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Treetop Tech: Uplifting German Foresters' Drone Perspectives through the Technology Acceptance Model

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### Abstract.

Forests play a key role in nature as they purify water, stabilize soil, cycle nutrients, store carbon and also provide habitats for wildlife. Economically, forest product industries provide jobs and economic wealth. Sustainable forest management and planning requires foresters' understanding of the forests dynamics for which the collection of field data is necessary, which can be time consuming and expensive. Unmanned aerial vehicles or drones can improve the efficiency of tradition acquisition since data collected by satellites or airplanes do not meet the needed spatial and temporal resolutions for regional or locally forestry objectives.

As drones are a cost-effective tool for several forest management purposes, this is the first study investigating the use of drones for forestry purposes and identifies factors influencing foresters' intention to use drones. For this purpose, 215 German foresters were surveyed from December 2021 to February 2022. Only 10 % of the participants use a drone for forestry purposes. By using partial least square structural equation modelling (PLS-SEM), an extended Technology Acceptance Model (TAM) was estimated to investigate factors influencing German foresters' intention to use drones. The TAM explains 42 % of the variation in the intention to use a drone. Based on the results, the main contributions of the survey can be summarized as follows.

Empirical Validation of TAM in Forestry Context: The TAM managed to explain 43% of foresters' intentions to use drones. This substantial explanatory power suggests that the TAM is an effective model for understanding technology adoption within the forestry context. This broadens the applicability of the TAM to a field that is becoming increasingly important.

Perceived Usefulness as Key Driver: The study identifies perceived usefulness for forest management (PUFM) as the most influential factor driving the intention to use drones. This finding can guide drone manufacturers and trainers to focus on emphasizing the practical advantages of drones, which can potentially enhance adoption rates.

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Identification of Key Barriers: Our research highlights the lack of technical knowledge and equipment as the primary obstacle to drone adoption among forest managers. This finding implies a need for enhanced training and support to this group, which could meaningfully foster drone adoption.

Highlighting Cost Perceptions: An interesting observation from our study contradicts the prevailing views in the existing literature. Despite drones being generally perceived as cost-effective tools, forest managers view them as expensive. This could be specific to the German forestry context, or it may reflect a broader misunderstanding about the costs and benefits of drone technology. This underscores the importance of effective communication about the long-term economic advantages of drone use in forest management.

The results are therefore of interest for several stakeholders like policy makers, manufacturers, extension services and practitioners.

#### Keywords.

Drone; Digitalization; Technology Acceptance Model; Partial Least Squares Structural Equation Modelling; Unmanned Aerial Vehicle; Forestry

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### Introduction

Forests play a key role in nature by purifying water, stabilising soils, cycling nutrients, storing carbon and providing habitats for wildlife (Yuan et al. 2015). With 159 million hectares of forest in 2020, the European Union (EU) contains 5% of the world's forest resources. In 2019, the growing stock of wood is estimated to be 28.4 billion m<sup>3</sup>, with Germany contributing the largest share (13.4%) (Eurostat 2021). In economic terms, forestry provides jobs and economic wealth (Yuan et al. 2015). The gross value added of forestry and logging accounted for 0.18% of the EU's GDP and employed 517,400 people in 2019 (Eurostat 2021).

Sustainable forest management and planning requires field data to improve foresters' understanding of forest dynamics (Dainelli et al. 2021a), which can be time-consuming and expensive to collect (Dainelli et al. 2021a; Zahawi et al. 2015). Unmanned aerial vehicles, or drones, can improve the efficiency of traditional data collection (Raparelli and Bajocco 2019), as data collected by satellites or aircraft do not meet the spatial and temporal resolutions required for regional or local forestry objectives. Drones can overcome these shortcomings as they can be equipped with GIS as well as infrared/thermal and multispectral cameras. These combine high spatial resolution, fast turnaround times and low operating costs, making them suitable for realtime applications. As a result, drones can be used for (precision) forest inventory, 3D mapping, disease detection and management, forest stockpile measurement, and forest fire management and documentation (Dainelli et al. 2021a; Raparelli and Bajocco 2019). According to Guimarães et al. (2020), drones are highly suitable for forestry due to: 1) low operational/material costs and high-guality data collection, 2) a wide range of sensors that can be attached for specific tasks, and 3) high temporal flexibility as they can be launched when needed, thus avoiding unfavourable weather conditions for data collection. Drones therefore offer a compelling means of substantially enhancing the decision-making capabilities of forest managers, while ensuring the sustainable use of forest ecosystems and resources, at modest cost.

