude did not have a clear directional influence, as the 95% CrI spanned zero (median difference = − 0.06 t/ha, 95% CrI: [− 0.97, 1.83]). In contrast to the strong effects on standing fuel loads, cogongrass invasion has little effect on litter fuel loads (Table S5). The model estimated a negative but uncertain invasion effect on litter fuel load, with the 95% CrI spanning zero (median difference = − 7.19 t/ha, 95% CrI: [− 35.25, 20.94], Pd = 0.69), and neither the invasion × season nor the invasion × latitude interactions were credible. Instead, season drives litter fuel load, with the spring averaging 1.40 t/ha (95% CrI: [0.10, 2.79], Pd > 0.98) more litter fuel than summer, and winter, averaging 1.16 t/ha (95% CrI: [0.08, 2.37], Pd > 0.97) more litter fuel than summer.

Cogongrass invasion had a minimal and uncertain effect on live, dead, and litter fuel moisture (Pd = 0.72, Pd = 0.85, Pd = 0.76, respectively; Table S6, S7, S8), which was instead primarily driven by seasonal patterns not associated with invasion (Figs. S5, S6). Live fuel moisture was most strongly shaped by season. Our model estimated that live fuel moisture was credibly lower in the spring and winter compared to the summer baseline. Specifically, moisture content was estimated to be a median of 56.15 percentage points lower in spring (95% CrI: [− 77.49, − 34.86]; Pd > 0.99) and 37.98 percentage points lower in winter (95% CrI: [− 61.03, − 15.22];

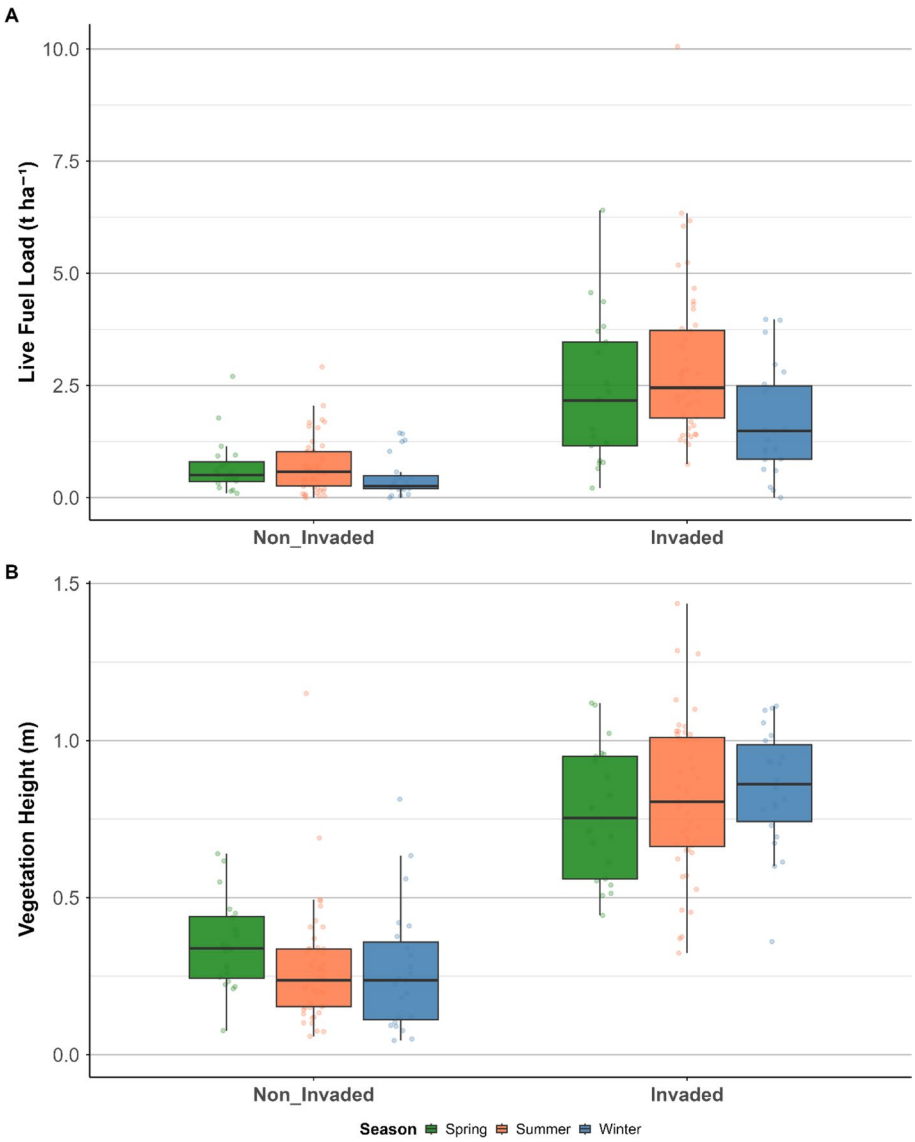

Fig. 2 Seasonal comparisons of live fuel load (**A**) and vegetation height (**B**) for non-invaded and invaded sites. Boxplots show medians and interquartile ranges; whiskers extend to 1.5 × IQR. Points are individual observations, colored by season

Pd > 0.99). Compared to summer, litter was credibly wetter in winter, with a median increase of 10.30 percentage points (95% CrI: [2.46, 17.76]; Pd > 0.99). Litter moisture in the spring also showed a strong trend toward lower values, with an estimated median loss of 8.89 percentage points (95% CrI: [− 15.67, − 2.19]; Pd > 0.99). For dead fuel moisture, neither season nor invasion status had a credible effect. Similarly, soil moisture responds to season but not invasion (Fig. S7; Table S9), with spring soil moisture 1.98 percentage points lower than in summer (95% CrI: [− 3.68, − 0.36], Pd = 0.99).

