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Comparing drone and field based methods for assessing *Cryptostegia grandiflora* density along the Mogalakwena river in South Africa

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Abstract

Biological invasions pose a global challenge and are one of the most severe threats to biodiversity, rangeland productivity, and human and animal health. In South Africa, recent attention has focused on the invasive woody climber *Cryptostegia grandiflora*. This study aimed to update data on *C. grandiflora* abundance in the Mogalakwena River Reserve (MRR). A field survey was conducted from May to July 2023, comparing plant density in 36 quadrats with previous surveys undertaken in 2013 and 2016. Additionally, the study evaluated the effectiveness of drone-based analysis for density assessment. High-resolution mosaics of the study area were created using Drone2Map in ArcGIS and analysed to estimate plant density. The results indicated a significant increase in density over the past decade, with higher densities observed on the eastern bank of the river. Statistical tests confirmed significant increase from both 2013 and 2016 to 2023, with no significant difference between 2013 and 2016. Regression analyses confirmed a strong association between field-based and drone-based estimates, though drone data systematically underestimated density, especially at higher infestation levels. This was supported by Spearman's correlation ($r=0.79$, $P<0.001$), Bland-Altman analysis, and the Wilcoxon Signed-Rank Test ($p=0.015$). Despite this, drone-based monitoring offers valuable potential for large-scale invasion assessment. The study underscores the importance of integrating drone technology with field-based surveys for comprehensive monitoring of invasive species and highlights the need for further calibration to improve drone-based accuracy. Effective management strategies are urgently needed to control the spread of *C. grandiflora* and mitigate biodiversity impacts.

Keywords Conservation strategies, *Cryptostegia grandiflora*, Drone, Invasive species monitoring, Plant density assessment, Spatial analysis

1 Introduction

The increasing porousness of biogeographical boundaries driven by globalization and the large-scale movement of goods, has led to an escalation in the number of invasive alien species worldwide [1, 2]. Biological invasions represent an ongoing and pressing environmental challenge. While they are widely recognized for their impact on



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biodiversity, invasive species also disrupt ecosystem processes, reduce agricultural productivity, and pose risks to human and animal health [1]. *Cryptostegia grandiflora* Roxb. ex R.Br., a plant commonly known as rubber vine, has had the attention of researchers and conservationists in South Africa for decades. Endemic to Madagascar [3], the woody climber was introduced to South Africa for ornamental purposes [4, 5]. However, it has since successfully colonised pastoral and riparian ecosystems within the country, rapidly suppressing native vegetation and establishing dominance, particularly in the Limpopo and Mpumalanga provinces [4, 6].

The economic consequences of *C. grandiflora* invasion are significant, affecting agricultural productivity, biodiversity, and infrastructure, and requiring extensive financial resources for management. The plant has demonstrated invasive success in several other countries. In Ethiopia, its spread in the East Shewa Zone has significantly reduced species diversity and forest cover, leading to biodiversity loss and impacting the agro-economy, particularly pastoralist communities [7]. Similarly, in Baja California, Mexico, the invasion of oases by *C. grandiflora* altered vegetation structures and threatened endemic species that rely on these fragile ecosystems [8]. The invasion of riparian zones can lead to increased flood risks and maintenance costs for water management systems. Rodríguez-Estrella et al. [8] reported the spread of *C. grandiflora* along rivers and floodplains, competing with native vegetation, altering water flow and increasing sedimentation, reducing water availability, and increasing the risk of erosion. In Australia, *C. grandiflora* has been labelled one of the worst invasive weeds due to its impact on rangelands, where dense infestations have reduced productive grazing land, leading to significant economic losses [9]. The weed is toxic to livestock and reduces livestock-carrying capacities, costing an estimated AU\$ 24.8 million annually to the Australian livestock industry [10]. These impacts prompted large-scale management efforts, including the eventual introduction of biological control agents. A globally coordinated effort to monitor and manage *C. grandiflora* is crucial, as its spread threatens not only local economies and ecosystems but also global agricultural sustainability, water security, and biodiversity conservation. Effective surveillance and early intervention are essential.

The regulatory framework governing alien and invasive species in South Africa consists of the Alien and Invasive Species Regulations (No. R. 1020/2020) [11] and the revised NEM: BA Alien and Invasive Species List [12]. These regulations classify problematic plant species and prescribe appropriate actions based on ecological threat, location, commercial use, invasive potential and management complexity. *Cryptostegia grandiflora* is classified under category NEM: BA 1b in terms of its invasive status within South Africa. Although control of *C. grandiflora* is mandated under South African regulations, effective control remains challenging. While local strategies have included physical control [4], dense infestations along riparian zones, as seen in the Mogalakwena River, are particularly difficult to manage due to limited accessibility and the plant's rapid regrowth potential. Other countries, such as Australia, herbicide applications [13] and biological control has been employed, most notably through the introduction of the rust fungus *Maravalia cryptostegiae* [3, 9].

1.1 Invasion history and monitoring challenges

The presence of the plant along the Mogalakwena River was first detected in 2005, in the Mogalakwena River Reserve (MRR). From 2012 onwards, studies conducted on the

reserve have underscored the escalating significance of this invasive species. In the first density survey conducted along a 7.2 km segment of the Mogalakwena River, [27] examined the various factors contributing to the rapid spread of *C. grandiflora* at a fine scale. The study highlighted soil moisture as a primary driver of the area's high invasiveness. It found a significant correlation between proximity to water sources, such as dams, and higher densities of *C. grandiflora*. The importance of soil moisture for the spread and seed germination of this invasive species has been supported by several studies [3, 8, 14, 15].