Despite the promised benefits of this tool for (sustainable) forest management, no study has focused on the use of drones in forestry from the users' perspective. In particular, the barriers and benefits of drone use as perceived by foresters have not yet been captured in the literature. As drones are not yet widely used, it is worth focusing on foresters' initial perceptions and attitudes towards drones. Michels et al. (2021) demonstrated that latent factors influence German farmers' decisions to adopt drones. Similarly, studies in different fields have found that attitudes and perceptions influence forest managers' decisions regarding the adoption of new practices (e.g., Laakkonen et al., 2018; Rodriguez-Franco and Haan, 2015; Blennow et al., 2014). Therefore, it is reasonable to hypothesise that these latent factors also influence forest managers' decisions regarding whether or not to adopt drones. Nevertheless, the literature has yet to document forest managers' perceived barriers and benefits of drone use. The Technology Acceptance Model (TAM) (Davis 1989) explicitly focuses on an individual's attitudes and perceptions to explain the adoption of a new technology. However, the TAM framework has not been applied to study the adoption of digital tools (e.g. drones) in forestry.

Against this background, the aim of this study is to capture factors influencing forest managers' intentions to adopt drones, as well as the perceived barriers and benefits of drone use. To this end, an online survey using a standardised questionnaire was conducted between December 2021 and February 2022, resulting in a sample of 215 foresters. To the best of our knowledge, this article is the first in-depth exploration of the perceived benefits and barriers of drone use from the perspective of forest managers. Additionally, the study presents an innovative application of the TAM in the context of drone use in forestry, validating the usefulness of the model in disentangling forest managers' decision-making processes regarding drone use. The results will be of interest to a range of stakeholders, including German policy-makers, researchers, suppliers and developers of drones and associated software.

## **Hypothesis Generation**

The TAM was proposed by Davis (1989), and is the most widely applied framework for studying an individual's intention to adopt a technology (Verma and Sinha 2018). In the TAM, perceived usefulness is defined by an individual's belief that something can improve his or her job performance. Perceived ease of use refers to an individual's belief that using a technology is effortless. TAM proposes a positive relationship between perceived usefulness and an individual's intention to use a technology. Thus, the more useful a technology is perceived to be, the stronger the intention to use it. In an analogous way, the easier the use of the technology is perceived to be, the stronger is the intention to use the technology. Furthermore, the model assumes that the easier the perceived use of a technology, the greater the perceived usefulness of the technology (Davis 1989). Figure 1 shows the adapted model in the context of forestry drones.

Zahawi et al. (2015) point out that certain skills are required to use drones effectively. Users need to learn basic flying skills for take-off and landing. In addition, knowledge of image processing, cloud datasets and georeferencing is required. Therefore, the original construct of perceived ease of use (PEOU) by Davis (1989) is divided into two sub-constructs for the perceived ease of use for controlling the drone for take-off, landing and flying (PEOU - Handling) and for the perceived ease of use for using data and knowledge of data formats (PEOU - Data). Thus, it can be expected that a forester who is familiar with data formats and drone control has a higher intention to use drones (ITU). Similarly, a forester who is already able to control a drone is more likely to become familiar with the data formats in which a drone delivers the collected data. This is reflected in the following hypotheses:

H1a: PEOU - Handling has a statistically significant positive effect on PEOU – Data

