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Monitoring costs of result-based payments for biodiversity conservation: Will UAV-based remote sensing be the game-changer?

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Abstract

Paying landowners for conservation results rather than paying for the measures intended to provide such results is a promising approach for biodiversity conservation. However, a key roadblock for the widespread implementation of such result-based payment schemes are the frequent difficulties to monitor target species for whose presence a landowner is supposed to receive a remuneration. Until recently, the only conceivable monitoring approach would be conventional monitoring techniques, by which qualified experts investigate the presence of target species on-site. With the rise of remote sensing technologies, in particular increased capabilities and decreased costs of unmanned aerial vehicles (UAVs), technological monitoring opportunities enter the scene. We analyse the costs of monitoring an ecological target of a hypothetical result-based payments scheme and compare the monitoring cost between conventional monitoring and UAV-assisted monitoring. We identify the underlying cost structure and cost components of both monitoring approaches and use a scenario analysis to identify the influence of factors like UAV and analysis costs, area size, and monitoring frequency. We find that although conventional monitoring is the least-cost monitoring approach today, future cost developments are likely to render UAV-assisted monitoring more cost-effective.

Keywords

biodiversity conservation; flowering resources; grassland; monitoring; costs; precision farming; remote sensing; result-based payments

1 Introduction

In order to conserve biodiversity in Europe and other parts of the world, payments which remunerate landowners for the implementation of specifically defined biodiversity conservation measures have become a key policy instrument (Engel, 2015; Gibbons et al., 2011). Remuneration is often designed as a spatially homogeneous compensation payment to cover the participant's opportunity costs of measure implementation (Markova-Nenova et al., 2022). However, landowners are compensated independently of the successful realisation of a conservation goal, e.g. that a target species remains or becomes present in the area where the conservation measure is applied. Moreover, the predetermination of conservation measures leaves little space for innovation and adaptation on the side of the landowners (Bartkowski et al., 2021; Burton and Schwarz, 2013). The ability of payment schemes to ensure good ecological outcomes – and do so in a cost-effective manner – is thus limited by the measures' ability to ensure those outcomes (Kaligarič et al., 2019; Matzdorf and Lorenz, 2010). Against this background, it is not surprising that the ecological outcome of current payment schemes is often poor (Batáry et al., 2015).

A promising alternative are so-called result-based payment (RBP) schemes[1] (Burton and Schwarz, 2013; Chaplin et al., 2021; Schroeder et al., 2013). In such schemes, landowners are not paid for their opportunity costs of measure implementation. Instead, payments are dependent on whether a specific conservation target is achieved in a particular location – e.g. if one or several predefined target or indicator species are found in the area enrolled in an RBP scheme (Russi et al., 2016). RBP schemes have several advantages. They leave it to the landowner to decide which conservation measures to implement, thus providing the landowner with an incentive for innovation and adaptation (Bartkowsik et al., 2021; Zabel and Roe, 2009). As they directly link ecological outcomes to payments they ensure that conservation targets are actually met (Chaplin et al., 2021). Finally, as only landowners will

[1] Different terms for what we refer to as RBP have been suggested, all referring to the same idea, some of which are "payment-by-results", "results-" or "success-oriented payment", "performance- ", "outcome-" or "output-based payments", and "objective driven payments" (see e.g. Burton and Schwarz, 2013).

participate in a scheme who can provide the desired ecological outcome at low costs, they tend to be cost-effective (Wätzold and Drechsler, 2005).

However, RBP schemes have not been implemented on a large scale, though some programmes exist. Examples of such programmes include the MEKA-4 programme in Germany (Oppermann and Briemle, 2002), the Flowering Meadows programme in France (de Sainte Marie, 2014) and a programme to protect wolverines and lynxes in Sweden (Zabel and Holm-Müller, 2008; see also Herzon et al., 2018 for an overview). One reason for this sluggish adaptation is that landowners have to bear the risk that – despite conservation efforts – a target species cannot be observed on their land (Drechsler, 2017). Probably the largest roadblock for the large-scale implementation of RBP, however, are high monitoring costs, as the presence of target species has to be verified on-site by qualified personnel through a monitoring process (Bartkowski et al., 2021; Burton and Schwartz, 2013; Hasund, 2013).

One emerging potential option to overcome this roadblock may be monitoring using unmanned aerial vehicles (UAVs). UAV-assisted remote sensing approaches have so advanced technologically in recent years that they can potentially be used in biodiversity-related monitoring activities (Librán-Embid et al., 2022). UAVs represent a small-scale alternative to satellite imaging which is successfully used for large-scale mapping of land-use forms and habitats (Petrou et al., 2015; Pietsch et al., 2018), but not (yet) able to monitor species which makes it currently irrelevant for monitoring in the context of RBPs. Importantly in the context discussed here, the costs of applying UAVs for monitoring as well as the costs of data analysis have decreased substantially.

The purpose of this paper is to investigate from the cost-side if UAV-assisted monitoring is about to become a potential alternative to on-site monitoring by qualified personnel (henceforth referred to as conventional monitoring). We start by presenting an overview of the state-of-the-art of UAV-assisted remote-sensing technologies and their likely development in the foreseeable future to provide some technical background for the cost assessments. We then outline a hypothetical case study based on target plant species as a biodiversity indicator in managed grassland. As remote sensing technologies to identify single or multiple species across large areas are not yet available, we have to find an alternative approach. We take the coverage of yellow flowers in grassland as an indicator for a hypothetical key plant species for a biodiversity-rich meadow, and assume that this is the target species to be monitored. We continue by providing cost models for UAV-assisted and conventional monitoring. The identification of monitoring cost components in the cost models allows us to identify the influence of possible changes in certain cost-components and cost parameters on the overall cost of both monitoring approaches. We finally assess the costs for the two monitoring approaches taking into account different sensitivity analyses and cost scenarios.

2 *Background information for UAV-assisted monitoring of biodiversity*

UAVs have evolved from backyard experiments to reliable, autonomous monitoring systems, with a global market size of $26.3 billion revenue in 2021, projected to steadily increase in the coming years (droneii.com, 2021). As a monitoring tool, UAVs are successfully utilized in civil domains such as mining (Shahmoradi et al., 2020), search and rescue (Alotaibi et al., 2019), and e.g. agricultural and environmental research applications (Whitehead et al., 2014). In the field of agriculture, UAVs are predicted to play a pivotal role to acquire necessary spatial crop information for precision farming applications, such as biomass for precision nitrogen application, crop health for precision disease control or classification of individual plants for precision weeding (Candiago et al., 2015; Tsouros et al., 2019).

UAV-assisted remote sensing approaches have thus reached a technological maturity to potentially be utilized in environmental monitoring activities at spatial scales inaccessible for satellite imaging (Librán-Embid et al., 2022). This is indicative of the future potential to monitor selected target species for conservation remotely and hence provide an alternative for labour intensive, on-site conventional monitoring. Moreover, the costs of these technologies, including data analysis, have decreased substantially in the past (Aiimpacts.org, 2017; Appdevelopermagazine.com, 2018. Ultimately, on-site inspections by trained personnel assessing biodiversity indicators may be replaced in the future by less costly, technology-assisted monitoring and potentially automatic data analysis (Latif, 2018; Schwieder et al., 2020). Further facilitation of monitoring processes can be expected from enhanced imaging technology such as improved image resolution and spectral bandwidth, semi-automated image recognition via improved pattern recognition by artificial intelligence, and developments in UAV technology such as increased flight speeds with easier operation.

Especially in relation to satellite imagery and airborne surveys, UAVs have specific advantages. Compared to crewed airborne surveys, which usually cover a much wider area, UAVs can be deployed much more flexibly, exactly when the information is needed and to a much lower price per flight (Whitehead et al., 2014). Compared to satellite images, UAV images can have a much higher spatial resolution, depending on camera properties and flight height. Typical spatial resolutions are in the range of a few mm to some cm, which is not possible from a satellite, making UAV imagery much more suitable for methods requiring high spatial resolution, such as identification of individual plant species (Carrio et al., 2017). Furthermore, UAV's can operate below clouds, significantly increasing the reliability compared to optical satellite images, which are often cloud-covered (Whitcraft et al., 2015).

Analysis of UAV images is often based on Structure from Motion analysis, which is used to create digital orthomosaics with precise geolocation based on overlapping georeferenced images (Jiang et al., 2020). The orthomosaics are then typically analysed using classification methods or more up-to-date and sophisticated methods such as object-based image analysis, machine learning, and deep learning (Whitehead et al., 2014). High-resolution images and deep learning approaches have for example been applied to estimate crop yields from flower phenology information in apple, strawberry and cotton production (Dias et al., 2018; Xu et al., 2018, Chen et al., 2018). Furthermore, deep learning of UAV images can already yield context-based information such as individual plants in more complex grassland environments (Zhang et al., 2020). Accordingly, UAV-assisted biodiversity monitoring at local scales is an emergent research area (see e.g. Reddy, 2021). However, most of the required analysis pipelines are computational intense, prohibiting many real-time applications and adding the costs of high-performance computers. An evaluation of this cost development compared to conventional monitoring is necessary to estimate the potential of UAV-based monitoring of individual species in heterogeneous systems as a future key technology to develop biodiversity-friendly management in agriculture (Librán-Embid et al., 2020).