Sites invaded by cogongrass had taller vegetation, though the magnitude of this effect varied by season and latitude (Fig. S3; Tables S10, S11). Invaded plots had significantly taller vegetation in all seasons than non-invaded sites (Pd > 0.99), but the effect was most pronounced in summer (median difference = 0.59 m; 95% CrI: [0.52, 0.65]; Pd > 0.99) and winter (median difference = 0.59 m; 95% CrI: [0.51, 0.69]; Pd > 0.99) compared to spring (median difference = 0.43 m; 95% CrI: [0.34, 0.52]; Pd > 0.99). This pattern was further influenced by a strong interaction with latitude (median estimate = − 0.11 m, 95% CrI [− 0.15, − 0.06]; Pd > 0.99). In invaded plots, vegetation height decreased by ~ 0.12 m

per unit increase in latitude, whereas non-invaded plots showed no consistent relationship.

Objective 2: influence of cogongrass presence on fire behavior

The alterations to fuel load and structure caused by cogongrass invasion resulted in a substantial increase in predicted surface fire behavior (Fig. 3). There was a greater than 0.99 probability (PP > 0.99) that invaded plots would experience a higher surface fire rate of spread, with a median estimated increase of 0.75 m/min (95% CrI: [0.63, 0.87]) as compared to non-invaded plots (Fig. 3A; Table S12). Invaded plots were also expected to have longer flame lengths (Table S13), with a median increase in flame length of 0.16 m, and a 95% probability of the true difference being between 0.10 m and 0.22 m (95% CrI: [0.10, 0.22]; Pd > 0.99; Fig. 3B). However, we did not find a credible relationship between cogongrass invasion and surface fireline intensity, as the 95% CrI overlapped zero (Fig. 3C; Table S14). Cogongrass invasion alters which fuel characteristics most strongly regulate crown fire behavior, shifting the relative influence of fuel moisture, canopy structure, and surface fuels between invaded and non-invaded plots. Crown fire transition ratio was greater in invaded plots, with a median increase of 0.03 (95% CrI: [0.01, 0.05]; Pd > 0.99; Fig. 3D; Table S15).

Litter and dead fuel load drive the amplified surface fire behavior in cogongrass-invaded sites (Fig. 4A, B; Table S16–21). In invaded plots, surface rate of spread and flame length were most strongly linked to litter ($\beta = 0.91$; $\beta = 0.46$, respectively) and dead fuel load ($\beta = 0.72$; $\beta = 0.36$, respectively), with little contribution from live fuel load (rate of spread, flame length, and fireline intensity βs are all ≈ 0.03). In non-invaded plots, litter and dead fuel loads contributed about half of the influence observed under invasion (e.g., litter fuel load effect on fire rate of spread, β = 0.49; dead fuel load effect on fire rate of spread, $\beta = 0.20$). Fuel moisture consistently negatively influenced fire behavior regardless of invasion status, though the effect was greater in invaded as compared to non-invaded plots. For instance, live and dead fuel moisture in invaded plots had a stronger fire rate of spread suppression effect ($\beta = -0.64$; $\beta = -0.70$, respectively), approximately 1.5–1.8 times the magnitude observed in non-invaded plots ($\beta = -0.40$; $\beta = -0.38$). For crown fire behavior, invaded plots show heightened sensitivity to fuel characteristics compared to non-invaded plots, responding more strongly to litter biomass ($\beta = 0.11$ vs. 0.08), dead biomass ($\beta = 0.09$ vs. 0.06), live fuel moisture ($\beta = -0.06$ vs. -0.04), and dead fuel moisture ($\beta = -0.08$ vs. -0.04; Table S22, S23). Canopy base height represents the only fuel attribute where