H1b: PEOU - Handling has a statistically significant positive effect on ITU

H1c: PEOU - Data has a statistically significant positive effect on ITU

Forest planning and management requires an understanding of both short- and long-term dynamics in the forest, as forest ecosystems are highly dynamic (Goodbody et al. 2019). Therefore, the collection of accurate and up-to-date data is crucial (Guimarães et al. 2020). Drones improve and facilitate data collection with high temporal and spatial accuracy (Dainelli et al. 2021a), which can be the basis for modern forest management (Dainelli et al. 2021b). Furthermore, the detection and monitoring of diseases caused by abiotic and biotic factors is essential for forest sustainability (Guimarães et al. 2020). Therefore, drones can be useful for forest management in general (e.g. forest inventory), but also for forest health in particular (e.g. disease detection). For this reason, the original construct of perceived usefulness (PU) by Davis (1989) was adapted to the construct of perceived usefulness for forest management (PUFM) and complemented by the upstream construct of perceived health management benefits (PHMB). In line with the TAM (Davis 1989), it is expected that a forester who finds it easier to evaluate the extraction of collected data will also perceive drones as more useful for forest management. This is reflected in the following hypotheses:

H2a: PEOU - Data has a statistically significant positive effect on PUFM

H2b: PEOU - Data has a statistically significant positive effect on PHMB

Finally, if the forester perceives the information collected by the drone as useful for forest health management, it can be assumed that they perceive the drone as useful for forest management in general. Both of these will increase a forester's intention to use drones, as shown in the following hypotheses:

H3a: PHMB has a positive statistically significant effect on PUFM

H3b: PHMB has a statistically significant positive effect on ITU

H4: PUFM has a statistically significant positive effect on ITU



Figure 1: Proposed TAM for the intention to use drones for forestry purposes. PEOU - Data = Perceived Ease of Use - Data, PEOU - Handling = Perceived Ease of Use - Handling, ITU = Intention to Use Drones, PHMB = Perceived Health Management Benefits, PUFM = Perceived Usefulness for Forest Management

## **Material and Methods**

### Structure of the Questionnaire

Prior to the start of the survey, the foresters were informed that they were free to stop the survey at any time without any consequences. They were also informed that the results of the survey would be completely anonymous and that no conclusions could be drawn about any individual. By answering the questions, the foresters agreed that their data would be processed anonymously. Between December 2021 and February 2022, the online survey was conducted.

The questionnaire was divided into four parts and was evaluated by practitioners before being sent to forest managers via e-mail notifications from professional forestry associations in Germany. In the first part, foresters were asked to provide socio-demographic and forestry information. In addition, foresters were asked to self-assess their risk attitude (Dohmen et al. 2011) and innovativeness on a 11-point Likert scale by answering the following contextualised questions:

In terms of your behavior in your forest enterprise, are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? (1 – risk averse...11 – risk seeking)

*In terms of your behavior in your forest enterprise, would you consider yourself to be an innovatively-minded person?* (1 – not at all open to innovations...11 – very open to innovations)

In the second part, foresters were asked questions regarding their use of satellite, smartphone and/or tablet for forestry purposes. In the third part of the survey users of drones were asked in which areas they use them and which benefits they see from using them. Non-users were asked in what areas they would use drones and what potential benefits they see. Non-users were also asked what barriers they see to the use of drones. The perceived benefits, barriers and areas of drone use were determined through discussions with experts and literature review (e.g. Berie and Burud 2018; Tang and Shao 2015; Dainelli et al. 2021a, 2021b; Guimarães et al. 2020; Raparelli and Bajocco 2019). In the fourth and final part, foresters were asked to rate 13 statements to assess the proposed TAM (Figure 1) on a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree). The statements were based on Davis (1989) and adapted to the current research context based on the literature (e.g. Dainelli et al. 2021b, 2021a; Guimarães et al. 2020; Raparelli and

Bajocco 2019; Tang and Shao 2015; Berie and Burud 2018) and discussions with experts. A test question, for which the answer to be clicked on was predefined, was implemented in between the statements. Participants who clicked the wrong answer were removed from the survey.