3 Hypothetical Case Study

3.1 General setting

In order to estimate the costs of conventional monitoring versus UAV-assisted monitoring we consider a hypothetical RBP scheme, which offers participating farmers a remuneration if a certain percentage (of one ha) of their grassland is covered by yellow flowers.

3.1.1 Case study area

Our hypothetical case study is located in the Solling Uplands of Lower Saxony, a marginal to hilly upland area in Central Germany. Regional mean air temperature is 8.2°C, annual precipitation sum is 879 mm (1961–1990). Several study sites are part of the experimental farm of the University of Göttingen (blue-shaded area in Fig. 1), ensuring reasonable estimations with respect to UAV-assisted monitoring operations and ecological expertise in on-site field research in the area (Hütt et al., 2021). Because a main function of expected monitoring costs is the area to be monitored, study sites were aggregated according to three scenarios: a medium-sized base case, and respective smaller and larger areas (Fig. 1).

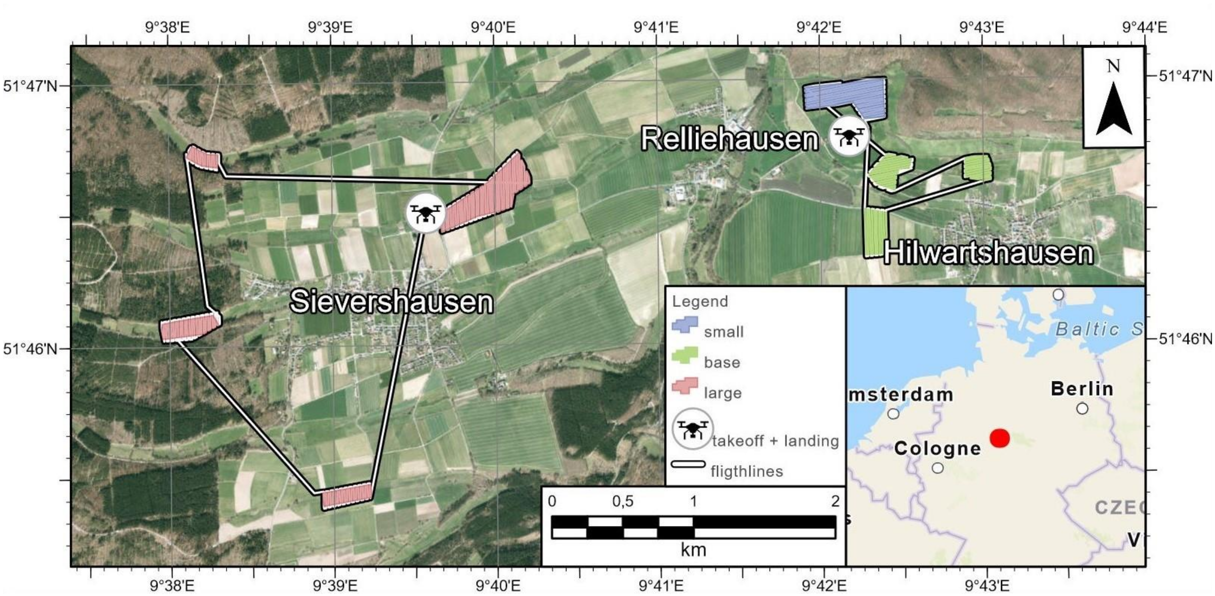

Figure 1: *Study region in the Solling, Lower Saxony, Germany. We calculate monitoring costs for three clusters of areas of different sizes (small area: blue; base case area: combined blue and green; large area: combined blue, green and red).*

3.1.2 Yellow flowering plants as indicator species

As remote sensing techniques to identify single or multiple species across large areas are still in development, we use coverage of yellow flowers (regardless of plant species identity) as proxy for a hypothetical key plant species. Yellow flower colour is identifiable by the current UAV and data processing procedures used in this study (see chapter 3.2.2). Yellow flowers are representative for the study area and can be digitally analysed by current, state-of-the art GIS (Fig. 2; highlighted in magenta colour for easier recognisability).

Although we use yellow flower colour as a proxy for a hypothetical target plant species in this study, flower cover per study area is a meaningful biodiversity indicator in itself. Flowering plant resources are naturally linked to their consumers and these interactions play a crucial role in the functioning of terrestrial ecosystems (Tylianakis et al., 2010; Valiente-Banuet et al., 2015). Accordingly, effects of landscape context and land management on pollinator community structures are mediated by the availability of flower resources (Roulston and Goodell, 2011). In grassland systems such as studied here, cover of selected yellow flower key plant species (ranging between 0 %

and 1.55 % of grassland area) relates significantly to pollinator community structure and functioning (Davidson et al., 2020).

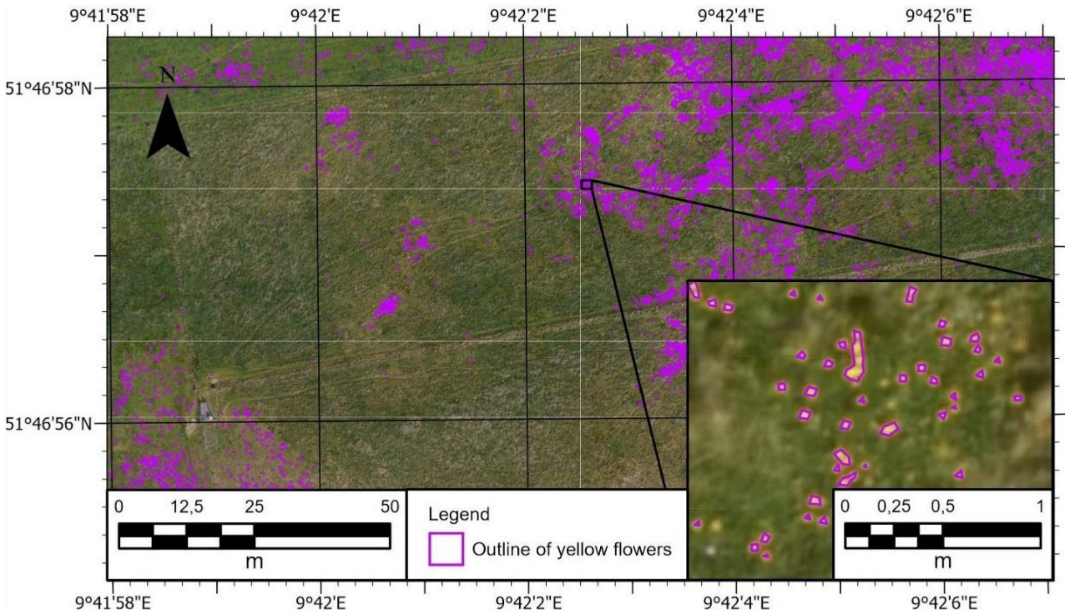

Figure 2: *Example of a Deep Learning Based Flower Detection of a UAV orthophoto in the case study area (small area scenario (blue) in Fig. 1). Yellow flowers are indicated as magenta-coloured dots. The lower right section of the image shows the level of spatial resolution with which flowers are identified. (Adapted from Müller, 2021)*

3.2 Monitoring approaches and scenario development

3.2.1 Conventional monitoring

We assume that for the conventional monitoring approach, qualified personnel has to travel to the monitoring location and has to survey the land in order to determine the presence of the target species (i.e. yellow flowers). Methods for recording floral resources vary substantially (Szigeti et al., 2016). For estimates of flowering plant communities, simple count variables like number or cover of flowers are time-consuming and recording durations vary around one order of magnitude (e.g. 0.12 h per m^2 for sampling quadrats (Kearns and Inouye, 1993) to 0.018 h per m^2 for transects (Hegland et al., 2010)). It is important to note that nearly always subplots are used to estimate floral resources for entire study areas, the median proportion of the study area covered by these subplots being 0.69 % (Szigeti et al., 2016). For identifying single, well recognizable flowering plant species we thus assume a conservative recording time of $0.2\frac{h}{ha}$ which is in the middle of the recording time spectrum. Based on our own experience with on-site monitoring, we assume on-site preparation to take 0.1 hours per ground point (i.e. local land parcel to be monitored), and post-processing 0.25 hours per ground point. Campaign planning is considered to take 0.5 hours for the whole study area per year. This survey is repeated with a certain frequency each year, as predefined by the RBP scheme. Collected data is then post-processed so that it can be used as a decision basis for the RBP.

3.2.2 UAV-assisted monitoring

In the UAV-assisted monitoring approach, qualified personnel brings the UAV to the monitoring location and surveys the area. The flight paths for UAVs in the monitoring region are planned each year in advance of the first monitoring campaign by the UAV operator. Depending on the area to be monitored, connecting flight paths between individually monitored fields including multiple travel stops and starting positions have to be set up (Fig. 2). UAV monitoring is repeated multiple times per year as defined by the RBP scheme. Next, the gathered information (e.g. digital photo footage of the area) is prepared for computer-assisted, automated image post-processing, which results in digital orthophoto mosaics by the UAV-operating technician.

In a GIS environment, automated image analysis can be used to classify individual flowers and then generate results based on flower coverage per area. The coverage is then – analogue to the conventional monitoring approach – used to decide whether an RBP is triggered or not. The precise parameter values used to estimate the monitoring costs for UAV-assisted monitoring are presented in Table 2.