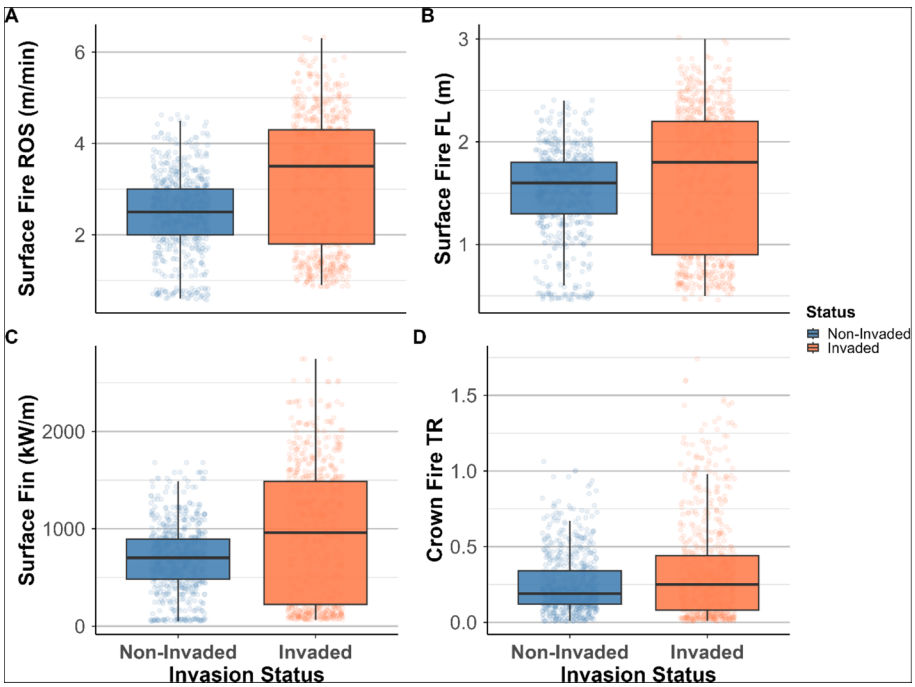

Fig. 3 Fire-behavior metrics compared between non-invaded and invaded sites. Panels: **A** surface fire rate of spread (ROS, m/min), **B** surface fire flame length (FL, m), **C** surface fireline intensity (Fin, kW/m), and **D** crown fire transition ratio (TR). Boxplots show medians (horizontal lines) and interquartile ranges (boxes); whiskers extend to 1.5 × IQR. Points are individual observations