#### Partial Least Squares Structural Equation Modelling

Structural equation modelling (SEM) allows the estimation of cause-effect relationships between independent (exogenous) and dependent (endogenous) latent variables or constructs. The constructs cannot be observed directly, but have to be measured by means of indicators and then estimated. The indicators are the statements rated by the participants in the survey (Sarstedt et al. 2014). There are two approaches to SEM: covariance-based SEM (CB-SEM) and variance-based SEM. CB-SEM minimises the discrepancy between the estimated and sample covariance matrices. In contrast, PLS-SEM is a nonparametric variance-based SEM that maximises the explained variance (R<sup>2</sup>) of the endogenous constructs (Hair et al. 2014; Hair et al. 2011). PLS-SEM is used in this study for the following reasons: PLS-SEM is less restrictive in terms of data structure than CB-SEM, which requires normally distributed data. In addition, PLS-SEM performs better when the sample size is small. Finally, PLS-SEM allows the use of constructs with only one or two indicators (Hair et al. 2014; Hair et al. 2022).

### Results

### **Descriptive Results**

The descriptive statistics for the sample are shown in Table 1.

| Variable    | Description  | Mean   | SD     | Min  | Max     |
|-------------|--|--------|--------|------|---------|
| Socio-demo  | ographic characteristics   |        |        |      |         |
| age         | Participant's age in years <sup>d</sup>  | 48.74  | 12.37  | 22   | 83      |
| edu         | Apprenticeship in forestry <sup>a</sup>  | 0.20   | -      | 0    | 1       |
| gender      | Male participant <sup>a</sup>  | 0.88   | -      | 0    | 1       |
| higheredu   | Technical college/ university degree in forest sciences <sup>a</sup>   | 0.47   | -      | 0    | 1       |
| innov       | Contextualized self-reported innovativeness value (1 to 11) <sup>b</sup>   | 8.07   | 1.78   | 3    | 11      |
| position    | Position of the participant in the forest enterprise   | -      | -      |      |         |
|             | Owner <sup>a</sup>   | 0.37   | -      | 0    | 1       |
|             | Manager <sup>a</sup>   | 0.34   | -      | 0    | 1       |
|             | Civil servant <sup>a</sup>   | 0.15   | -      | 0    | 1       |
|             | Other <sup>a</sup>   | 0.14   | -      | 0    | 1       |
| risk        | Contextualized self-reported risk attitude value   | 5.89   | 2.02   | 1    | 11      |
|             | (1 to 11) °  |        |        |      |         |
| Forest ente | rprise   |        |        |      |         |
| company     | Company organization   |        |        |      |         |
|             | Private forest enterprise <sup>a</sup>   | 0.61   | -      | 0    | 1       |
|             | Federal state-owned enterprise <sup>a</sup>  | 0.13   | -      | 0    | 1       |
|             | Communal forest enterprise <sup>a</sup>  | 0.14   | -      | 0    | 1       |
|             | Other <sup>a</sup>   | 0.12   | -      | 0    | 1       |
| region      | Location of the forest enterprise in Germany<br>West (Schleswig-Holstein, Lower Saxony, North Rhine-Westphalia,<br>Hesse, Rhineland-Palatinate or Saarland) <sup>a</sup> | 0.34   | -      | 0    | 1       |
|             | East (Brandenburg, Saxony, Saxony-Anhalt, Mecklenburg Western Pomerania or Thuringia) ª  | 0.25   | -      | 0    | 1       |
|             | South (Baden-Württemberg or Bavaria) <sup>a</sup>  | 0.41   | -      | 0    | 1       |
| size        | Size of forest area in hectares <sup>d</sup>   | 10,594 | 45,773 | 0.53 | 330,000 |
| drone       | Current user of a drone <sup>a</sup>   | 0.10   | -      | 0    | 1       |
| ex-drone    | Past user of a drone; current non-user <sup>a</sup>  | 0.06   | -      | 0    | 1       |

#### Table 1: Descriptive statistics (N = 215)

SD = Standard deviation

<sup>a</sup> Variable is binary coded [0;1]

<sup>b</sup> Contextualized self-reported innovativeness: values of 1 to 5: not at all open to innovations, value of 6: neutral, values of 7 to 11, very open to innovations

<sup>°</sup>Contextualized self-reported risk attitude based on Dohmen et al. (2011): values of 1 to 5: risk averse, value of 6: neutral, values of 7 to 11: risk-seeking