3.2.3 Scenario Development

For our analysis, we define a base case that characterises the monitoring setup and conditions in both monitoring approaches with a medium value parametrisation. The base case consists of a semi-clustered, 3-field conservation area of 20 ha size (green and blue areas in Fig. 1) which can be accessed with two travel stops by conventional monitoring personnel with 4.5 km travel distance and 0.12 hours travel time, and can be approached from one base location for UAV monitoring with no additional on-site travel. A medium monitoring precision for conventional monitoring is assumed of 0.2 hours/ha, and the monitoring campaign is taking place 3 times a year. We assume a travel distance of 10 km to the study region, with a respective travel time of 15 minutes. Based on these considerations, we calculate the costs of the individual cost components annually, and aggregate the discounted annual costs for each monitoring approach over a period of five years. This is necessary to allow a comparison of both costs, as conventional monitoring costs can entirely be calculated on an annual basis, while for UAV-assisted monitoring parts of the costs (i.e. UAV and auxiliary equipment maintenance) arise regularly every five years, while other costs arise annually. We use real values (without inflation) for our cost calculations. We assume an increase of real labour costs by 1.1% per year, based on the average increases of real wages for employees of public administrations in Germany since 2015 (Destatis, 2021b). We consider a constant real discount rate of 3% (Umweltbundesamt, 2012; van der Pol et al., 2021) to allow net present value calculation of all cost components.[2]

To reflect possible variations and uncertainties in monitoring characteristics and RBP related aspects, we developed different scenarios. Each scenario is based on variations of specific, interrelated parameters relative to the base case. The scenarios consider four different factors, which influence costs directly related to monitoring activities each with a low and high value variant, resulting in eight individual scenarios and two combined scenarios. Parameters related to each scenario (Tab. 1) are varied simultaneously to their respective low and high values in each scenario, while all other parameters remain unchanged. The following four factors are considered:

[2] Economists apply discounting in order to make costs that occur in different years as well as benefits comparable. To discount a certain cost value from any year X to the base-year 0, the nominal costs from year X are multiplied by the discount factor 1/(1+r)^X, where r is the discount rate. For details on discounting, see Boardman (2017). In our cost assessment, discounting allows the present value of UAV-assisted monitoring, for which some expenses (e.g. new UAVs) occur only every once (we assume every five years), while expenses for all other cost components arise on an annual basis.

UAV costs reduction. Of particular interest in the context of UAV-assisted monitoring is the expectable decrease of costs for equipment for UAV technology. In addition, the deployment of LiDAR based UAV technology – in particular RGB in combination with LiDAR – can heavily reduce the amount of computation time required for post-processing and analysis. At the same time an increase in quality and resolution of generated outputs is reached. Hence, more precise monitoring results are possible at lower computation costs per monitored hectare of conservation area. We thus analyse the costs of UAV-assisted monitoring with UAV and equipment costs to be assumed lower than in the base case. A *high UAV costs reduction scenario* assumes UAV and equipment costs to be 0.33 times the base case values, while the *moderate UAV costs reduction scenario* assumes costs to be 0.66 times the base case values.

Analysis costs reduction. Future improvements in technology may also occur in post-processing and analysis of UAV-assisted monitoring. Software-side innovations, combined with automation of workflows, may reduce the human workload and computation times for post-processing and analysis and hence reduce costs for UAV-assisted monitoring. We thus assume, similar to the scenarios for UAV equipment costs, a *high analysis costs reduction scenario* with 0.33 times the base case analysis costs, as well as *moderate analysis costs reduction scenario* with 0.66 times the base case costs.

Area. With respect to conservation area, we consider a *small area scenario* with only one grassland parcel (blue in Fig. 1). In the *small area scenario*, only one travel stop for conventional monitoring and one travel stop for UAV-assisted monitoring is necessary. For the *large area scenario*, eight areas (blue, green and red in Fig. 1) participate, which necessitates four travel stops for conventional monitoring, as the grassland parcels are spatially more distributed. It also requires two starting positions for UAV-assisted monitoring (compare Fig. 3). Consequentially, associated aspects like travel costs and time, and monitoring duration vary.

Frequency. Regarding the monitoring frequency, in the *low frequency scenario* we assume one monitoring campaign per year. The *high frequency scenario* assumes five monitoring campaigns per year.

Travel distance. For travel distance, we consider two different distance scenarios (short, long) and the resulting travel times to the case study area. The short travel distance scenario assumes a travel distance of 5 km for the monitoring personnel to the study area, with a resulting travel time of 10 minutes. The long travel distance scenario assumes a travel distance of 20 km and 25 minutes. We assume 5 minutes of travel preparation plus 1 minute per kilometre.

Precision. The low monitoring precision scenario assumes a low precision for the estimation of flower coverage in the conventional monitoring alternative, resulting in monitoring durations of 0.1 hour per ha, while the high monitoring precision scenario assumes a monitoring duration of 0.4 hours per ha.

Labour costs. We assume labour costs to increase over time. Hence, we calculate a low labour cost scenario with a 0.6% increase of labour costs per year and a high labour cost scenario with a 1.6% annual increase.

Discount rate. We assume a low discount rate scenario with 1% discount rate, and a high discount rate scenario with 5% discount rate. Discount rates remain unchanged for over the complete study period of 20 years.

Table 1: *Overview about parameters in the different scenarios. For each scenario, the respective parameters are changed accordingly, while all other parameters remain unchanged.*

Scenarios		**low**	**base case**	**high**
Travel distance	**Parameter**			
travel distance to case study areas (km)	$e_{off-site}$	5	10	20
travel time (minutes)	$t_{off-site}$	10	15	25
Area				
size of grassland area to be monitored (ha)	a	10	20	40
resulting in x ground points for UAV monitoring	n_{GP}^{UAV}	1	1	2
resulting in x hours for UAV monitoring	t_{mon}^{UAV}	1	2.5	3.5
travel time on-site UAV (hours)	$t_{on-site}^{UAV}$	0	0	0.13
travel distance on-site UAV (km)	$e_{on-site}^{UAV}$	0	0	6.1
resulting in x ground points for GT	n_{GP}^{CM}	1	4	8
travel time on-site GT (hours)	$t_{on-site}^{CM}$	0	0.12	0.58
travel distance on-site GT (km)	$e_{on-site}^{CM}$	0	4.5	18
Precision (*conventional monitoring only*)				
monitoring hours (per ha)	t_{mon}^{CM}	0.1	0.2	0.4
Frequency				
monitoring frequency per year	$freq$	1	3	5
UAV costs reduction				
UAV cost multiplier	m_{UAV}	0.33	1	
Analysis costs reduction				
analysis cost multiplier	m_A	0.33	1	
Labour costs				
labour cost (cost progression per year)	r_L	0.6%	1.1%	1.6%
Discount rate				
discount rate	r	1%	3%	5%
Strong technological progress				
UAV cost multiplier	m_{UAV}	0.33	1	
analysis cost multiplier	m_A	0.33	1	
High monitoring demand [a]				
size of grassland area to be monitored (ha)	a		20	40
monitoring frequency per year	$freq$		3	5

[a] Besides the size of grassland area to be monitored, also other area-related parameters from the *large area scenario* change in the *high monitoring demand scenario* accordingly.

Finally, we investigate the costs of two combined scenarios with each combined scenarios consisting of two related individual scenarios. This is motivated by our interest in future opportunities in addition to present costs. We consider these scenarios as under future technological conditions or with a substantial implementation of UAV-assisted monitoring in the future the corresponding costs may be affected in a combined and thus stronger way than captured with the scenarios described above.

Strong technological progress. Substantial technological progress may occur on a more general basis and thus lead to a strong decrease in costs for both UAVs and analysis. This scenario thus combines the *high UAV costs reduction* and *high analysis costs reduction scenarios* in the sense that we assume both the UAV cost multiplier and the analysis cost multiplier to be 0.33.

High monitoring demand. In addition to our case study, RBP schemes may be implemented broadly resulting in a high demand for related monitoring activities and the possibility to use the monitoring equipment widely. In order to capture such a situation, we combine the *high area* and *high frequency scenarios* by assuming the monitoring of 40 ha five times per year.

4 Cost models

In this section, we describe our assumptions regarding the cost structure of the two monitoring alternatives and explain how we calculate the costs. We divide the costs of both monitoring approaches into four cost components; labour costs, data post-processing and analysis costs, travel costs and equipment costs. Each cost component depends on monitoring specific characteristics. Based on these cost components, we first estimate the costs for each of the two monitoring approaches for each monitoring campaign, and then the annual costs of monitoring. Based on the annual costs we calculate the discounted sum of all cost components over a period of five years, to capture different temporal characteristics of the cost structure for both monitoring approaches. In the following, we provide a detailed description of the individual cost components. For an overview of the individual cost parameters, see Table 2.