Understanding changes in spatio-temporal density in this reserve, is not only essential for assessing the progression of this specific invasion but also holds broader ecological significance. By tracking shifts in population density, this study provides valuable insights into the species' growth dynamics in a South African context [16]. Given the increasing global spread of invasive species, such data contribute to a more comprehensive understanding of invasion ecology. Furthermore, long-term monitoring of *C. grandiflora* serves as a model for assessing invasive plant threats worldwide, aiding in the development of resource allocation strategies, and targeted management interventions in other vulnerable ecosystems [17, 18]. This study not only informs local conservation efforts but also enhances global biosecurity frameworks aimed at mitigating the ecological and economic impacts of biological invasions.

In the past, several sampling methods have been used to estimate woody climber densities, yet each presents significant limitations [19–21]. Traditional ground-based measurements vary widely in stem measurement locations, ranging from the largest point along the stem to fixed heights above the root collar at ground level (e.g., 20–130 cm), leading to inconsistencies in density, basal area, and biomass estimates [20]. Additionally, the inclusion of vegetatively produced ramets alongside independently rooted individuals often inflates density estimates, further complicating standardisation. Another commonly used approach, the Crown Occupancy Index (COI), assesses woody climber infestation based on canopy coverage [19]. While COI provides valuable insights into large-scale infestation patterns, it lacks precision in distinguishing overlapping crowns and fails to capture structural variations in infestation severity. Drone-based data offers high-resolution canopy assessments [21] and have the potential to enhance woody climber density estimation; however, distinguishing climbers from trees remains challenging due to spectral overlap, requiring manual validation [19, 21]. These methodological discrepancies highlight the need for improved, standardised approaches to accurately quantify woody climber densities and their ecological impacts.

The study aimed to achieve two primary objectives. The first objective was to test if the density of *C. grandiflora* along the Mogalakwena River has significantly increased over time [27, 28]. The second objective of the study was to evaluate the effectiveness of drone-based data compared to conventional field survey techniques for assessing the density of *C. grandiflora*. The study hypothesised that the drone-based approach would yield results comparable to those obtained through the field-based survey. Conducting a comprehensive field survey poses challenges, particularly near the river where the dense presence of *C. grandiflora* and safety concerns regarding crocodiles and hippos hinder accessibility. Despite the clear spread of the species in the region, there has been no systematic monitoring to track changes in its density over time, and no assessment of whether drone technology could serve as a viable monitoring alternative. Using drone

technology can provide a more efficient and comprehensive approach to invasive species monitoring [21] by enabling large-scale monitoring in highly invaded areas [19, 22].

2 Methods

2.1 Study species

Cryptostegia grandiflora (Apocynaceae) has become widely naturalised and invasive across tropical and subtropical regions worldwide, including Australia, India, Southeast Asia, and parts of Africa [5, 23]. The plant is a woody perennial climber with twining, whip-like shoots. *Cryptostegia grandiflora* can develop into a shrub reaching 1–2 m in height; however, when supported by other vegetation, it can climb up to 40 m high [3, 5]. The natural habitat of *C. grandiflora* is in arid regions, but it thrives in watercourses and areas with a high water table where annual rainfall ranges between 400 and 1400 mm [3, 8, 23]. The plant is intolerant of shade, which slows its growth rate and limits its occurrence to open areas and forest margins [24]. The rapid spread of *C. grandiflora*, particularly along waterways, poses a significant threat to biodiversity, as it forms dense thickets that suppress native vegetation [7, 17, 23]. The stems, leaves and unripe pods exude a white, milky, toxic sap that is harmful to both humans and animals [3].

2.2 Study site

The research was conducted in Limpopo Province, South Africa, on a privately owned 1500 ha game reserve, the Mogalakwena River Reserve (MRR) (Fig. 1), which is divided by the Mogalakwena River into an eastern portion of 1100 ha and a western portion of 400 ha [25].

South Africa exhibits high climate variability. The MRR is in the hot interior region, characterised by a semi-arid, hot climate with erratic seasonal rainfall [26]. On average the area receives 350–500 mm rainfall annually, mainly during the summer months from October to April [25]. The MRR is situated within the Savanna biome [26], characterised by a dominant lower layer of grasses and an upper layer of woody vegetation. The biomes are further subdivided with MRR falling into the class Limpopo Sweet Bushveld [26]. The vegetation is generally short and shrubby, with open woodlands covering only a small proportion of the MRR along river banks [25].

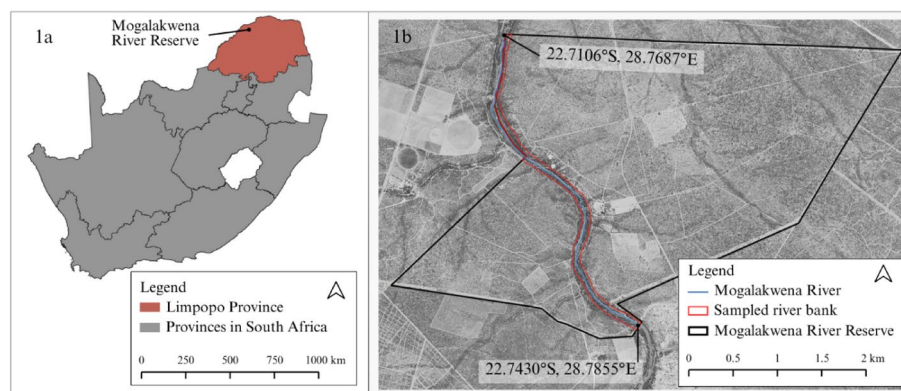


Fig. 1 Location of the Mogalakwena River Reserve within Limpopo Province, South Africa (**a**); and borders of the Mogalakwena River Reserve including the sampled riverbank (**b**). The Mogalakwena River divides the property into an eastern and western part. The mapped section spans from approximately 22.7106°S, 28.7687°E to 22.7430°S, 28.7855°E