<sup>d</sup> Continuous variable

The potential areas of drone use and the expected benefits associated with drone use are shown separately for users and non-users in Figures 2 and 3. The results for users and non-users are almost identical in terms of potential areas of drone use (Figure 2). Drones are most frequently used for documenting storm damage, monitoring tree stands to detect infestation and/or predicting pest attacks, which are also the areas where non-users would be likely to employ a drone. Similarly, both drone users and non-users see several benefits related to the use of drones (Figure 3). These include a timelier response to calamities, faster decision support and faster, more accurate data collection. Figure 4 shows the reasons given by non-users for not using drones. The most frequently mentioned reasons are underdeveloped technical equipment and insufficient technical knowledge to effectively use the data provided by drones. Cost is another important barrier to the use of drones. Other reasons given by forest managers in the open response section include insubstantial forest sizes, perceived lack of meaningful benefits in relation to the effort required, potential disturbance of wildlife, lack of resources for adequate training in drone operation, and limited range of drones.



Figure 2: Areas of drone use by user (N=21) and potential areas of drone use by non-user (N=194). Multiple answers possible.



Figure 3: Benefits of drone use of user (N=21) and expected benefits of drone use by non-user (N=194). Multiple answers possible.



Figure 4: Reasons against drone use by non-user (N=194). Multiple answers possible.

### Estimation Results of the Technology Acceptance Model

For the outer model (Table 2) all needed quality criteria are met, indicating that the model has indicator reliability, internal consistency, convergent and discriminant validity (Hair et al., 2022). For discriminant validity, the 95th percentile confidence intervals (Cl<sub>95</sub>) of the heterotrait-monotrait (HTMT) ratios are also calculated. In addition to not exceeding the 0.9 threshold (max. 0.866), discriminant validity is ensured if the Cl95 does not contain a value of 1 (max. 0.994) (Henseler et al., 2015). Finally, none of the variance inflation factors (VIFs) exceed the threshold of 5, indicating that multicollinearity is not an issue for this model (Hair et al., 2022).