4.1 Conventional monitoring

We start calculating the annual costs of conventional monitoring by assuming the total costs $C^{GT}(t)$ to be the sum of labour costs ($C_L^{CM}(t)$), analysis costs ($C_A^{CM}(t)$), travel costs ($C_T^{CM}(t)$), and campaign planning costs ($C_{plan}^{CM}(t)$); hence

$$C^{CM}(t) = (C_L^{CM}(t) + C_A^{CM}(t) + C_T^{CM}(t)) * freq + C_{plan}^{CM}(t). \tag{1}$$

The labour costs of monitoring activities are calculated as

$$C_L^{CM}(t) = w^{CM}(t) * (t_{prep}^{CM} * n_{GP}^{CM} + t_{mon}^{CM} * a) \tag{2}$$

with $w^{CM}(t)$ being the hourly wage for conventional monitoring personnel in year t, t_{prep}^{TM} the time necessary for preparation for each ground point (i.e. separate field) to be monitored, n_{GP}^{CM} the number of ground points, t_{mon}^{CM} the time necessary to monitor one hectare and a the area in hectares. We assume an hourly wage $w^{CM}(0) = 42.87€$ for trained monitoring personnel (with a Master degree) to perform conventional monitoring operations. Hourly wages were calculated by dividing the annual gross labour costs (70,933 €; Niedersächsisches Ministerialblatt, 2019) by the number of effective work days per year (210)[3] and by the daily work hours in the German federal state of Lower-Saxony (7.8h; TV-L, 2019; i.e. 70933€ / (210 * 7.96h) = 43.30 €/h). For the case study area, we assume a single person to be able to conduct conventional monitoring on the three different possible area sizes. Preparation per ground point t_{prep}^{CM} is assumed to take 0.1 hours (*based on own experience in field work*), while n_{GP}^{CM}, t_{mon}^{CM} and a are defined by the selected scenario (Table 1).

The time necessary to monitor a hectare of grassland by conventional monitoring (t_{ha}^{CM}) is calculated as

$$t_{ha}^{CM} = s_{mon}^{CM} * 10{,}000 \frac{m^2}{ha} * \rho_{sp}. \tag{3}$$

[3] We estimated 250 workdays per year, reduced by 30 vacation days and 10 sick days (Niedersächsisches Ministerium für Inneres und Sport (2021), Statista (2021)).

To calculate the base case parameter value of $t_{ha}^{CM} = 0.2 \frac{\text{hours}}{\text{ha}}$, we assume $s_{mon}^{CM} = 0.01 \frac{h}{m^2}$ according to the lower end estimation of Kearns and Inouye (1993) and Hegland et al. (2010), and the proportion of area covered by sampling subplots $\rho_{sp} = 0.002$ (Szigeti et al., 2016).

Analysis costs are calculated as

$$C_A^{CM}(t) = w^{CM}(t) * t_{ana}^{CM} * n_{GP}^{CM} \tag{4}$$

with $t_{ana}^{CM} = 0.25\ h$ the time it takes to post-process and analyse collected data per ground point and n_{GP}^{CM} the number of ground points.

Travel costs are calculated as

$$C_T^{CM}(t) = f * \left(e_{off-site} + e_{on-site}^{CM}\right) + w^{CM}(t) * (t_{off-site} + t_{on-site}^{CM}) \tag{5}$$

with f the travel costs per km (assumed to be travelled by car), $e_{off-site}$ and $e_{on-site}^{CM}$ the distance to be travelled to the monitoring location and at the monitoring location. Travel at the monitoring site can be necessary due to the scattered location of individual areas to be monitored (see Figure 1). $t_{off-site}$ and $t_{on-site}^{CM}$ are the corresponding travel time to and within the monitoring location. We assume $f = 0.3 \frac{€}{km}$ (Niedersächsische Reisekostenverordnung, 2017). On-site travel distance $e_{on-site}^{CM}$ and time $t_{on-site}^{CM}$ are monitoring type and scenario-specific, while off-site travel $e_{off-site}$ and time $t_{off-site}$ is equal for both monitoring modes but also scenario-specific.

The aforementioned cost components (Eqs. (1) to (5)) arise for every monitoring campaign which are repeated multiple times per year ($freq$), depending on the selected scenario. Every year, one-off costs for campaign planning ($C_{plan}^{CM}(t) = t_{plan}^{CM} * w^{CM}(t)$) arise ($t_{plan}^{CM} = 1h$ *based on own planning experience*). For conventional monitoring, we assume no specific costs for equipment, as inexpensive, standard, low-tech equipment is utilised (i.e. regular office supplies for sub-plot establishment and documentation in the field). For an overview of fixed cost components and scenario-specific parameters, see Tables 1 and 2.

Table 2: *Overview about the monitoring cost parameters for conventional monitoring and UAV-assisted monitoring.*

General parameters		
f	travel costs per km	$0.3\,\frac{€}{km}$
Conventional monitoring parameters		
t_{ha}^{CM}	time necessary to monitor a hectare of grassland by conventional monitoring	$0.2\,\frac{\mathrm{h}}{\mathrm{ha}}$
s_{mon}^{CM}	time to monitor a m^2 (our cost calculations use the per ha monitoring time t_{ha}^{GT}, which assumes that sampling quadrats on a fraction each ha ($\rho_{sp} = 0.002$) is monitored with this precision)	$0.01\,\frac{h}{m^2}$
ρ_{sp}	proportion of area covered by sampling subplots	0.002
$w^{CM}(t)$	hourly wage for conventional monitoring personnel in year t	43.30 €/h
t_{prep}^{CM}	preparation time per ground point	$0.1\,h$
t_{ana}^{CM}	Post-processing and analysis time per ground point	$0.25\,h$
t_{plan}^{CM}	time for annual campaign planning	$0.5\,h$
UAV-assisted monitoring parameters		
$w^{UAV}(t)$	hourly wage of a trained technician able to operate the UAV in year t	40.24€
t_{prep}^{UAV}	preparation time per UAV ground point	$0.5\,\frac{\mathrm{h}}{\mathrm{ground\ point}}$
t_{A}^{UAV}	time necessary for a technician to prepare data for post-processing and analysis measured per hectare	$0.1\,\frac{h}{ha}$
t_{comp}^{UAV}	time it takes for computer assisted data post-processing and image analysis measured per hectare	$1.1\,\frac{h}{ha}$
w^{comp}	computation costs per hour	1.93 €
b	battery costs per UAV operating hour	$1.92\,\frac{€}{h}$
$U(t)$	purchasing costs for UAV equipment (every 5 years)	6,328 €
$A(t)$	purchasing costs for auxiliary equipment (every 5 years)	2,000 €
$Maint(t)$	maintaining costs for UAVs (annually)	129 €
$Bat(t)$	replacement batteries (twice every year)	189 € *per battery*
t_{plan}^{UAV}	annual time for campaign planning	$1h$

4.2 UAV-assisted monitoring

Necessary time and resources for UAV-assisted monitoring are estimated based on our own experience of similar monitoring campaigns. We assume the following underlying annual cost relations which – similar to our assumption for the costs of conventional monitoring in Eq. (1) – consist of four different cost components:

$$C^{UAV}(t) = \left(C_L^{UAV}(t) + C_A^{UAV}(t) + C_T^{UAV}(t) + \ C_B^{UAV}\right) * freq + C_{Invest}^{UAV}(t) + C_{plan}^{UAV}(t) \tag{6}$$

with $C_L^{UAV}(t)$ the labour costs of UAV monitoring, $C_A^{UAV}(t)$ the post-processing and analysis costs, $C_T^{UAV}(t)$ the travel costs, and C_B^{UAV} battery charging costs. Each cost component however is defined differently compared to the corresponding components in conventional monitoring. Monitoring operations are repeated multiple times annually ($freq$). Expenses for UAVs and auxiliary equipment ($C_{Invest}^{UAV}(t)$) only arise every five years (representing the life time of that type of equipment), hence this category is dependent on time t, rendering the total $C^{UAV}(t)$ also time dependent.

Labour costs of UAV-assisted monitoring ($C_L^{UAV}(t)$) are defined as follows:

$$C_L^{UAV}(tT = w^{UAV}(t) * \left(t_{prep}^{UAV} * n_{GP}^{UAV} + t_{mon}^{UAV}\right) \tag{7}$$

with $w^{UAV}(t)$ being the hourly wage of a trained technician able to operate the UAV in the field in year t, t_{prep}^{UAV} the preparation time per UAV ground point, n_{GP}^{UAV} the number of UAV ground points, and t_{mon}^{UAV} the monitoring time. We assume $w^{UAV}(0)$ to be $\frac{65918\,€}{210 * 7.8\,h} = 40.24\,€$ (Niedersächsisches Ministerialblatt, 2019; TV-L, 2019), and $t_{prep}^{UAV} = 0.5$ hours per ground point (*based on own experience*), while n_{GP}^{UAV} and t_{mon}^{UAV} are scenario-specific (Table 1).

Post-processing and analysis costs are assumed to be as follows:

$$C_A^{UAV}(t) = (w^{UAV}(t) * t_A^{UAV} + w^{comp} * t_{comp}^{UAV} * m_A) * a \tag{8}$$

with t_A^{UAV} the time necessary for a technician to prepare data for post-processing and analysis measured per hectare, t_{comp}^{UAV} the time it takes for computer assisted data post-processing and image analysis measured per hectare, w^{comp} the hourly costs of computation, m_A the analysis cost multiplier we apply in the scenario analysis, and a the area size in hectares. We assume $t_A^{UAV} = 0.1\frac{h}{ha}$, $t_{comp}^{UAV} = 1.1\frac{h}{ha}$ with $0.1\frac{h}{ha}$ for post-processing and data preparation and $1\frac{h}{ha}$ for analysis (*based on own data processing experience*). Computation costs per hour w^{comp} are assumed to be 1.93 € (hourly rate for an AWS on-demand, g3.4xlarge MS Windows server, located in Germany; AWS, 2019). The analysis costs multiplier m_A and area size a are scenario-specific.