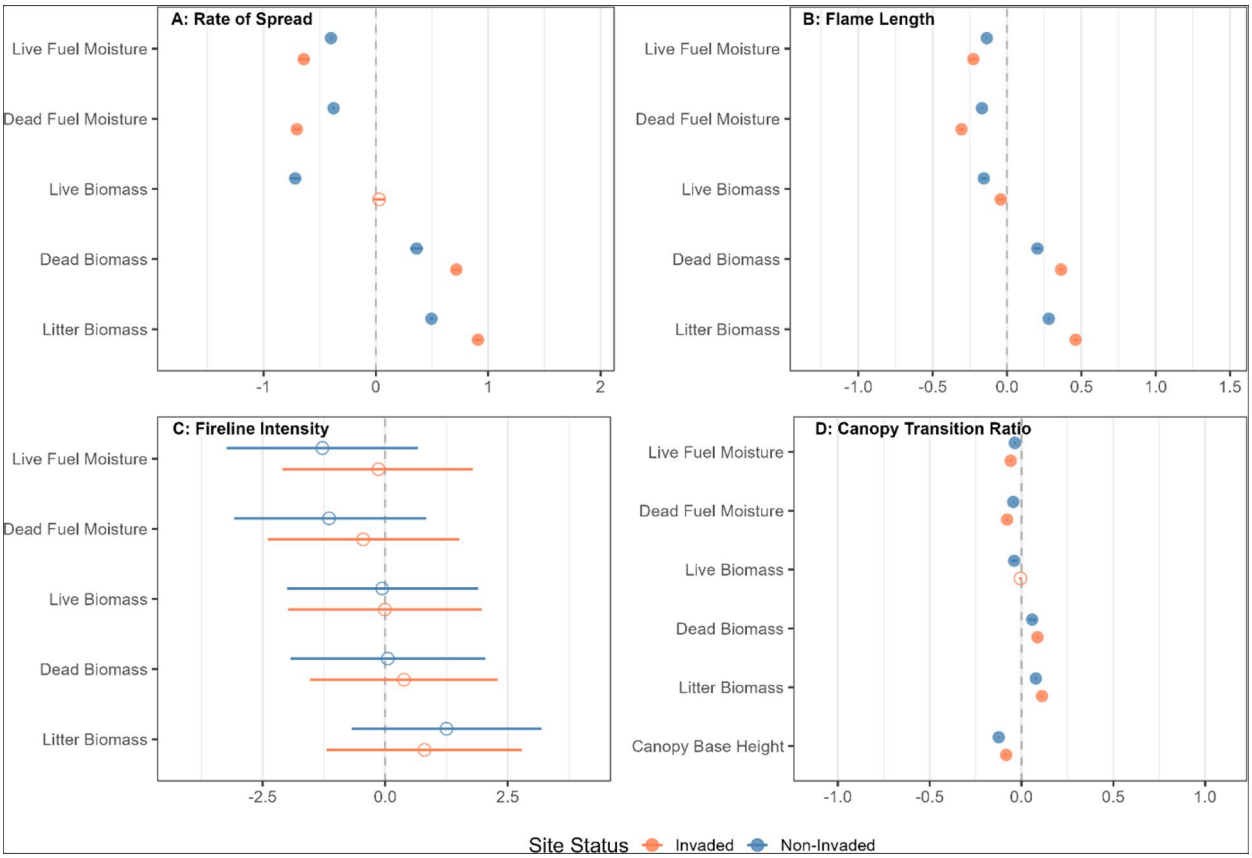

Fig. 4 Standardized regression coefficients (β) for predictors of fire-behavior metrics, estimated separately for invaded (circles) and non-invaded (triangles) sites. Panels: **A** surface fire rate of spread (ROS), **B** surface fire flame length (FL), **C** surface fireline intensity (Fin), and **D** crown fire transition ratio (TR). Points are posterior mean estimates; horizontal bars are 95% credible intervals (CrIs); the dashed vertical line marks zero. Predictors whose CrIs exclude zero are considered statistically credible and are denoted with filled circles

non-invaded plots exceed invaded plots in sensitivity (invaded $\beta = -0.08$; non-invaded $\beta = -0.12$).

Objective 3: seasonal cogongrass invasion influence on fire behavior

The effect of cogongrass invasion was consistently positive on surface fire rate of spread and flame length, though the magnitude of the increase varied seasonally (Fig. 5; Tables S24, S25). The effect was most pronounced during the spring, where invasion led to a median increase in surface fire rate of spread of 2.60 m/min (95% CrI: [2.38, 2.82]; Pd > 0.99; Fig. 5A; Table S28) and flame length of 0.80 m (95% CrI: [0.73, 0.87]; Pd > 0.99; Fig. 5B; Table S29), compared to non-invaded plots. While the effect of invasion was smaller in other seasons, it remained highly credible (PP = 0.99 for all metrics). In winter, the median increase in rate of spread and flame length was 1.81 m/min (95% CrI: [1.62, 2.01]) and 0.56 m (95% CrI: [0.48, 0.63]), respectively, compared to non-invaded plots. The invasion effect was least pronounced during the summer, with median increases of 1.14 m/min for the rate of spread (95% CrI: [0.97, 1.32]) and 0.34 m for flame length (95% CrI: [0.28, 0.41]). There were no credible seasonal or invasion-related effects for surface fireline intensity, as the 95% CrIs overlapped zero (Tables S26, S30). Invasion consistently increased the probability of fire transitioning to the canopy across all seasons (PP > 0.99), with magnitudes that mirrored the patterns observed in surface fire risk (Tables S27, S31). The effect of cogongrass invasion was greatest in spring (median difference = 0.29; 95% CrI: [0.26, 0.33]), followed by winter (median difference = 0.17; 95% CrI: [0.14, 0.20]), and was smallest in summer (median difference = 0.07; 95% CrI: [0.04, 0.09]; Fig. 5C).

Discussion

Cogongrass invasion substantially altered fuelbed characteristics and predicted fire behavior across seasons and geographic gradients. Invasion increased live and dead fuel loads and produced taller vegetation, with stronger effects in summer and at lower latitudes. Live and dead fuel loads in invaded sites were up to 3.0 t/