| Indicator Indicator Indicator Indicator   Perceived Usefulness for Forest Management (PUFM) 2.788 - - 0.885 0.658   pufm1 = I think drones could provide information that I can 2.386 0.922 1.608 0.795*** | or   |       |       |          |       | AVE   |
|--|--|-------|-------|----------|-------|-------|
| Perceived Usefulness for Forest Management (PUFM)   2.788   -   -   0.885   0.658     pufm1 = I think drones could provide information that I can   2.386   0.922   1.608   0.795***                       |  |       |       |          | 211   |       |
| pufm1 = I think drones could provide information that I can 2.386 0.922 1.608 0.795***   | Usefulness for Forest Management (PUFM) 2.788                | -     | -     | -        | 0.885 | 0.658 |
| · · · · · · · · · · · · · · · · · · ·  | = I think drones could provide information that I can 2.386  | 0.922 | 1.608 | 0.795*** |       |       |
| use to make better decisions in my forestry enterprise   | nake better decisions in my forestry enterprise              |       |       |          |       |       |
| pufm2 = I think that the use of drones will accelerate my 2.740 0.982 1.746 0.817***   | = I think that the use of drones will accelerate my 2.740    | 0.982 | 1.746 | 0.817*** |       |       |
| work by providing more detailed information about the forest   | providing more detailed information about the forest         |       |       |          |       |       |
| stand  |  |       |       |          |       |       |
| pufm3 = By using drones, I can increase productivity in my 2.972 1.056 1.894 0.828***  | = By using drones, I can increase productivity in my 2.972   | 1.056 | 1.894 | 0.828*** |       |       |
| forestry enterprise  | enterprise   |       |       |          |       |       |
| pufm4 = I think the use of drones will allow me to manage 3.056 1.123 1.794 0.804***   | = I think the use of drones will allow me to manage 3.056    | 1.123 | 1.794 | 0.804*** |       |       |
| my forestry enterprise more sustainably  | stry enterprise more sustainably                             |       |       |          |       |       |
| Perceived Ease of Use - Data (PEOU - Data)   3.180   -   -   0.864   0.680   | I Ease of Use - Data (PEOU - Data) 3.180                     | -     | -     | -        | 0.864 | 0.680 |
| peoud1 = I think I am capable of evaluating the data that a 2.949 1.088 1.777 0.838***   | = I think I am capable of evaluating the data that a 2.949   | 1.088 | 1.777 | 0.838*** |       |       |
| drone collects   | ollects  |       |       |          |       |       |
| peoud2 = The data formats in which a drone collects 3.605 1.140 1.574 0.813***   | = The data formats in which a drone collects 3.605           | 1.140 | 1.574 | 0.813*** |       |       |
| information and their evaluation possibilities are familiar to   | tion and their evaluation possibilities are familiar to      |       |       |          |       |       |
| me   |  |       |       |          |       |       |
| peoud3 = The information a drone provides are easy for me 2.986 1.009 1.459 0.822***   | = The information a drone provides are easy for me 2.986     | 1.009 | 1.459 | 0.822*** |       |       |
| to use for my forest enterprise  | or my forest enterprise                                      |       |       |          |       |       |
| Perceived Ease of Use - Handling (PEOU - Handling) 2.700 0.848 0.737   | I Ease of Use - Handling (PEOU - Handling) 2.700             | -     | -     | -        | 0.848 | 0.737 |
| peouh1 = I think the control of drones for forestry purposes 2.563 0.981 1.298 0.817***  | = I think the control of drones for forestry purposes 2.563  | 0.981 | 1.298 | 0.817*** |       |       |
| is easy for me to learn  | for me to learn  |       |       |          |       |       |
| peouh2 = Overall, I find drones to be easy to use 2.837 0.987 1.298 0.897***   | = Overall, I find drones to be easy to use 2.837             | 0.987 | 1.298 | 0.897*** |       |       |
| instruments for forestry operations  | ents for forestry operations                                 |       |       |          |       |       |
| Perceived Health Management Benefits (PHMB) 2.237 0.886 0.795  | I Health Management Benefits (PHMB) 2.237                    | -     | -     | -        | 0.886 | 0.795 |
| peb1 = The use of drone facilitates control of the stocks and 2.093 0.863 1.532 0.903***   | The use of drone facilitates control of the stocks and 2.093 | 0.863 | 1.532 | 0.903*** |       |       |
| enables earlier intervention in the event of damages to  | s earlier intervention in the event of damages to            |       |       |          |       |       |
| protect the stock  | the stock  |       |       |          |       |       |
| peb2 = Using drones, I can better assess the health of the 2.381 0.927 1.532 0.879***  | Using drones, I can better assess the health of the 2.381    | 0.927 | 1.532 | 0.879*** |       |       |
| stock and can take more targeted actions   | nd can take more targeted actions                            |       |       |          |       |       |
| Intention to Use Drones (ITU) 2.798 0.946 0.898  | to Use Drones (ITU) 2.798                                    | -     | -     | -        | 0.946 | 0.898 |
| itu1 = I intend to use drones for forestry purposes 2.884 1.125 2.735 0.949***   | intend to use drones for forestry purposes 2.884             | 1.125 | 2.735 | 0.949*** |       |       |
| itu2 = It is likely that I will use drones in the future for my 2.712 1.162 2.735 0.946***   | is likely that I will use drones in the future for my 2.712  | 1.162 | 2.735 | 0.946*** |       |       |

| Table 2. Fo | stimation | results | of the | outer | model | (N=215) |
|-------------|-----------|---------|--------|-------|-------|---------|

SD = Standard deviation; VIF = Outer variance inflation factor; CR = Composite reliability; AVE = Average variance extracted Cut-off level: Loadings > 0.7; CR > 0.7; AVE > 0.5.

Statements were translated from German into English and evaluated using a 5-point Likert scale (1 = high disagreement; 5 = high agreement).

p < 0.001 (p < 0.01; p < 0.05) is indicated by \*\*\* (\*\*; \*)