Travel costs are defined as

$$C_T^{UAV}(t) = f * \left(e_{off-site} + e_{on-site}^{UAV}\right) + w^{UAV}(t) * (t_{off-site} + t_{on-site}^{UAV}) \tag{9}$$

with – similar to the corresponding conventional monitoring cost component – $e_{on-site}^{UAV}$ being the distance travelled between ground points on-site, and $t_{on-site}^{UAV}$ time for traveling $e_{on-site}^{UAV}$. Both values are scenario-specific.

We assume battery-charging costs to be as follows:

$$C_B^{UAV} = b * t_{mon}^{UAV} \tag{10}$$

with b the costs of charging the UAV batteries per operating hour. Each battery with the capacity of 0.1 kWh has to be charged at $0.15 \frac{€}{kWh}$ (corresponds roughly to electricity costs for firms; Destatis, 2021a), and needs two charging cycles per hour of flight (DJI.com, 2021). Hence, battery costs per hour of UAV operation equal $b = 0.1kWh * 0.15 \frac{€}{kWh} * 2 = 0.03 \frac{€}{h}$.

To calculate the costs of UAV and auxiliary equipment purchases, we assume that the average lifetime of a UAV (DJI Phantom 4 RTK) and its auxiliary equipment is 1,000 operating hours, and that every year, a UAV is used for an average of 200 operating hours for monitoring operations in various monitoring projects. Hence, the lifetime of a UAV is expected to be five years, after which a new UAV and auxiliary equipment has to be purchased. Additionally, regular replacement batteries have to be purchased. Expecting 100 operating hours per battery, one replacement battery has to be purchased every year. Hence, we calculate investment costs for equipment as

$$C_{Invest}^{UAV}(t) = \left(U(t) + A(t) + Maint(t) + Bat(t)\right) * m_{UAV} \tag{11}$$

with $U(t)$ being the UAV purchasing costs of 6,328 € for a DJI Phantom 4 RTK (DJI.com, 2021), and $A(t)$ the auxiliary equipment costs of 2,000€. Every 200 operating hours, the UAV needs professional maintenance, $Maint(t)$, with annual maintenance costs of 129 € (Der-schweighofer.de, 2021). The costs for replacement batteries $Bat(t)$ are 189 € for each replacement battery, necessary twice a year. The UAV cost multiplier m_{UAV} is a scenario specific parameter to be assumed 1 in the base case.

Similar to conventional monitoring, the aforementioned cost components (Eqs. (6) to (11)) arise for every monitoring campaign ($C_L^{UAV}(t)$, $C_A^{UAV}(t)$, $C_T^{UAV}(t)$, and C_B^{UAV}) which are repeated multiple times a year ($freq$), or arise periodically once every five years (C_{Invest}^{UAV}), depending on the selected scenario. Additional to these repeated costs components, one-off costs for campaign planning of one hour for a technician is assumed per year ($C_{plan}^{UAV}(t) = t_{plan}^{UAV} * w^{UAV}(t)$; with $t_{plan}^{UAV} = 1h$ *based on own campaign planning experience*).

4.3 Cost comparison

For the cost comparison, we have to consider that we have identical annual costs for conventional monitoring but high initial investment costs for UAV-assisted monitoring and lower costs in the following years. For UAV-assisted monitoring, equipment (i.e. UAVs and auxiliary equipment) is replaced once every 5 years, while all other expenses can be easily calculated on an annual basis (Eq. 10). In order to compare these different cost streams, we discount all individual annual expenses (i.e. components in Eqs. (1) and (6)) to calculate their net present values (cp. Schöttker and Wätzold, 2018), and sum up all net present values over a 5-year period for each approach.

This aggregation allows us to generate a common basis for a cost comparison – regardless of actual time of occurrence – and include the full life cycle of all different cost components which average out potential spikes of expenses in individual years (e.g. due to necessary and expensive equipment purchase) over time. Hence, the summed-up costs for UAV-assisted monitoring are calculated as

$$C_{5-year}^{UAV} = \sum_{t=t_{start}}^{t_{start}+5} C^{UAV}(t) * (1+r)^{-t} \tag{12}$$

with t being the respective year, t_{start} the first year of the 5-year period, and $C^{UAV}(t)$ the total annual expenses of UAV-assisted monitoring in year t (Eq. 6), and r the real discount rate. Similarly, the cumulated expenses for conventional monitoring for the 5-year period are calculated as

$$C_{5-year}^{CM} = \sum_{t=t_{start}}^{t_{start}+5} C^{CM}(t) * (1+r)^{-t} \tag{13}$$

with $C^{CM}(t)$ the total annual expenses of conventional monitoring (Eq. 1).

5 *Results*

5.1 Base Case

Under base case parametrisation and hence under current technological conditions we found that UAV-assisted monitoring causes discounted costs of 4,477.99 € over a period of 5 years, and thus is 501.28 € more expensive across this period than conventional monitoring, which causes costs of 3,976.72 € (see Tab. 3). The two monitoring approaches differ substantially in the distribution of costs between the underlying cost components. With conventional monitoring 69.3% of the costs arise for the monitoring activities themselves and are caused mainly by labour costs during that time. In contrast, with UAV-assisted monitoring, the monitoring activities themselves are less expensive and only cause 39.0% of the total costs over the five-year period. However, for UAV-assisted monitoring additional costs arise for computationally intensive and thus costly data post-processing and analysis (39.4%), while data post-processing and analysis is less labour and computationally intensive for conventional monitoring and thus only causes 15.7% of costs. Surprisingly, within UAV-assisted monitoring the costs for UAV's and necessary equipment, which only needs to be purchased once in the first year of the five-year period (i.e. the 'investment' category) were found to be rather small in size (8.9% of UAV-monitoring costs). Other cost categories (travel costs, campaign planning, and equipment) were found to be comparable in size and overall less important in terms of costs contributions.

Table 3: *Overview of aggregated and discounted real costs and their relative proportions in conventional and UAV-assisted monitoring. Difference refers to costs of UAV-assisted monitoring minus costs for conventional monitoring.*

Cost category	**Conventional monitoring**		**UAV-assisted monitoring**		**Difference**
	real	**%**	**real**	**%**	
Travel	492.12 €	12.4%	375.78 €	8.4%	-116.34 €
Monitoring	2,754.29 €	69.3%	1,745.21 €	39.0%	-1,009.08 €
Analysis	625.98 €	15.7%	1,764.34 €	39.4%	1,138.36 €
Planning	104.33 €	2.6%	193.91 €	4.3%	89.58 €
Equipment	- €	0.0%	1.06 €	0.0%	1.06 €
Investment	- €	0.0%	397.69 €	8.9%	397.69 €
Total	**3,976.72 €**	**100.0%**	**4,477.99 €**	**100.0%**	**501.28 €**

5.2 Scenario Analysis

To analyse the influence of changes in certain parameters on the costs of the two monitoring approaches and the different cost components, we calculated eight different scenarios. We find that variations in the corresponding parameters show only minor changes in the results, compared to the base case parametrisation and do not change the ranking order of the two monitoring approaches in terms of costs, leaving conventional monitoring the least cost alternative overall. For an overview of the individual scenario results, we refer the reader to Section A in the Appendix.

This is, however, different for the two combined scenarios where the ranking order of the two monitoring approaches in terms of costs is changed. For the *strong technological progress scenario*, we find that a combined reduction of technology related costs to 33% caused costs for UAV-assisted monitoring to decrease below the costs of conventional monitoring (Fig. 3). In this scenario, UAV-assisted monitoring did cause costs of 3,808.96 € compared to 3,976.72 € for conventional monitoring which equals a cost advantage for UAV-assisted monitoring for 167.75€. For an overview about the monetary values, see Tab. B1 in Appendix B.

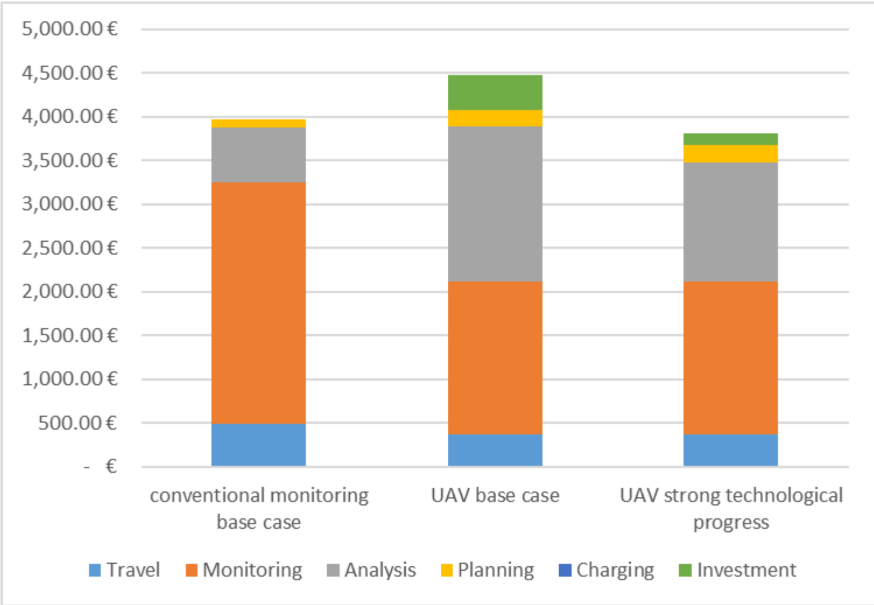

Figure 3: *Overview of the different cost components in base case parametrisation for conventional monitoring (a), UAV-assisted monitoring (b) and the strong technological progress scenario (c).*

We also find that in the *high monitoring demand scenario* the ranking of the monitoring approaches changes compared to the base case parametrisation, rendering UAV-assisted monitoring with 12,163.99 € less costly by 603.53 € compared to conventional monitoring with 12,767.53 € (Fig. 4). Under base case conditions, conventional monitoring was found to be 501.28 € less costly than UAV-assisted monitoring. For an overview about the monetary values, see Tab. B2 Appendix B.