2.3 Sampling method and data collection

2.3.1 Field-based sampling method and data collection

Cryptostegia grandiflora typically occurs within 30 m of the river edge [27]. Therefore, the field survey focused on a 30 m riparian buffer, analysing a 4.5 km stretch of the Mogalakwena River on the eastern bank and a 2.7 km section on the west. The study was conducted from May to July 2023, and the methodology replicated previous surveys done on the reserve [27, 28].

The river length within the study area was divided into 36 sections, each measuring 200 m in length and 30 m in width. Within each section, a single sampling unit was established (30×30 m quadrat), centred on a randomly generated GPS point. Each quadrat was further divided into four sub-quadrats (15×15 m) to support consistent plant counts and structural measurements (Fig. 2).

In each sub-quadrat, the number of *C. grandiflora* individuals was recorded by counting distinct ramets. Due to the species' clonal growth form and the difficulty of defining individual woody climber plants, stems were considered separate ramets if they emerged from the soil surface at horizontal distances greater than 10 cm, following established ecological definitions of modular plant growth [20]. This approach allowed for consistent and reproducible estimation of local stem density.

To standardise efforts and align with prior research at the reserve [27, 28], a maximum threshold of 100 counted individuals per sub-quadrat was implemented. This cap corresponds to an approximate density of 400 plants/quadrat, which exceeds double the threshold for 'dense infestation' (≥ 180 plants/quadrat) defined by [13]. Once this threshold was reached, counting ceased under the rationale that additional plants would not alter the classification of the area as highly infested. This approach provided a practical, conservative solution in the absence of a locally established infestation threshold. Although counts were recorded at the sub-quadrat level, all final calculations were aggregated and reported at the quadrat level (30×30 m). That is, the total number of *C. grandiflora* individuals in each quadrat was computed as the sum of individuals across its four sub-quadrats.

The authors acknowledge that this approach may underestimate true abundance in densely infested quadrats, as counts were intentionally capped for practical and comparative reasons. As a result, abundance values in quadrats that reached the threshold

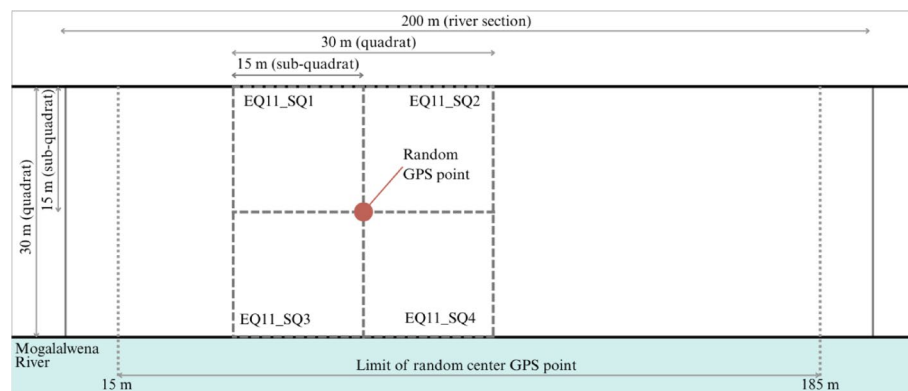


Fig. 2 Schematic of the sampling unit used in the field survey. Each 200 m river section contained one 30×30 m quadrat centred on a randomly generated GPS point, placed within the riparian buffer zone. Each quadrat was subdivided into four 15×15 m sub-quadrats and were labelled systematically (Eq. 11_SQ1 to Eq. 11_SQ4) to support field data collection and ensure spatial traceability across sampling units

reflect minimum estimates. To address this, we interpret survey results with an emphasis on infestation categories (low: 1–89, moderate: 90–179, dense: ≥ 180 individuals), rather than exact numeric values. This strategy ensured consistency with previous surveys.

In addition to stem counts, structural measurements were conducted in each sub-quadrat. The stem diameter and height of three individuals per sub-quadrat were recorded. Diameters were measured with a calliper at 10 cm above the ground. Each stem was measured for individuals with multiple stems, and the average was calculated. Plant height or climbing extent on host vegetation was visually estimated in the field.

2.3.2 Drone-based sampling method and data collection

Differentiating woody climbers from trees based on spectral properties is challenging due to forest type and climate variations [18]. Seasonal changes in leaf phenology, as noted by Schnitzer (2005) [29], can aid detection, particularly in dry forests, where woody climbers retain their leaves longer. Therefore, the drone flights were conducted during winter, on June 17, 2023, between 11 am and 1 pm. The weather conditions during the flight were variable; initially, there was cloud cover and mild gusts of wind, which later transitioned into sunny weather. The aerial mapping included a section of a 4.5 km stretch of the Mogalakwena River, spanning from the northern boundary ($-22.710571, 28.768742$) of the MRR to the southern boundary ($-22.743038, 28.785499$) of the reserve (Fig. 1b). The flight path covered an area of 60 ha, with approximately 40 ha constituting land and the remaining portion water.