Table 3 shows the results for the inner model. The R<sup>2</sup> of the target construct ITU is 42.9%. R2 values above 0.26 are considered substantial by Cohen (1988) and values above 0.33 are considered moderate by Chin (1998). This result indicates that the TAM can account for a large proportion of the latent variables in the decision-making process. Furthermore, all Q<sup>2</sup> values exceed the threshold of 0, which contributes to the robustness of the model. However, the model does not support all the hypotheses. Hypotheses H1b and H2a are not supported, implying that the mere ability to control a drone has no statistically significant effect on a forest manager's intention to use it. Similarly, the perception of health management benefits does not have a statistically significant effect on forest managers' intention to use drones. In contrast, hypothesis H1a (PEOU - Handling  $\rightarrow$  PEOU - Data) is supported as the path coefficient is statistically significant with the expected positive sign. This suggests that if the handling of a drone is perceived to be easy, then the use of the data provided by the drone is also perceived to be easy. This implies that a forest manager who is comfortable with controlling a drone may also be inclined to familiarise himself with the data formats and information provided by the drone, thereby

increasing his perception of the ease of use of the data. Hypotheses H4a (PEOU - data  $\rightarrow$  PUFM), H4b (PEOU - Data  $\rightarrow$  PHMB) and H1c (PEOU - Data  $\rightarrow$  ITU) are also supported by the model, with all path coefficients being statistically significant and having the expected positive sign.

These combined results suggest that understanding and familiarity with data formats are particularly critical for enhancing the perceived usefulness for forest management, perceived health management benefits, and intention to use drones. Furthermore, Hypothesis H3 (PHMB  $\rightarrow$  PUFM) is supported, implying that obtaining information about the health of the forest via drones enhances the perceived usefulness of drones for forest management. Finally, Hypothesis H2b (PUFM  $\rightarrow$  ITU) is supported, suggesting that when drones are perceived as useful for forest management, forest managers are more likely to use them.

| Path coefficient β | p-value   | t-Statistics <sup>b</sup>                              | Support H?  |
|--------------------|---|--|---|
| a 0.613***         | < 0.001   | 12.860   | Yes   |
| b 0.086            | 0.297   | 1.136  | No  |
| lc 0.186*          | 0.016   | 2.296  | Yes   |
| 2a 0.030           | 0.651   | 0.452  | No  |
| 2b 0.473***        | < 0.001   | 7.071  | Yes   |
| 3 0.397***         | < 0.001   | 7.123  | Yes   |
| la 0.463***        | < 0.001   | 9.032  | Yes   |
| lb 0.149*          | 0.049   | 1.968  | Yes   |
|                    | Path coefficient β     1a   0.613***     1b   0.086     1c   0.186*     2a   0.030     2b   0.473***     3   0.397***     4a   0.463***     4b   0.149* | $\begin{array}{c c c c c c c c c c c c c c c c c c c $ | Path coefficient βp-valuet-Statistics b1a $0.613^{***}$ < 0.001 |

| Table 3: | Estimation | results | for the | inner   | model | (N=215)  | а |
|----------|------------|---------|---------|---------|-------|----------|---|
| Table J. | Loundton   | resuits | ior the | IIIIIGI | model | (11-215) |   |

<sup>a</sup> H = Hypothesis, PEOU - Data = Perceived Ease of Use - Data, PEOU - Handling = Perceived Ease of Use - Handling, ITU = Intention to Use Drones, PHMB = Perceived Health Management Benefits, PUFM = Perceived Usefulness for Forest Management <sup>b</sup> Bootstrapping results with 10,000 subsamples.

 $R^{2}(ITU) = 0.429$ ;  $R^{2}(PHMB) = 0.022$ ;  $R^{2}(PUFM) = 0.426$ ;  $R^{2}(PEOU - Data) = 0.376$ ;  $Q^{2}(ITU) = 0.364$ ;  $Q^{2}(PHMB) = 0.007$ ;  $Q^{2}(PUFM) = 0.270$ ;  $Q^{2}(PEOU - Data) = 0.248$ 

p < 0.001 (p < 0.01; p < 0.05) is indicated by \*\*\* (\*\*; \*)

Figure 5 provides an importance-performance map (IPMA) showing the constructs' index scores and their total effect on the target construct, ITU. The index values, which range from 0 (lowest performance) to 100 (highest performance), represent the performance of each construct. The total effects represent the impact of each construct on the prediction of the target construct, ITU. This means that a one-unit increase in the index value will result in an increase in the index value of the target construct by the total effect amount.