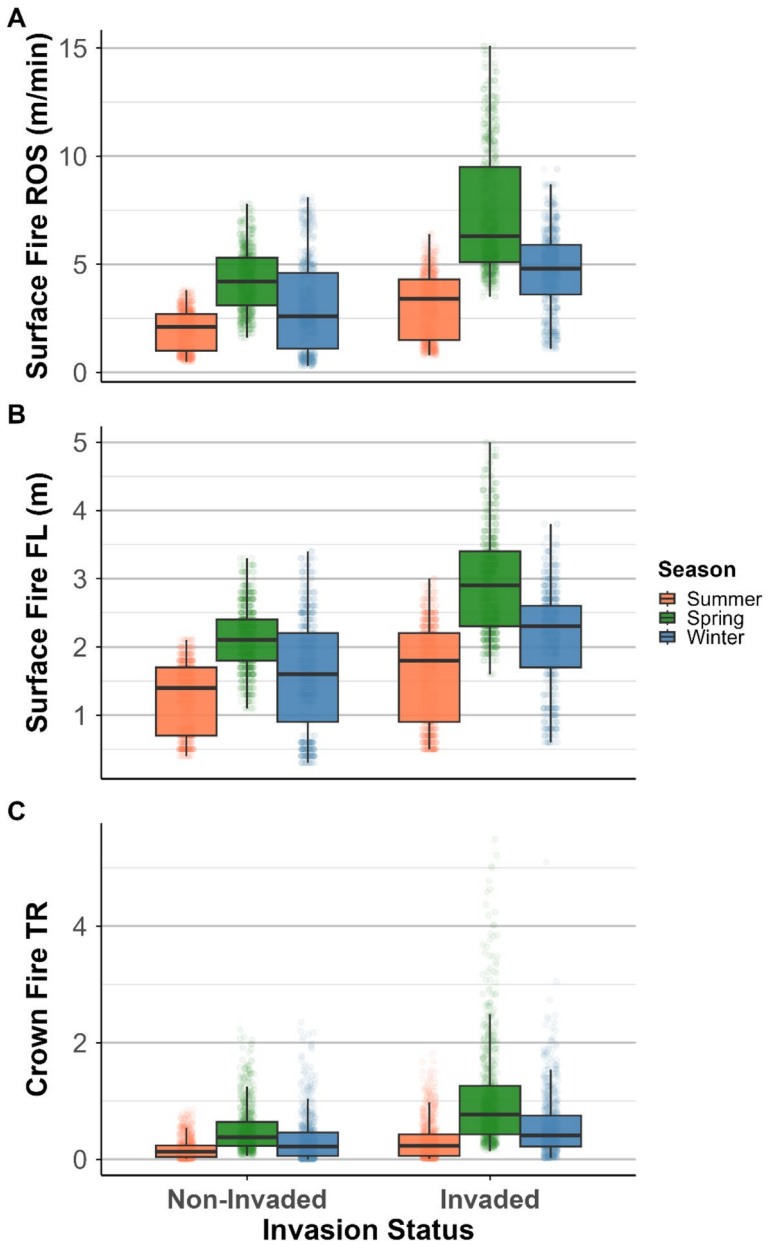

Fig. 5 Boxplot showing seasonal differences in surface and crown fire behavior by invasion status. Colors denote season (summer = orange, spring = green, winter = blue); *x*-axes contrast non-invaded vs invaded plots; points are individual observations overlaid on boxplots (median, IQR, whiskers). Panels display: **A** surface fire rate of spread (ROS; m/min), **B** surface fire flame length (FL; m), and **C** crown fire transition ratio (TR)

ha greater than in non-invaded areas, while vegetation height increased by more than half a meter. These changes created dense, vertically continuous fine fuels, characteristics known to enhance fire propagation and intensity in grass-invaded systems (D'Antonio and Vitousek 1992; Brooks et al. 2004; Balch et al. 2013). Although litter mass did not differ consistently with invasion, litter and dead fuel loads were the dominant predictors of elevated fire behavior when cogongrass was present, resulting in greater dead fuel biomass that supported higher rates of spread and longer flame lengths. This pattern is consistent with previous work demonstrating that increases in fine fuel biomass and continuity elevate fire intensity, while seasonal declines in fuel moisture amplify energy release and fire spread (Kidnie and Wotton 2015; McGranahan et al. 2016; Cardoso et al. 2018). Modeled surface fires in invaded plots exhibited higher rates of spread, longer flame lengths, and greater fireline intensities across all seasons, particularly in spring when live fuel moisture

was lowest. Invasion also modified vertical fire dynamics, enhancing the probability of surface-to-crown fire transition. Together, these results demonstrate that cogongrass invasion reorganizes surface fuels in ways that amplify fire behavior and alter vertical fire propagation across southeastern pine ecosystems.

The increases in surface fire rate of spread and flame length we report may appear modest in operational terms, but they reflect simulations run under comparatively conservative fire-weather conditions, namely a fixed low wind speed (6 km/h) and the moderate fuel and litter moisture levels we measured in the field. Our regression results indicate that fire behavior in cogongrass-invaded fuels is considerably more sensitive to fuel moisture than in non-invaded fuels. Because this sensitivity is steeper in invaded fuels, the modest differences we report under moderate conditions likely understate the divergence in fire behavior that would emerge as fuel moisture drops further during drought or as wind speed rises above the conservative value presented here. Rather than a fixed, modest increase in fire danger, cogongrass invasion may be better characterized as making fuels disproportionately more dangerous under fire-weather extremes, under which conditions fires are more difficult to suppress and more likely to produce severe ecological effects.

Cogongrass increases crown transition ratio, elevating tree torching potential. By elevating the surface rate of spread and flame length, cogongrass effectively lowers the threshold for crown ignition, increasing the likelihood of torching even where active crown fire remains unlikely (Wagner 1977; Scott and Reinhardt 2001). Beyond the immediate mortality and economic loss that may be caused by tree torching (Dey and Schweitzer 2018; Varner et al. 2021), frequent torching events and severe crown scorch reduce timber value and destabilize the open-canopy and frequent-fire regimes essential for high-diversity ground layers and pine recruitment (Wade 1989; Glitzenstein et al. 2003; Wear and Greis 2013). Moreover, torching trees create more extreme fire behavior (e.g., spot potential) that make fires more difficult to control. With wildfire occurrence increasing in many southeastern forests, the added impacts of torching on fire behavior have become increasingly relevant (Donovan et al. 2023). Although canopy bulk densities in well-maintained southeastern pine ecosystems are typically low enough that sustained crown fires remain relatively rare (Brockway and Outcalt 1998; Frost 1998; Scott and Reinhardt 2001), many pine forests in the southeast are no longer maintained with fire. The wildland-urban interface (WUI) has been documented to have higher-density forests and increased fuel loads due to fire suppression and limited prescribed burning (Sonti et al. 2023; Kreider et al. 2024), along with a greater prevalence of invasive species (Gavier-Pizarro et al. 2010). Because cogongrass invasion is strongly associated with anthropogenic disturbance, particularly along roadsides and forest edges (Holzmueller and Jose 2012), where activities such as soil disturbance and road construction may have facilitated its spread (Willard et al. 1990; King and Grace 2000), cogongrass-dominated fuels may increasingly overlap with WUI forests where stand conditions are already conducive to more intense fire behavior. This spatial convergence of altered fuel characteristics and altered stand structure may compound crown fire risk in WUI areas. Future research could quantify how cogongrass invasion interacts with stand structural characteristics in WUI settings to influence actual crown fire occurrence and severity, particularly in fire-suppressed forests where canopy conditions may amplify the effects of altered surface fuels.