The flights were performed using a DJI Mini 2 drone model, equipped with a camera model DJI FC7303 with the following specifications: 1/2.3" CMOS sensor and 12 megapixels. The photos were saved in JPEG format. Prior to the mapping process, the camera angle was adjusted to 90°, and the flight trajectory followed the parameters of Cine mode, with a flight speed of 4.0 m/sec and an altitude of 80 m above ground level. In total, 978 photographs were captured during the flight.

2.4 Data analysis

The collected data were compiled in Microsoft Excel [30]. R statistical software (version 4.3.1.) and RStudio [31] were used to conduct the statistical analyses.

2.4.1 Analysis of field-based data

Summary statistics and the number of plants per quadrat (30×30 m) were calculated in RStudio. The density results were compared to previous studies [27]. A simple moving average (SMA) was calculated to account for spatial clustering within the sections. This approach was chosen to ensure consistency with previous studies conducted at the reserve, specifically [28], where a moving average density was applied to smooth spatial variations between quadrats. Normal distribution was assessed with the Shapiro-Wilk test [32], then the Kruskal-Wallis test [33] was used to examine significant differences in density between the three years. Pairwise differences were further investigated using the Dunn test [34] with Bonferroni correction [35]. Differences were considered significant at $p < 0.05$. A density map showing levels of invasion along the river was compiled using a colour scale, based Osmond (2004). Spearman's Rank correlation test [36] was employed to assess the relationship between *C. grandiflora* density and distance to irrigation dams. The distance from each quadrat to the nearest irrigation dam was

measured in ArcGIS Pro 3.1 [37], by calculating the linear distance along the riverbank between the quadrat's centre point and the closest dam. Riverbank paths were digitized from the drone imagery to present the actual course of the river.

The predominant stem diameter and height were determined using summary statistics, including the median and interquartile range (IQR). A linear regression model was initially fitted to examine the relationship between stem diameter and height. Due to heteroscedasticity in residuals, a log-log transformation was applied. Spatial autocorrelation in height was tested using Moran's I, and spatial regression models (spatial lag and spatial error models) were fitted to account for spatial dependence. Model selection was based on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC).

2.4.2 Analysis of drone-based data

Raw drone images were stitched using ArcGIS Drone2Map [38] to create high-resolution mosaics. These ortho mosaics were imported into ArcGIS Pro 3.1. Initial visual inspection indicated that *C. grandiflora* displayed a bright green canopy, contrasting with the surrounding deciduous vegetation, which had largely shed its leaves during winter. However, *Croton megalobotrys* Mull. Arg., *Senegalia schweinfurthii* (Brenan & Exell) Seigler & Ebinger var. *schweinfurthii*, and *Philenoptera violacea* (Klotzsch) Schrire retained foliage with a similar colour and structure, making them likely sources of misidentification.

To delineate *C. grandiflora* canopies, the Segment Anything Model (SAM) in ArcGIS Pro [39] was applied for automated segmentation. Following segmentation, visual identification was conducted by a single trained individual to differentiate *C. grandiflora* from morphologically similar species. The classification was based on distinct structural features, including the presence of whip-like trailing shoots, which are characteristics of *C. grandiflora* but absent in *C. megalobotrys*. Additionally, the fine-textured feathery canopy of *S. schweinfurthii* distinguished it from *C. grandiflora*, which has broader, glossier, brighter leaves. *P. violacea* could be distinguished from *C. grandiflora* by its larger, more rigidly structured leaves, its typically wider-spaced branching pattern, and its tendency to have a more balanced, rounded crown, as opposed to the irregular, sprawling form of *C. grandiflora*. Appendix A provides additional documentation on species that posed a risk of misidentification, including morphological distinctions as observed in aerial imagery.

To ensure accuracy in species classification, ground truthing was conducted by two individuals. The process involved systematic verification of suspected canopies in the field. The final dataset was refined by removing misclassified individuals, ensuring that only confirmed *C. grandiflora* crowns were included in the analysis. Misclassified segments were manually removed in ArcGIS, based on comparison with field-verified species. While the SAM model was used to delineate *C. grandiflora* from drone imagery, traditional classification accuracy metrics such as overall accuracy, F1-score, and confusion matrices were not computed. Although field-based verification of suspected canopies was conducted, no manually delineated reference polygons or pixel-level ground-truth data were produced to enable such analysis. Instead, the reliability of UAV-derived segmentation was assessed indirectly through comparison with field-based density estimates using statistical methods described later in this chapter.

A total of 31 quadrats were included in the drone-based analysis. Five quadrats (Eq. 1, Eq. 2, Eq. 18, WQ1, WQ2) were excluded due to incomplete or unusable aerial imagery caused by flight path limitations. These quadrats were therefore omitted from all drone-based density estimates and from the statistical comparison with field-based data to ensure consistent sample sizes and prevent bias in method agreement analyses. Drone-based density was estimated by calculating the total canopy area (m²) of classified *C. grandiflora* segments within each 30 × 30 m quadrat using the ‘Calculate Geometry’ tool in ArcGIS. This area was converted to percentage coverage relative to total quadrat area (900 m²). While the drone captures aerial canopy extent, the field survey quantifies stem density (ramet counts). For comparison, field-based density was normalized by dividing the total ramet count by the maximum (400 individuals) and expressing it as percentage (1). Although these measures represent different ecological dimensions (canopy cover vs. stem density), they were used to evaluate consistency between methods across spatial units.

$$\text{Density}_{\text{field}} = \left(\frac{\text{Actual Plant Count}}{400} \right) \times 100$$

where: 400 represents the maximum possible density per quadrat (corresponding to the dense infestation threshold).