The IPMA can help identify areas for improvement. According to the literature (Ringle and Sarstedt, 2016), attention should be focused on constructs that have high importance (as shown on the x-axis) but relatively low performance (as shown on the y-axis). In this case, these are PEOU-data and PUFM. This suggests that efforts to improve the acceptance and use of drones among forest managers could be effectively targeted at these areas. Improvements in PEOU - Data and PUFM could lead to higher intention to use drones among forest managers.



Figure 5: Importance-performance map (IPMA) for the targeted construct Intention to Use Drones (ITU).

### **Discussion and implications**

The detailed examination of the inner model results (Table 3) and the IPMA (Figure 5) highlights that PUFM (Perceived Usefulness for Forest Management) and PEOU (Perceived Ease of Use) - Data are crucial factors for increasing forest managers' intention to use drones. These constructs have the highest total effects on ITU (Intention to Use) and rank highest in performance index values.

Drones vs. Traditional Methods: Drones can improve spatial and temporal data collection, making it more efficient and cost-effective (Raparelli and Bajocco 2019; Tang and Shao 2015). However, forest managers often do not perceive drones as cost-saving tools and cite high costs as a barrier. This gap suggests a need for better communication about the long-term economic benefits of drones.

Perception Gap and Training Needs: Despite recognizing that drones enhance data collection speed and accuracy (Tang and Shao 2015; Berie and Burud 2018), forest managers are uncertain about their decision-making benefits. With a low agreement score on drones' utility for decision-making, there is a clear need for training. Forest managers need education on drone applications, cost and time savings, and decision support. Future research should delve into specific drone applications like forest monitoring to understand barriers, motives, and expectations better.

Technical Knowledge and Equipment: The descriptive findings indicate a gap in technical knowledge and equipment among non-users, aligning with the construct PEOU - Data. Effective drone use requires knowledge in GIS and remote sensing software (Zahawi et al. 2015). Successful adoption necessitates training for forest managers (Dainelli et al. 2021b). Drone providers should clarify necessary equipment and data formats, and regular in-person support could aid in data analysis. Developers should create user-friendly software to support various tasks.

Digitalization and Costs: Research should explore forest managers' familiarity with digital aspects like data formats and security to help developers make user-friendly software. This can reduce perceived costs, including software purchase and time for designing flight routes and data analysis. Although forest managers are familiar with data formats, they need more training to use these formats effectively with drones. Financial support for consultation and training might be beneficial.

Basic Skills and External Services: The construct PEOU - Handling indicates that forest managers need assistance with basic flying skills and drone mechanics, underscoring the importance of ongoing in-person training. Further research should explore forest managers' willingness to pay for drone usage assistance, reflecting their perceived value and commitment to this technology. Exploring the market for service providers offering drone operation and data analysis could also be valuable, catering to managers who see benefits but prefer not to operate drones themselves.

# Conclusion

Drones, with their multiple uses and applications, have the potential to be a valuable tool to support forest managers in their daily work. However, their adoption by German forest managers is currently limited. This study aimed to identify the underlying factors that influence forest managers' intention to use drones. Data were collected from 215 German forest managers between December 2021 and February 2022, and their perceived barriers and motives for using drones were also assessed. Using the TAM framework, a structural equation model based on PLS-SEM was estimated to examine the factors influencing forest managers' intention to use drones. The results revealed that the construct of Perceived Usefulness for Forest Management had the strongest predictive power in determining their intention to use drones. Regarding barriers, the study found that lack of technical knowledge and equipment were the most important obstacles to adopting drones among forest managers. These findings have important implications for a range of stakeholders. Policymakers can gain valuable insights into the current state of drone

adoption and perceptions in forestry, which can inform and improve existing programmes and initiatives. International drone suppliers and associated software developers can use these findings to improve their products and adapt marketing strategies to address forest managers' barriers and concerns related to drone use. Extension services and professionals involved in supporting forest managers can use the results to better understand the barriers that forest managers face and to provide targeted training and education activities to help them effectively integrate drones into their forest management practices. In addition, the study contributes to the scientific literature by extending the application of the TAM framework to the field of precision forestry and by highlighting the importance of Perceived Usefulness for forest management as a key predictor of intention to use drones.

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