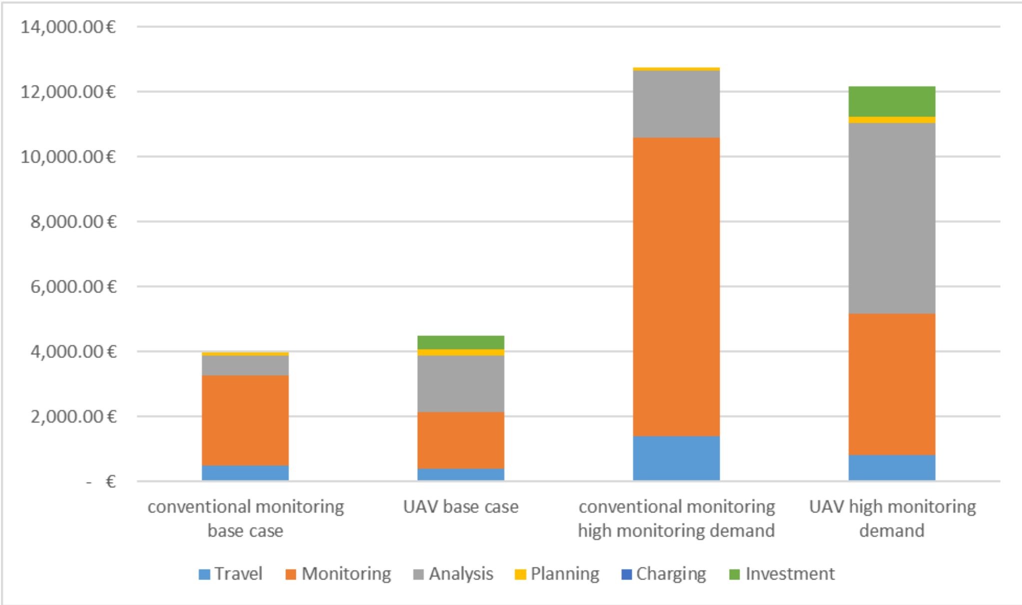

Figure 4: *Overview of the different cost components in (a) the base case parametrisation for (b) the high monitoring demand scenario, each for both monitoring approaches.*

6 Discussion and Conclusion

The objective of this work was to investigate from the cost perspective if UAV-assisted monitoring is about to become a potential alternative to conventional monitoring in the context of result-based payment schemes. We compared the cost structure and possible cost development (taking into account future technological development for UAV and analysis equipment as well as increases in monitoring demand) of the two monitoring approaches in the context of a hypothetical result-based payment scheme that used flowering resources as an indicator for on-site biodiversity.

We found that under current technological and economic conditions, conventional monitoring is the least-cost approach for monitoring activities. Eight scenarios, in which we separately varied individual factors (UAV equipment costs, analysis-equipment costs, area, frequency, travel distance, monitoring precision, labour costs, and discount rate) that influenced the considered cost components, showed no impact on the ranking order of the two monitoring approaches with respect to costs. However, our results indicate that in a setting of strong technological progress in terms of UAV costs and analysis costs at the same time, and a generally high monitoring demand the ranking order of the two monitoring approaches changes, rendering UAV-assisted monitoring the least-costly monitoring approach.

Generally, we identified labour costs as the overall main driver for monitoring costs in either approach. Costs for data collection and analysis for UAV-assisted monitoring slightly exceed respective costs for conventional monitoring, while the opposite is true for travel costs. Surprisingly, UAV monitoring equipment costs alone did not prove to be a main cost driver. However, as UAV-assisted monitoring necessitates complex data post-processing, overall costs for equipment, post-processing and analysis turned out to be higher for UAV-assisted monitoring than for conventional monitoring, and consequentially rendered it less cost-effective under current conditions.

Adopting a general perspective, our results indicate that from a cost perspective UAV-assisted monitoring is not yet an alternative to conventional monitoring for result-based payment schemes. However we can show that likely cost reductions for UAVs, auxiliary equipment and analysis technology are able to change that and render UAV-assisted monitoring the least costly approach in the future. In our analysis, we neglected several factors that increase the likelihood of such a scenario. For example, we ignored that due to technological progress –additionally to decreasing operating and equipment costs – the operating range of UAVs, monitoring speed and precision might increase (Maddikunta et al., 2021). In the same sense, we neglected the potential use of multiple or autonomous UAVs at the same time (Ju and Son, 2018) – a potential technique to monitor larger areas or larger clusters of smaller sites. Such an approach would also reduce labour costs on a per hectare basis, while keeping the equipment costs (per hectare) unchanged and thus reduce costs for UAV-assisted monitoring.

Moreover, future autonomous UAVs might be able to not only collect data for regulatory monitoring purposes as sketched in our analysis, but might beyond that collect business related data for famers and landowners such as grazing area conditions (Borra-Serrano et al., 2019) or crop growth (Bendig et al., 2013). The corresponding likely increase in UAV technology dissemination among landowners (for business purposes) would then enable administrations to utilise existing technology of the landowner, as monitoring activities might already be covered by the usual business use of UAVs on the landowners site and no additional monitoring campaigns for result-based payments need to be issued.

Considering the application range of UAV-assisted monitoring, future technological development for monitoring and analysis (higher image resolution, multi-spectral imaging, deep learning) might as well enable the remote detection of indicators other than flowering resources (Banerjee et al., 2020; Basavegowda et al., 2022). The progression in and utilisation of advanced pattern recognition algorithms and deep learning for the analysis of image data might enable monitoring that goes far beyond the detection of flowery resources as analysed in this study (Christin et al., 2019). One can conceive the identification of more complex patterns in the monitored flora and the consequential identification of corresponding habitats or ecological conditions, or the recognition of e.g. bird's nests through specific patterns within collected image data. Extending data collection towards the collection of thermal imagery could e.g. allow for monitoring of certain animal species, including detection, localisation and behavioural analysis within monitored habitats (Gonzales et al., 2016). Utilising other sensory information such as audio data could extend the range of detectable animal species further e.g. by allowing to differentiate between and to localise endangered bird species (Wilson et al., 2017). In such situations, the application of UAV-assisted monitoring would remain a relatively low-cost approach, while monitoring different indicators via conventional monitoring likely remains more time and labour intensive and thus more costly. This increased pool of data sources might allow a broader application of such novel monitoring approaches and enable the transfer from the specific conservation project perspective supposed in this work to a landscape scale perspective.

Our research has focused on one opportunity to use technological progress – here in the field of UAVs and data processing – to improve a policy instrument to conserve biodiversity. We see many areas where technological progress in different fields has potentially a large impact to enhance biodiversity conservation in different ways. Examples include further opportunities of UAV-based remote sensing to identify conservation opportunities and monitor biodiversity change (Librán-Embid et al., 2022; Petrou et al., 2015), the potentially positive impact of precision farming on biodiversity due to less pesticide use (Finger et al., 2019), and the use of software-based decision support for the design of biodiversity conservation instruments (Sturm et al., 2018). In order to halt the decline of biodiversity in an effective and cost-effective way, we think that much more research is needed to explore these opportunities.

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Appendix

A. Original scenarios

A.1 UAV and equipment costs

In this scenario, we assumed lower costs for the purchase and maintenance of UAV and auxiliary equipment that is the UAV and auxiliary components, batteries, and professional annual maintenance service, reflected in the 'investment' cost component. In the *high UAV cost reduction scenario* we assumed that only 33% of the base case costs arise in this category, while in the *moderate UAV-cost reduction scenario* we assume 66% of base costs (see Tab. 1 in the main text).

We found, that in the *high UAV cost reduction scenario* the costs for UAV-assisted monitoring were reduced by 266.45 € compared to the base case but still surpassed the costs for conventional monitoring by 234.83 € (Fig. A1). In the *moderate UAV cost reduction scenario* the reductions in costs were even lower at 135.21 € compared to the base case. Hence, under current technological conditions and even with high reductions in costs for UAV-assisted monitoring equipment, conventional monitoring is still the superior monitoring approach.