To evaluate the agreement between the methods, the following error analyses were conducted: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Bias. Normality of both datasets was assessed using the Shapiro-Wilk test, Q-Q plots, and density plots. While field-based density values were normally distributed ($p = 0.073$), drone-based values were not ($p = 0.002$). Based on this outcome, Spearman’s rank correlation was used to test for monotonic association between the two datasets. A simple linear regression model was fitted to investigate systematic deviations and to explore the potential for correction. To further examine method agreement, Bland-Altman analysis [40] was conducted, to assess mean difference and limits of agreement. Additionally, the Wilcoxon Signed-Rank Test [41] was used to determine whether paired differences between methods were statistically significant. Finally, polynomial regression and density-stratified models were also tested, but did not improve prediction accuracy and were not used in the final correction model.

3 Results

3.1 Density based on the field survey and comparison between the three years

A total of 4410 individuals were recorded during the 2023 field survey. The number of *C. grandiflora* individuals per 30 × 30 m quadrat ranged from 0 to 376. The species was absent in only four of the 36 quadrats. The results from each quadrat have been categorised into no, low, moderate or dense invasion categories and moving averages were calculated for comparison to the 2013 and 2016 maps (Fig. 3). Over 30% of quadrats fell into the dense infestation category (≥ 180 individuals), with several sub-quadrats reaching or nearing the maximum count threshold of 100 individuals/sub-quadrat. Due to the application of this cap, these values represent conservative estimates of true abundance. The eastern bank of the river demonstrated higher levels of invasion than the west, with

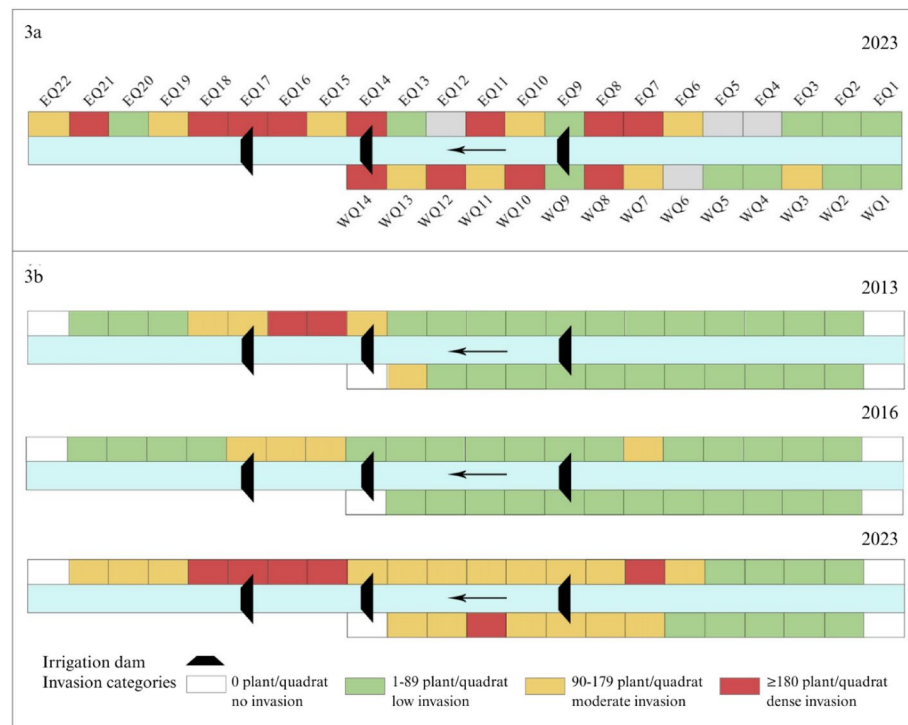


Fig. 3 Spatial distribution of *C. grandiflora* infestation levels by quadrat. Each of the 36 sections contains one 30×30 m quadrat. Infestation levels are classified as: no invasion (0, grey), low (1–89 individuals/quadrat, green), moderate (90–179 individuals/quadrat, orange), and dense (≥180 individuals/quadrat, red). Observed infestation categories in 2023 are based on raw field counts (a); and comparison of infestation categories for 2013, 2016, and 2023 are based on moving average calculations (b). EQ=East quadrat; WQ=West quadrat. Note: values in the dense category may be underestimated due to an applied counting threshold (see Methods 2.3.1.)

an average of 136 individuals per quadrat (40% of quadrats classified as dense), compared to 100 individuals/quadrat (25% of quadrats classified as dense) on the western bank.

There was a statistically significant increase in the density of *C. grandiflora* between 2013/2016 and 2023, but no significant difference was observed between 2013 and 2016 (Fig. 4a). Spearman's rank correlation analysis revealed a significant negative correlation between the density of *C. grandiflora* and the distance to the closest dam ($r(34) = -0.424$, $p = 0.01$). This indicates that as the distance to the nearest dam increases, the density of *C. grandiflora* tends to decrease (Fig. 4b). Table 1 presents a comparative analysis of *C. grandiflora* density categories across the three years (2013, 2016, and 2023).