Seasonally, cogongrass amplified surface fire behavior most strongly in late winter and early spring, when many prescribed fires are applied in longleaf pine savannas (Chiodi et al. 2018; Waldrop and Goodrick 2018). Consequently, the greatest increase in fire intensity may occur during the period when managers most frequently use prescribed fire. This pattern parallels seasonal changes in live fuel moisture and dead fuel accumulation. Grass-dominated fuelbeds are most conducive to rapid surface fire spread during spring and fall transitions, when fine fuels are cured, and moisture levels are low (Scott and Burgan 2005; Platt et al. 2015). Historically, Indigenous peoples across the southeast used fire extensively during late fall, winter, and early spring to manage vegetation, promote forage, and improve hunting visibility (Frost 1998; Fowler and Konopik 2007). Contemporary prescribed burning continues this legacy, with most burns conducted from November through March when fuels are dry, temperatures are moderate, and winds are predictable (Chiodi et al. 2018; Waldrop and Goodrick 2018). Although cogongrass achieves peak biomass and vegetation height during summer, we found high live fuel moisture content during active growth, which likely limits fire spread potential. As cogongrass senesces through fall, we found these abundant fuels cure, generating highly flammable fine-fuel material, such that vegetation productivity gains of summer are effectively translated into amplified fire behavior by late winter and early spring. Our findings suggest that cogongrass elevates

fire spread and flame length potential most notably during late winter and early spring, indicating that invasion could intensify fire behavior during the same period when prescribed burning is most common, thereby potentially narrowing operational safety conditions and increasing the risk of escaped burns. By maintaining elevated overall fine-fuel loads throughout the dormant season, cogongrass has the potential to extend the duration of flammable conditions beyond historical norms (D'Antonio and Vitousek 1992; Lippincott 2000; Brooks et al. 2004). Such season-lengthening effects, also noted for other invasive grasses (Balch et al. 2013), may complicate efforts to maintain safe and ecologically beneficial fire regimes across the region.

Latitudinal gradients moderated invasion effects on both fuel loads and vegetation height. The increase in live and dead fuel loads in invaded areas diminished toward higher latitudes within our study range (28.5°N to 31.6°N), which may reflect underlying climatic controls on cogongrass productivity. Within the southeastern US, winter temperatures appear to constrain cogongrass productivity and biomass accumulation at northern range margins, with prolonged soil freezing particularly limiting to the species (Wilcut et al. 1988; Adhikari et al. 2025). Average winter temperatures over the last five years across our sites varied by 5° Celsius, suggesting this as a potential mechanism (Abatzoglou 2013; Huntington et al. 2017; Climate Engine 2026). However, warming winters are increasing its potential for northward expansion (Rad et al. 2025), and climate projections suggest further broadening of suitable habitat (Bradley et al. 2010). Thus, projected shifts in future climate conditions indicate that the fuel and fire behavior changes associated with cogongrass invasion are unlikely to remain geographically static.

Our findings provide evidence for cogongrass's potential to generate positive grass-fire feedbacks similar to those documented in other grass-invaded systems. Classic invasive grass-fire feedbacks operate through two linked components: (1) invasive grasses alter fuel characteristics in ways that increase fire frequency, intensity, or both, and (2) these altered fire regimes disproportionately favor the invasive grass over native species, creating conditions that further promote grass dominance and fuel accumulation (Brooks et al. 2004; Fusco et al. 2019). In classic invasive grass-fire feedback systems, like those observed with fountain grass (*Pennisetum setaceum*) in Hawaiian shrublands (D'Antonio and Vitousek 1992) and gamba grass (*Andropogon gayanus*) in Australian savannas (Setterfield et al. 2010), these linked processes create a cycle where intensified fires cause differential mortality that favors the invader, further promoting grass dominance and fuel accumulation (Brooks et al. 2004). Our results suggest that cogongrass has the potential to alter several fuel components necessary to shift fire behavior in southeastern pine ecosystems. Specifically, the observed increases in flame length and transition ratio suggest that areas invaded by cogongrass could generate greater crown scorch and heat exposure, potentially exceeding lethal thresholds for overstory pines and sensitive understory species (Hare 1965; Peterson and Ryan 1986). However, whether cogongrass uniquely benefits from these altered fire behaviors remains uncertain. While cogongrass exhibits prolific rhizomatous growth and rapid post-disturbance recovery (Dozier et al. 1998), many native southeastern species also possess fire-adapted traits, such as subterranean storage organs. Future research could assess whether the altered fire behavior generated by cogongrass invasion translates to changes in actual fire regime characteristics (e.g., fire frequency, severity, extent) that disproportionately favor cogongrass proliferation over native species, thereby completing the feedback cycle. Such studies could also evaluate how fire-induced changes interact with the species' documented allelopathic effects on soil microbes and neighboring vegetation to reinforce invasion (Inderjit and Dakshini 1991; Xuan et al. 2012; Hagan et al. 2013).