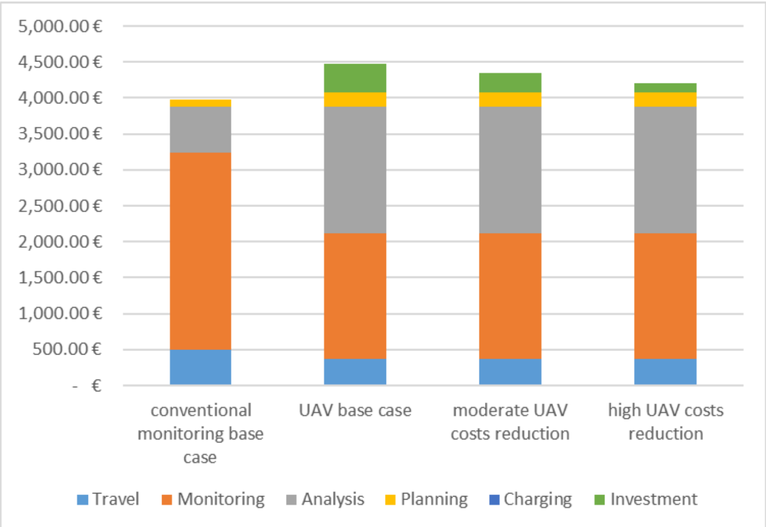

Figure A1: *Overview of the different cost components in base case parametrisation for conventional monitoring (left), and UAV-assisted monitoring (second from left), and the two cost scenarios with high and moderate UAV and equipment cost reduction (third and fourth from left).*

A.2 Analysis costs

Next, we assumed reduced costs for computer-assisted data post-processing and analysis – an analysis type necessary for UAV-assisted monitoring, reflected in the 'Analysis' cost component. In the *high analysis costs reduction scenario* we assumed – similar to the two UAV cost scenarios in section A.1 – a reduction of analysis costs to 33% of the base case costs, and in the *moderate analysis costs reduction scenario* we assumed a reduction to 66% of the base case costs.

We found that – again similar to the findings in A.1 – that a substantial reduction in costs for analysis in either scenario still does not render UAV-assisted monitoring the superior alternative in terms of cost, compared to conventional monitoring (Fig. A2). While cost reductions of 402.58 € (*high analysis costs reduction scenario*) and 204.29€ (*moderate analysis costs reduction scenario*) can be observed, conventional monitoring remains (marginally) less costly by 98.70 €.

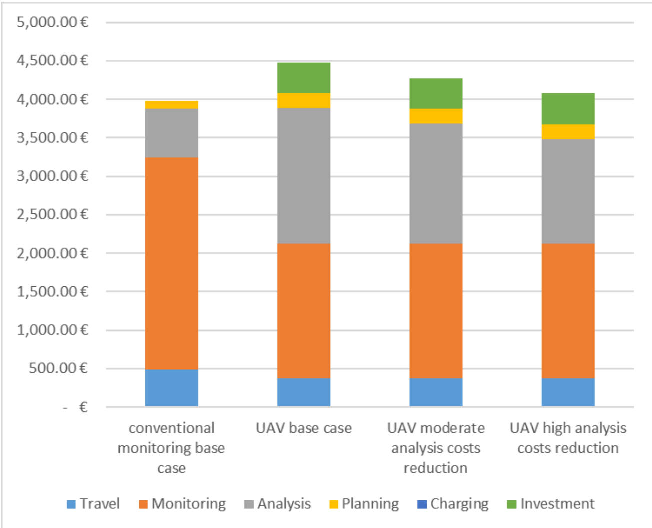

Figure A2: *Overview of the different cost components in base case parametrisation for conventional monitoring (left), and UAV-assisted monitoring (second from left), and the two high and moderate analysis costs reduction scenarios with reduced costs for computer-assisted post-processing and analysis (third and fourth from left).*

A.3 Area

Next to different scenarios for cost components, we analysed a low and high value scenario for the monitored area. In the *small area scenario,* we assumed a 10 ha area to be monitored in the hypothetical scheme, either conventionally or UAV-assisted, while the *large area scenario* assumed 40 ha. As the monitoring area determined several other parameters of the cost model – such as number UAV ground points, on-site travel times and distances, and monitoring duration (compare Tab. 1 in the main text) – changes in this parameter cause changes in various cost components for both monitoring approaches.

We found that in the *small area scenario* the cost advantage of conventional over UAV-assisted monitoring marginally increases (510.70 €), compared to the base case (501.28 €). In contrast, in the *large area scenario*, UAV-assisted monitoring becomes the least-cost monitoring alternative, with a cost advantage of 326.29 € over conventional monitoring. We find it a reasonable result that with increases in monitored area, UAV-assisted monitoring faces an increasing cost-advantage over conventional monitoring. The main underlying reason is that increases in monitored area cause the largest cost component for conventional (i.e. 'Monitoring') to increase substantially due to large increases in labour costs. In contrast, with UAV-assisted monitoring, costs increase almost equally in the 'Monitoring' and 'Analysis' cost component, though not as strong.

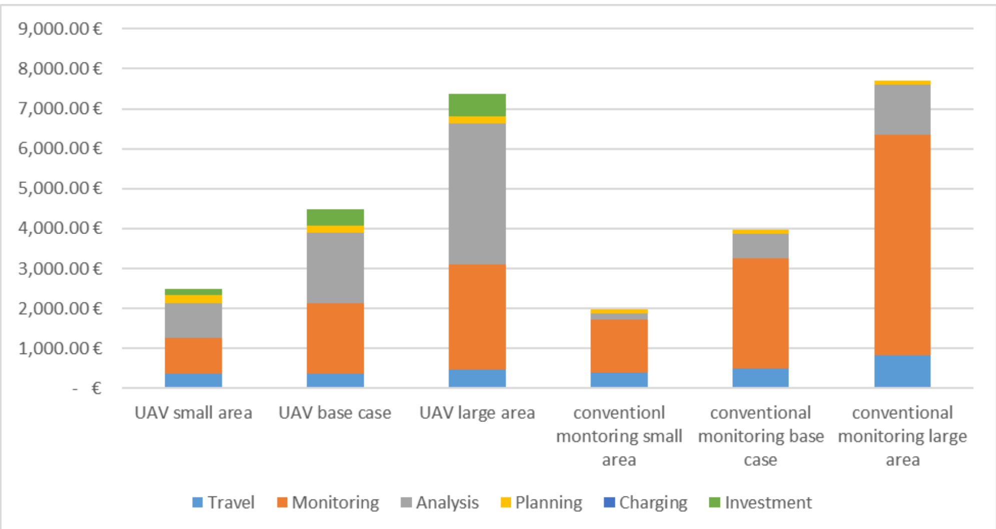

Figure A3: *Overview of the different cost components for small and large area scenarios for UAV-assisted and conventional monitoring.*

A.4 Monitoring frequency

Next, we analysed scenarios with differing monitoring frequencies and their effect on costs of both monitoring approaches. In the *low frequency scenario* we assumed only one monitoring campaign per year, while in the *high frequency scenario* we assumed five campaigns (compared to three campaigns in the base case).

We found, that with more frequent monitoring campaigns (and hence more cumulative area monitored) over the course of a year, conventional monitoring increases its cost advantage over UAV-assisted monitoring to 775.74 €, compared to 501.28 € in the base case and 226.81 € in the *low frequency scenario*.

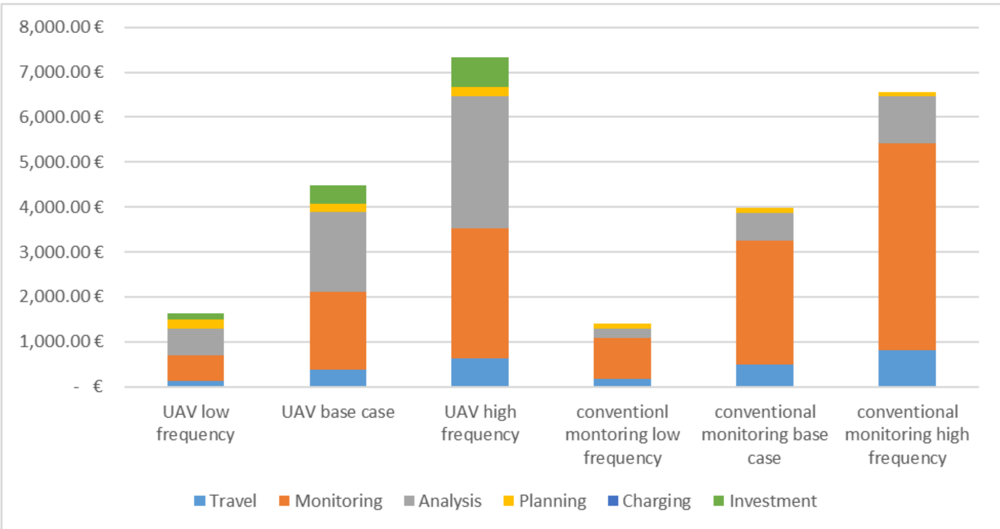

Figure A4: *Overview of the different cost components for low and high monitoring frequency scenarios for UAV-assisted and conventional monitoring.*

A.5 Travel distance

In the travel distance scenario, variations of the underlying parameters resulted almost identical changes in both monitoring approaches. Although total travel distance is lower in the UAV-assisted monitoring approach as monitoring operations are undertaken from one central position and thus no "on-site" travelling is necessary, the generally small size of travel related costs renders the changes in outcome unsubstantial.