Cryptostegia grandiflora showed a predominant stem diameter of 2.1 cm (IQR = 1.7 cm) (Fig. 5a) and a predominant height of 3.67 m (IQR = 4.02 m) (Fig. 5b). Spearman's rank correlation analysis indicated a significant positive correlation between stem diameter and height ($r(297) = 0.81$, $p < 0.001$) (Fig. 6a). The log-log regression model improved model fit ($R^2 = 0.83$, $p < 0.001$), with an estimated scaling exponent $\beta_1 = 1.09 \pm 0.05$ (Fig. 6b). Moran's I confirmed significant spatial autocorrelation in plant height ($I = 0.28$, $p < 0.001$). Among spatial models, the spatial error model (SEM) had the lowest AIC (AIC = 414.61) and effectively removed spatial dependence in residuals ($I = 0.057$, $p = 0.11$). Thus, the SEM best described the diameter-height relationship while accounting for spatial structure.

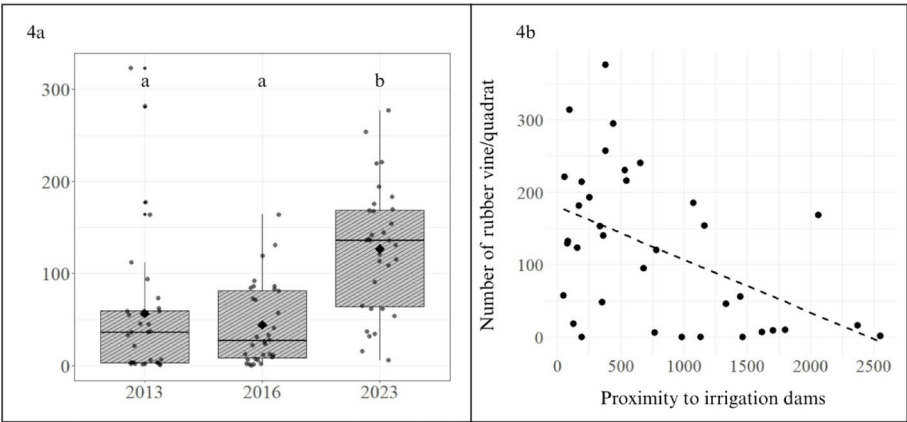


Fig. 4 The means, medians, and variations in the number of plants per quadrat among the three years, including the distribution of quadrats. Boxes with different superscripts are significantly different ($p < 0.05$) (a); Scatter plot showing the relationship between the density of *C. grandiflora* and the distance to the closest dam. The negative correlation ($r(31) = -0.424, p = 0.01$) is represented by the downward trendline (b)

Table 1 Comparison of *C. grandiflora* infestation levels across three surveys conducted in 2013 (Kern), 2016 (Riou), and 2023 (this study). Infestation categories are based on the number of individuals per 30 × 30 m quadrat

	2013	2016	2023
*Total counted individuals	2070	1574	4410
*Highest number of plants per quadrat	323	164	376
Number of quadrats with no invasion (0 individuals)	0	0	0
Number of quadrats with low invasion (1–89 individuals)	26	28	9
Number of quadrats with moderate invasion (90–179 individuals)	4	4	17
Number of quadrats with dense invasion (≥ 180 individuals)	2	0	6

* The numbers indicate the actual number of counted individuals. The rest of the data represent numbers after calculating the moving average for each quadrat

A maximum of 100 counted individuals/sub-quadrat (400/quadrat) was implemented in all surveys. Values for dense quadrats may underestimate true abundance due to this threshold

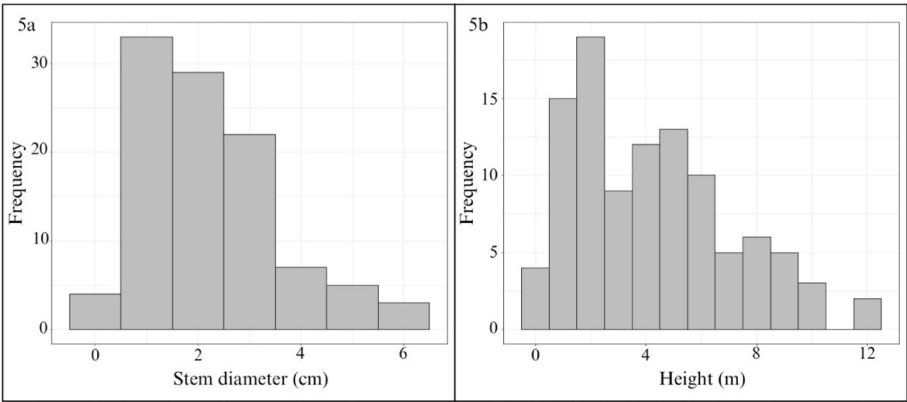


Fig. 5 Predominant stem diameter (a) and height (b) of *C. grandiflora*

3.2 Density based on the drone-based method and comparison of the two methodologies

Drone-based canopy coverage was derived from 31 quadrats that had previously been surveyed in the field for plant counts. These quadrats exhibited a range spanning from 0 to 91% coverage, with *C. grandiflora* being absent from four of them. Consistent with the field-based results, the eastern bank of the river demonstrated greater invasion levels