Management implications

Taken together, our results indicate that cogongrass creates fuel beds that are vertically continuous and higher in live and dead fuel loads, increasing surface fireline intensity and spread while altering crown fire dynamics. Seasonal and latitudinal contingencies underscore that invasion effects are not static but are shaped by climatic controls on fuel accumulation, drying, and microclimate (Facelli and Pickett 1991; Scott and Burgan 2005). In regions and seasons where fine fuels are abundant and dry, particularly in spring, cogongrass invasion could be expected to markedly elevate fire behavior. These findings have important implications for fire management in the southeastern US. In cogongrass invaded areas, prescribed burn prescriptions may benefit from adjustment to account for elevated fire behavior, potentially requiring narrower burn windows to maintain operational control (Waldrop and Goodrick 2018). The elevated torching potential we documented suggests careful consideration may be warranted when conducting prescribed burns in cogongrass invaded areas near high-value timber stands or at the WUI. As cogongrass continues to expand across this fire-frequent region, future research could prioritize investigating whether the fire behavior alterations we documented translate into a self-reinforcing grass-fire cycle, particularly by assessing how repeated cogongrass-fueled fires affect native community composition, fire

return intervals, and the long-term trajectory of invasion spread. Understanding this feedback will be critical for developing effective management strategies that prevent the transformation of southeastern pine ecosystems into grass-dominated systems.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s42408-026-00574-5.

Supplementary Material 1: Table S1: Fuel and Moisture Quantiles by Invasion Status and Season. Biomass values are in tonnes/ hectare, moisture is denoted as a percentage, and height is in meters. Table S2: Posterior estimates of live biomass, based on a Bayesian regression model including latitude, season, invasion status, and their interactions. Values represent posterior means with 95% HPDI (highest posterior density interval), posterior probability of direction (Pd), effective sample sizes (ESS), and $\hat{r}$ convergence diagnostics. Bolded rows indicate credible variables. Table S3: Pairwise comparisons of live biomass between invaded and non-invaded sites within each season, based on estimated marginal means. Values represent posterior mean differences with 95% highest posterior density intervals (HPDI) and posterior probability of direction (Pd). Bolded rows indicate credible variables. Table S4: Posterior estimates of dead biomass, based on a Bayesian regression model including latitude, season, and invasion status. Values represent posterior means with 95% HPDI (highest posterior density interval), Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S5: Posterior estimates of litter biomass, based on a Bayesian regression model including latitude, season, and invasion status. Values represent posterior means with 95% HPDI (highest posterior density interval), Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S6: Posterior estimates of live fuel moisture, based on a Bayesian regression model including latitude, season, and invasion status. Values represent posterior means with 95% HPDI (highest posterior density interval), Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S7: Posterior estimates of dead fuel moisture, based on a Bayesian regression model including latitude, season, and invasion status. Values represent posterior means with 95% HPDI (highest posterior density interval), Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S8: Posterior estimates of litter fuel moisture, based on a Bayesian regression model including latitude, season, and invasion status. Values represent posterior means with 95% HPDI (highest posterior density interval), Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S9: Posterior estimates of soil moisture, based on a Bayesian regression model including latitude, season, and invasion status. Values represent posterior means with 95% HPDI (highest posterior density interval), Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S10: Pairwise comparisons of vegetation height between invaded and non-invaded sites within each season, based on estimated marginal means. Values represent posterior mean differences with 95% highest posterior density intervals (HPDI) and posterior probability of direction (Pd). Bolded rows indicate credible variables. Table S11: Posterior estimates of vegetation height, based on a Bayesian regression model including latitude, season, invasion status, and their interactions. Values represent posterior means with 95% HPDI (highest posterior density interval), Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S12: Posterior estimates of surface fire rate of spread, based on a Bayesian regression model including invasion status. Values represent posterior means with 95% HPDI (highest posterior density interval), Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S13: Posterior estimates of surface flame length, based on a Bayesian regression model including invasion status. Values represent posterior means with 95% HPDI (highest posterior density interval), Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S14: Posterior estimates of surface fireline intensity, based on a Bayesian regression model including invasion status. Values represent posterior means with 95% HPDI (highest posterior density interval), Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S15: Posterior estimates of crown transition ratio, based on a Bayesian regression model including invasion status. Values represent posterior means with 95% HPDI (highest posterior density interval), Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S16: Posterior estimates from a secondary Bayesian regression of surface fire rate of spread at invaded sites. Values represent posterior means with 95% credible intervals (CI), Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S17: Posterior estimates from a secondary Bayesian regression of surface fire rate of spread at non-invaded sites. Values represent posterior means with 95% CI, Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S18: Posterior estimates from a secondary Bayesian regression of surface flame length at invaded sites. Values represent posterior means with 95% credible intervals (CI), Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S19: Posterior estimates from a secondary Bayesian regression of surface flame length at non-invaded sites. Values represent posterior means with 95% CI, Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S20: Posterior estimates from a secondary Bayesian regression of surface fireline intensity at invaded sites. Values represent posterior means with 95% credible intervals (CI), Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S21: Posterior estimates from a secondary Bayesian regression of surface fireline intensity at non-invaded sites. Values represent posterior means with 95% CI, Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S22: Posterior estimates from a secondary Bayesian regression of crown transition ratio at invaded sites. Values represent posterior means with 95% credible intervals (CI), Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S23: Posterior estimates from a secondary Bayesian regression of crown transition ratio at non-invaded sites. Values represent posterior means with 95% CI, Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S24: Posterior estimates of surface fire rate of spread from a seasonal Bayesian regression model including season, invasion status, and their interaction. Values represent posterior means with 95% HPDI (highest posterior density interval), Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S25: Posterior estimates of surface flame length from a seasonal Bayesian regression model including season, invasion status, and their interaction. Values represent posterior means with 95% HPDI (highest posterior density interval), Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S26: Posterior estimates of surface fireline intensity from a seasonal Bayesian regression model including season and invasion status. Values represent posterior means with 95% HPDI (highest posterior density interval), Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S27: Posterior estimates of crown transition ratio from a seasonal Bayesian regression model including season, invasion status, and their interaction. Values represent posterior means with 95% HPDI (highest posterior density interval), Pd, ESS, and $\hat{r}$. Bolded rows indicate credible variables. Table S28: Pairwise comparisons of surface fire rate of spread between invaded and non-invaded sites within each season, based on estimated marginal means. Values represent posterior mean differences with 95% highest posterior density intervals (HPD) and posterior probability of direction (Pd). Bolded rows indicate credible variables. Table S29: Pairwise comparisons of surface flame length between invaded and non-invaded sites within each season, based on estimated marginal means. Values represent posterior mean differences with 95% highest posterior density intervals (HPD) and posterior probability of direction (Pd). Bolded rows indicate credible variables. Table S30: Pairwise comparisons of surface fireline intensity between invaded and non-invaded sites within each season, based on estimated marginal means. Values represent posterior mean differences with 95% highest posterior density intervals (HPDI) and posterior probability of direction (Pd). Bolded rows indicate credible variables. Table S31: Pairwise comparisons of crown transition ratio between invaded and non-invaded sites within each season, based on estimated marginal means. Values represent posterior mean differences with 95% highest posterior density intervals (HPDI) and posterior probability of direction (Pd). Bolded rows indicate credible variables. Figure S1. Distribution of sampling locations across each study forest. Panel A: All sampling sites; Panel B: Bogue Chitto National Wildlife Refuge; Panel C: Blackwater River State Forest; Panel D: Escambia Experimental Forest; Panel E: Private property 1; Panel F: Private property 2; Panel G: Jay Research Forest;