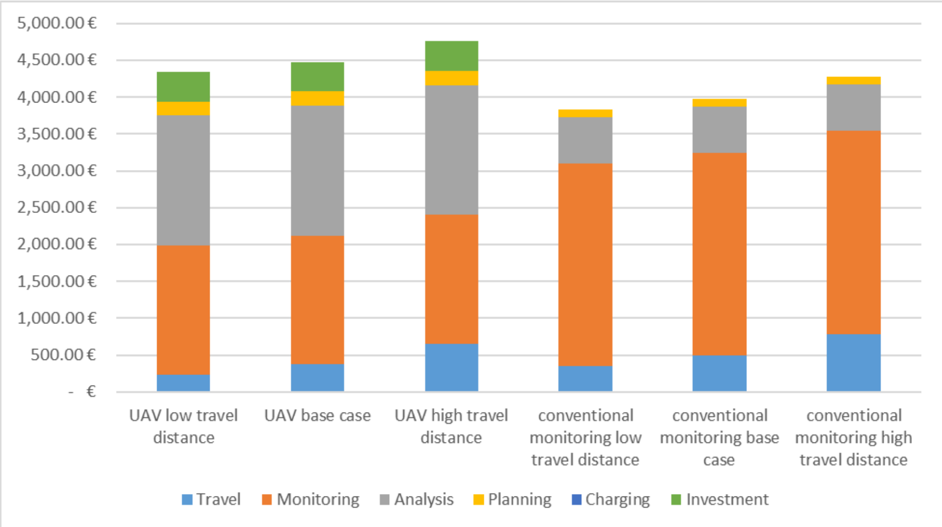

Figure A5: *Overview of the different cost components for the low and high travel distance scenarios for UAV-assisted and conventional monitoring.*

A.6 Monitoring precision

Changes in monitoring precision only affect the conventional monitoring approach. We assumed that the actual monitoring activities can be performed either with a small level of precision in which the reviewer takes 0.1 hours per hectare of monitoring activity, or with high precision, in which 0.4 hour per hectare of monitoring activity are assumed for conventional monitoring. While in the *low precision scenario* the cost advantage of conventional monitoring increases to 2002.63 € for UAV-assisted monitoring, compared to the base case parametrisation with a cost advantage of 501.28 €. In the *high monitoring precision scenario*, UAV-assisted monitoring becomes advantageous compared to conventional monitoring by 1753.23 €.

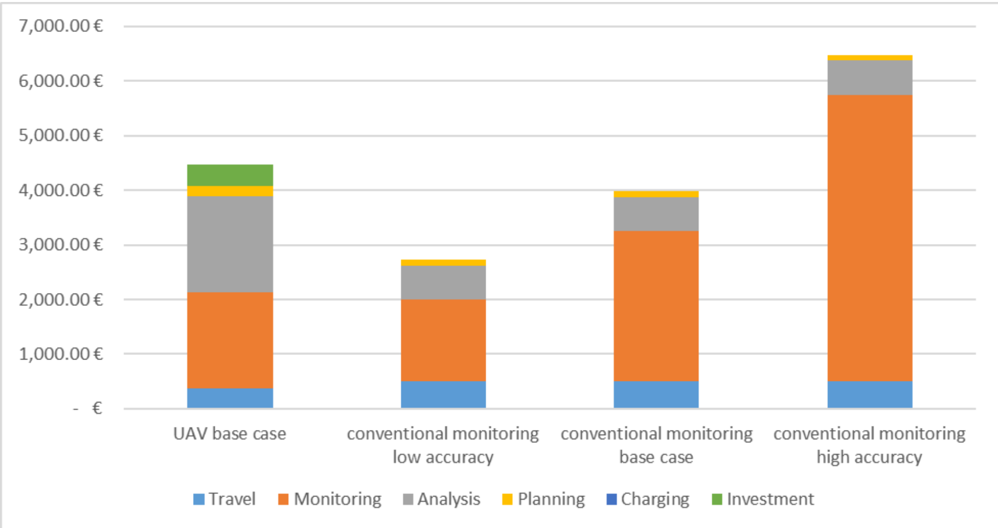

Figure A6: *Overview of the different cost components for low and high monitoring precision scenarios for UAV-assisted and conventional monitoring.*

A.7 Labour costs

Variations in labour cost, i.e. hourly wages, have almost identical and beyond that, small effects on the costs of both monitoring approaches. Hence, the ranking order of the monitoring approaches does not change with changing labour costs.

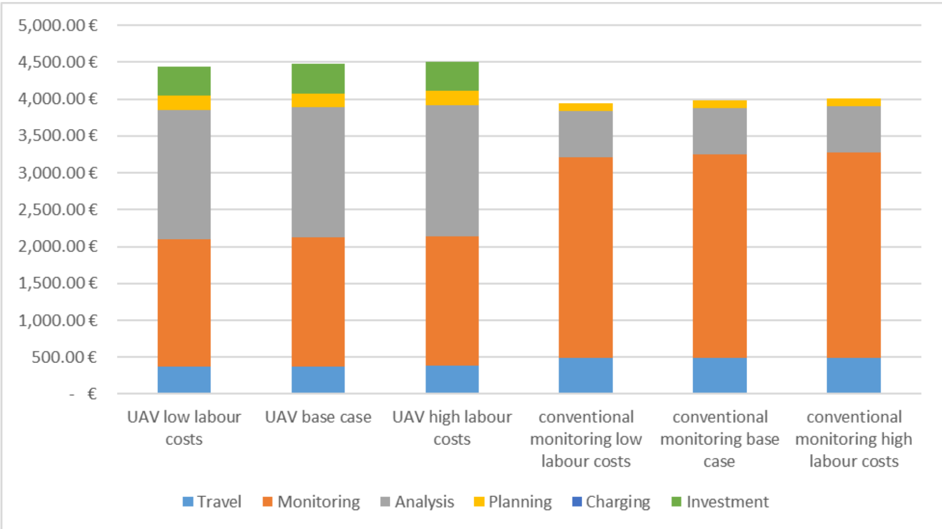

Figure A7: *Overview of the different cost components for low and high labour costs scenarios for UAV-assisted and conventional monitoring.*

A.8 Discount rate

Similar to the aforementioned scenario, also changes in the discount do not change the ranking order of two monitoring approaches. Although the structure of cash flows in both approaches differs. UAV-assisted monitoring is front-end loaded with almost all equipment costs arising in the first year of the considered 5-year reference period, while with conventional monitoring costs are spread evenly over the 5-year period. However, the size of equipment costs in the UAV-assisted monitoring approach is not large enough to cause major differences in the discounted sum of costs over the 5-year period due changes in discount rates.

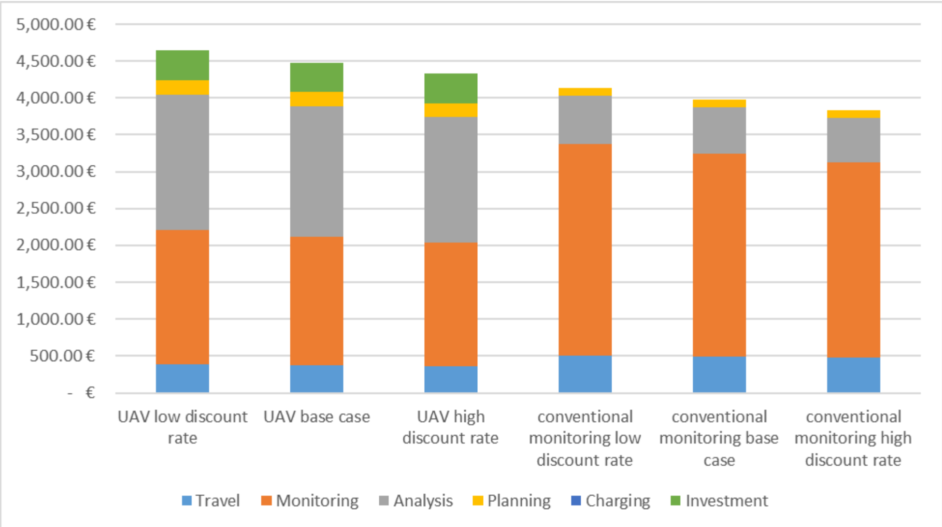

Figure A8: *Overview of the different cost components for low and high monitoring precision scenarios for UAV-assisted and conventional monitoring.*

B. Data for combined scenarios

Table B1: *Overview of costs in conventional monitoring and UAV-assisted monitoring for base case parametrisation and in the strong technological progress scenario for UAV-assisted monitoring.*

Costs	**Conventional monitoring base case**	**UAV base case**	**UAV Strong technological progress**
Travel	492.12 €	375.78 €	375.78 €
Monitoring	2,754.29 €	1,745.21 €	1,745.21 €
Analysis	625.98 €	1,764.34 €	1,361.76 €
Planning	104.33 €	193.91 €	193.91 €
Equipment	- €	1.06 €	1.06 €
Investment	- €	397.69 €	131.24 €
Total	3,976.72 €	4,477.99 €	3,808.96 €
		501.28 €	-167.75 €
Difference to conventional monitoring base case	492.12 €	375.78 €	375.78 €

Table B2: *Overview of costs in conventional monitoring and UAV-assisted monitoring for base case parametrisation and in the high monitoring demand scenario.*

Costs	**Conventional monitoring base case**	**UAV base case**	**Conventional monitoring high monitoring demand**	**UAV high monitoring demand**
Travel	492.12 €	375.78 €	1,395.63 €	795.50 €
Monitoring	2,754.29 €	1,745.21 €	9,180.98 €	4,363.04 €
Analysis	625.98 €	1,764.34 €	2,086.59 €	5,881.14 €
Planning	104.33 €	193.91 €	104.33 €	193.91 €
Equipment	- €	1.06 €	- €	2.48 €
Investment	- €	397.69 €	- €	927.93 €
Total	3,976.72 €	4,477.99 €	12,767.53 €	12,163.99 €
Difference	501.28 €		-603.53 €	