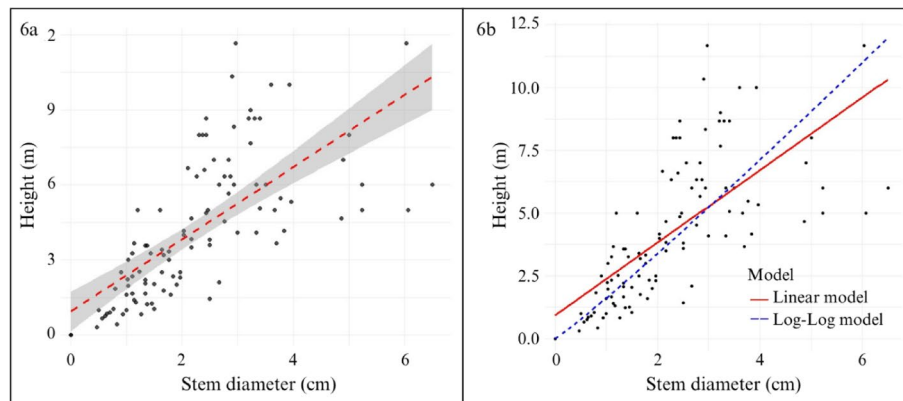


Fig. 6 Relationship between stem diameter and plant height in *C. grandiflora*. Scatter plot showing a significant positive correlation between stem diameter and height, with a fitted linear regression line (dashed red) and 95% confidence interval (shaded grey) (a); comparison of linear (solid red) and log-log (dotted blue) regression models, demonstrating improved model fit in the log-log transformation (scaling exponent $\beta_1 = 1.09 \pm 0.05$, $p < 0.001$) (b)

compared to the west, with an average coverage of 25% per quadrat in the east and 20% in the west.

To evaluate the agreement between drone- and field-based density estimates, three standard performance metrics were calculated: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and mean bias. Results revealed a MAE of 14.85%, RMSE of 20.46%, and a mean bias of -9.97% , indicating that drone estimates tended to underestimate field observations, particularly at higher densities.

To further assess the relationship between the two methods, multiple regression techniques were tested to identify the best-fitting model. A linear regression model (Appendix B, Fig. 9a) revealed a significant positive relationship between field-based (independent variable) and drone-based (dependent variable) estimates ($\beta_1 = 0.61$, $p < 0.001$), with the model explaining 53.45% of the variance in drone-derived densities ($R^2 = 0.53$). A Spearman's rank correlation was conducted due to non-normality in the drone dataset, revealing a stronger monotonic relationship ($r(29) = 0.79$, $p < 0.001$). A LOESS-smoothed regression curve supported these findings (Appendix B, Fig. 9b), indicating good agreement at lower infestation levels but growing discrepancies as density increased, evidence of density-dependent bias. Bland-Altman analysis was also conducted to characterise the nature and range of discrepancies. The mean difference between field and drone measurements was -9.97% , with limits of agreement spanning from -45.57% to $+25.63\%$. This further confirmed a systematic underestimation at higher densities, visualized in the Bland-Altman plot (Appendix B, Fig. 10). The Wilcoxon Signed-Rank Test [41] indicated a statistically significant difference between the two methods ($Z = -2.42$, $p = 0.015$), reinforcing the conclusion that drone-based estimates do not directly align with field-derived values.

To address the observed bias, a correction model was applied to the drone-based estimates. The linear correction formula improved error metrics, reducing MAE to 11.18% and RMSE to 14.13%, though the mean bias remained unchanged at -9.97% . Attempts to refine this correction using polynomial regression or stratified density-based models did not yield further improvements in accuracy.

4 Discussion

The study provides a comprehensive analysis of the density of *C. grandiflora* over a 10-year period, utilising both traditional field surveys and emerging drone-based methods. Density measurements for woody climbers are inherently complex due to their multi-stemmed growth patterns and clonal propagation. As discussed in the introduction, traditional ground-based sampling methods often vary in their definition of individuals, leading to inconsistencies in density estimates [19, 20]. Our study followed a ramet-based counting approach, which aligns with the concept of clonal propagation, where spatially distinct stems (ramets) function independently but remain genetically identical [42]. While this approach ensures consistency in data collection, it likely overestimates genet abundance by counting multiple stems from the same root system as separate individuals. Conversely, the drone-based method provided additional insights by offering high-resolution canopy assessments, which, despite its advantages, exhibited systematic underestimation as evidenced by the bias and Bland-Altman analysis.

The significant differences in density between 2013/2016 and 2023 highlight a troubling increase in the spread of this invasive species. The higher density observed in 2023, particularly in the eastern bank of the river, underscores the urgency of effective management strategies to control its spread. The lower density of *C. grandiflora* observed in 2016, relative to 2013, was likely influenced by severe environmental conditions. During this period, the 2015/16 El Niño event led to one of the most intense droughts on record, severely impacting water availability in the Mogalakwena River and the broader Limpopo Province [43]. This year the Mogalakwena River reached historically low water levels. Given that *C. grandiflora* relies on consistent water availability for growth and establishment, these extreme drought conditions likely suppressed recruitment and survival rates, leading to the observed decline in density.

The increase in *C. grandiflora* density from 2013 to 2023 suggests a rapid expansion of the species. This trend could be attributed to favourable environmental conditions and ineffective control measures [1, 16, 44]. Environmental and human-mediated disturbances play a crucial role in structuring plant communities and can often favour the establishment of invasive species [16, 17, 44]. In riparian habitats, periodic flooding re-routes the water courses and disturbs riverbanks and vegetation structure. These events form gaps in the non-woody ground cover and provide favourable, resource-rich conditions for the establishment of invasive species.