Panel H: Ocala National Forest; Panel I: Withlacoochee State Forest. Figure S2. Methodological framework for fuel and fire behavior analysis. The diagram outlines the progression from regional field sampling, fuel and fire modeling, and statistical synthesis used to determine key outcomes of cogongrass invasion on fuel dynamics and fire behavior. Figure S3. Latitudinal comparisons of live fuel load (A) and vegetation height (B) for non-invaded and invaded sites. The lines show the medians and interquartile ranges of invaded and non-invaded sites. Points are individual observations, colored by invasion status. Figure S4. Boxplot showing dead fuel load differences by invasion status; x-axes contrast non-invaded vs invaded plots; points are individual observations overlaid on boxplots (median, IQR, whiskers). Figure S5. Boxplot showing live fuel moisture differences by season; x-axes contrast summer (red), spring (green), and winter (blue) seasons; points are individual observations overlaid on boxplots (median, IQR, whiskers). Figure S6. Boxplot showing litter fuel moisture differences by season; x-axes contrast summer (red), spring (green), and winter (blue) seasons; points are individual observations overlaid on boxplots (median, IQR, whiskers). Figure S7. Boxplot showing soil moisture differences by season; x-axes contrast summer (red), spring (green), and winter (blue) seasons; points are individual observations overlaid on boxplots (median, IQR, whiskers).

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Authors' contributions
C.R., C.W., and V.D. acquired research funding. A.I. II., C.W., C.R., and V.D. conceptualized the project. C.W. and D.M. designed the modeling analysis. A.I. II., K.B., P.A., and S.K. collected field data. A. I. II., C.W., C.S., and V.D. validated statistical findings. A. I. II., K.B., and N.W. prepared all figures. A.I. II., C.W., and V.D. wrote the main manuscript text. All authors reviewed the manuscript.

Data availability
The data and code used to conduct the analysis are available at the following GitHub repository: https://github.com/alanivory/Cogongrass_Fuel_Dynamics.

Declarations

Competing interests
The authors declare no competing interests.

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