Several studies previously suggested the availability of consistently elevated soil moisture as the main contributor to the increased abundance of *C. grandiflora* [8, 14, 15]. This correlates with the findings of the current study, where greater densities were observed in proximity to irrigation dams. In other studies, initial invasion by *C. grandiflora* is similarly limited to riparian areas, although expansion into upland areas away from watercourses has occurred in some systems where the water table is high [3, 8].

As expected, a significant positive correlation was observed between stem diameter and height, consistent with allometric growth patterns commonly found in woody plants. Spatial analysis revealed significant spatial autocorrelation in plant height, confirming non-random spatial structuring. Among spatial models, SEM provided the best fit (AIC = 414.61), effectively accounting for spatial dependence and improving predictive accuracy. These findings indicate that *C. grandiflora* forms dense thickets with structurally dominant individuals, likely enhancing its competitive ability. Taller

individuals with increased stem diameters have greater access to light and structural support from host vegetation, facilitating their spread. This growth pattern suggests that *C. grandiflora* is not only increasing in density but also stature, reinforcing its capacity to overtop and suppress native flora. The expansion of structurally dominant individuals implies a proportional increase in the population of individuals capable of climbing and suffocating native flora. These structural characteristics underscore the necessity for targeted control measures aimed at limiting both the establishment and vertical spread of *C. grandiflora* in invaded ecosystems. The dense thickets formed by this species have outcompeted native vegetation, leading to a loss of biodiversity and alterations in ecosystem functions [7, 8, 17].

Drones have become increasingly valuable in ecological studies for habitat assessment [18, 19, 21, 22]. However, relying solely on georeferenced data for ground truth can be impractical [18, 45]. Few studies have compared woody climber infestations using both field surveys and drone methodologies [18, 19, 21, 45]. Two of these reported positive correlations between drone-based and field-based estimates. Waite et al. [21] found a strong correlation between drone-based and ground-based estimates of woody climber infestation at individual tree and plot levels in eastern Sabah, Malaysia. Similarly, [19] identified significant relationships between most ground-derived metrics and the top-of-canopy woody climber leaf coverage over tree crowns in the northern Republic of the Congo.

The strong positive correlation between the two methods in the current study supports the reliability of drone-based methods in vegetation monitoring [19, 21, 22]. However, systematic differences between field and drone-based estimates suggest that underestimation is primarily due to canopy occlusion and challenges in detecting small or understory plants [18, 19]. Bland-Altman analysis and Wilcoxon Signed Rank-Test further confirmed these discrepancies, reinforcing that field-based measurements capture plant density more effectively, while drone imagery is better suited for large-scale spatial assessment. Visser et al. [18] highlighted the challenges of using drones to differentiate woody climbers from surrounding vegetation due to spectral property variations. The authors also claim that in dry forests, the longer leaf retention of woody climbers may enhance their detectability. In this study, surveys were conducted during the winter season, when most native vegetation had shed leaves, increasing the visual contrast and improving the aerial identification of *C. grandiflora*. Additionally, overestimation by the drone-based method occurred in specific quadrats where density shifted from non-invaded to lightly invaded states (1–89 plants/quadrat). This was likely due to *C. grandiflora* plants climbing host trees outside the sample plots, coinciding with plot boundaries, a discrepancy also noted by [45].

These findings emphasise the strengths and limitations of each method. While field surveys provide more accurate plant density estimates, drone imagery enables broader spatial assessments that traditional surveys cannot achieve efficiently. One significant limitation of the study is the use of an entry-level professional drone, which, while effective for general assessments, lacks the capabilities of more sophisticated models. Despite these limitations, integrating drone-based data with field surveys enhances the accuracy of invasion monitoring. Future advancements in drone technology, particularly multispectral and LIDAR applications, could improve accuracy and help mitigate current detection limitations [46]. The adoption of hybrid methodologies, incorporating both

field-based validation and remote sensing, is recommended for improved long-term monitoring and management of invasive woody climbers.

5 Conclusion

This study highlighted the significant increase in *C. grandiflora* density over the past decade and evaluated the effectiveness of drone-based monitoring compared to traditional field surveys. While field surveys remain invaluable for providing ground-truth data, drones offer substantial advantages in covering large and inaccessible areas efficiently. Our findings revealed that drone-based estimates consistently underestimated plant density, likely due to challenges in detecting smaller individuals or understory plants. Although correction models improved accuracy, further refinement in image processing and classification is needed to match field-level precision.

Despite this limitation, drone-based monitoring remains an invaluable tool for assessing large-scale invasion patterns, particularly in remote or ecologically sensitive areas. As *C. grandiflora* continues to threaten riparian systems, especially under increasing drought conditions in southern Africa [17], integrated monitoring approaches are critical. Future research should prioritise improving image resolution, incorporating AI-based classification, and using drones to evaluate treatment effectiveness. Combining drone and field methods represents a practical and scalable strategy for managing invasive species and safeguarding biodiversity.

Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1007/s44396-025-00013-w>.

Supplementary Material 1

Supplementary Material 2

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Author contributions

V.K.: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualisation. C.K.: Conceptualisation, Methodology, Resources, Supervision, Writing – review & editing. G.J.v.R.: Conceptualisation, Methodology, Resources, Supervision, and Writing—review & editing. F.K.: Conceptualisation, Methodology, Resources, Software. Lars Schmidt: Conceptualisation, Supervision, Writing – review & editing.

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Data availability

Data is provided within the supplementary information files.

Declarations

Ethics approval and consent to participate

The authors declare no competing interests.

Consent for publication

Not applicable.

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