D5.4 GIS FOR DIGITALLY TWINNED ASSET MANAGEMENT

INFCON

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ABSTRACT

This deliverable describes the developed tools GISI and RISA. A specific tool GISI is developed to integrate all of the data related to monitoring, condition assessment and maintenance of infrastructures into GIS for asset management on all levels, from short to long term decision making. RISA tool is developed to predict different maintenance scenarios based on the inspection and monitoring of assets. The tool allows end-users to interactively review and utilise specific outputs of the risk assessment and the consequence modelling in risk analysis. The tool presents the user with different maintenance that could be chosen based on KPIs.

KEYWORDS

GIS, infrastructure management, maintenance, risk

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ACRONYMS & DEFINITIONS

AI	Artificial Intelligence
CNN	Convolutional Neural Network
DT	Digital Twin
DV	Deduct value
FOD	Foreign Object Debris
GIS	Geographic Information System
GISI	GIS integrator for digital-twin-based asset management
O&M	Operation and Maintenance
PCI	Pavement Condition Index
RISA	Risk based status assessment tool
UAV	Unmanned Aerial Vehicle
TMD	Tire Mark Density

ASHVIN PROJECT

ASHVIN aims at enabling the European construction industry to significantly improve its productivity, while reducing cost and ensuring absolutely safe work conditions, by providing a proposal for a European wide digital twin standard, an open source digital twin platform integrating IoT and image technologies, and a set of tools and demonstrated procedures to apply the platform and the standard proven to guarantee specified productivity, cost, and safety improvements. The envisioned platform will provide a digital representation of the construction product at hand and allow to collect real-time digital data before, during, and after production of the product to continuously monitor changes in the environment and within the production process. Based on the platform, ASHVIN will develop and demonstrate applications that use the digital twin data. These applications will allow it to fully leverage the potential of the IoT based digital twin platform to reach the expected impacts (better scheduling forecast by 20%; better allocation of resources and optimization of equipment usage; reduced number of accidents; reduction of construction projects). The ASHVIN solutions will overcome worker protection and privacy issues that come with the tracking of construction activities, provide means to fuse video data and sensor data, integrate geo-monitoring data, provide multi-physics simulation methods for digital representing the behavior of a product (not only its shape), provide evidence based engineering methods to design for productivity and safety, provide 4D simulation and visualization methods of construction processes, and develop a lean planning process supported by real-time data. All innovations will be demonstrated on real-world construction projects across Europe. The ASHVIN consortium combines strong R&I players from 9 EU member states with strong expertise in construction and engineering management, digital twin technology, IoT, and data security / privacy.

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1 INTRODUCTION

A relatively recent concept in the area of operational and maintenance infrastructure management is digitalization through the creation of digital twins of transportation infrastructure. A digital twin provides vast potential to enhance the life cycle management of transportation infrastructure and serves as the foundation for operational and maintenance decision-making. It can be used as a support for risk-based management and operational planning by providing a comprehensive information-based view of infrastructure assets ensuring that decision-makers have access to both most current and historic information. This approach enhances the overall resilience and efficiency of infrastructure asset management enabling proactive risk mitigation and facilitating data-driven decision-making processes.

This report describes work on the preparation, elaboration, execution and evaluation of the GIS integrator for Digital Twin-based asset management in spatially distributed assets. It depicts the development of the system and also describes the exemplary implementation of the GIS integrator on the demonstration projects. The risk based predictive maintenance model is developed incorporating outputs of novel quantitative methodologies that estimates relevant consequences of the asset “failure” on the owners and end-users, using a series of KPIs. The model considers different maintenance strategies and allows end-users to interactively review and utilise specific outputs of the risk analysis and the consequence modelling in the risk assessment.

The target group for this document are project partners, demonstration project owners, in particular infrastructure managers, decision makers, contractors or consultants responsible for maintenance planning and execution.

2 GIS INTEGRATOR FOR DIGITAL TWIN BASED ASSET MANAGEMENT – GISI TOOL

The integration of monitoring, condition assessment, and maintenance of infrastructure into GIS (Geographic Information System) can be a very useful tool for asset management. This approach involves using GIS technology to map, monitor, and manage infrastructure assets, including roads, bridges, buildings, and other structures. Mapping of infrastructure assets is used to create a comprehensive database. This includes information such as the location, condition and age of each asset, as well as details of any previous maintenance work or repairs that have been carried out. Monitoring of infrastructure condition using embedded sensors and remote sensing devices such as drones or satellites is applied to collect various data about materials and structural integrity. The acquired data is fed into the GIS system to provide visualization of the condition of infrastructure assets and to establish trends and patterns. It provides asset managers a tool for identification of potential issues before they become serious problems, and plan maintenance and repair works accordingly. This involves identifying critical areas that require attention based on condition assessments and prioritizing work based on the level of risk associated with each asset or part of the asset. Finally, the use of GIS based tools can help better in visualization of the asset condition to infrastructure managers and stakeholders, and make better data-driven decisions (Barret&Ramdas, 2018).

2.1 Description of the tool

The proposed GISI tool, GIS integrator for digital-twin-based asset management in spatially distributed assets, aims to integrate all the data related to monitoring and condition assessment into digital twin model and enable visualization of quantification and categorization of damages of the asset in question. Digitally collected information, in our case images collected by drone, served also for the digital twin development. The input data are the existing information about the structure (e.g. CAD or BIM model), historical records of the inspections, and finally newly collected information, in this cased drone based images. Condition assessment is performed using AI-based damage detection models, developed within WP3 (Krestenitis & Ioannidis, 2022)

The overall tool process sequence of actions, see Figure 1, is as follows:

1. Collate the high-resolution image data from the site by the application of UAV.
2. Development of digital twin model of the asset.
3. Apply Damage detection model (if existing for the expected failures). Alternatively apply existing standard visual assessment procedures.
4. Condition assessment is then performed. From the detected damages, semantic information such as defect type, defect size, defect number, and geolocation can be inferred. (D3.1, Krestenitis & Ioannidis, 2022)
5. The output from defect detection model is then input to the GISI tool.
6. GISI performs condition assessment by categorising and quantifying the damages. Depending on the asset type and existing standards, threshold values have to be established. For instance, in case of airport runway ASTM D5340 (2020) and Guideline document (FAA, 2014)) were used. In this case the tool determines Pavement Condition Index (PCI) for airport runway case

study. For bridges for example damages would be classified and quantified according to the existing national practice and also used for the determination of Bridge Condition Index (BCI), (ATKINS, 2002).
7. Determine probability of failure based on the identified and quantified damages.
8. Using existing numerical (physical, mechanical) models or empirically developed models based on the historical data, develop prediction performance models.
9. GISI then predicts the probability of failure and performance for each failure mode under conditions of ageing, loading, and extreme events.
10. The result from step 5 serves as an input to the tool RISA which can then give different maintenance scenarios based on different KPIs (Stipanovic & Skaric, 2023).

Primary users of the tool will be asset owners or managers together with the maintenance engineers and structural engineers. Pre-conditions for the comprehensive and credible results of the tool is adequate amount of good quality image data of the site under study for monitoring and condition assessment. The tool is expected to be used throughout the whole lifecycle of the asset- especially during its operation and maintenance (O&M) cycle.

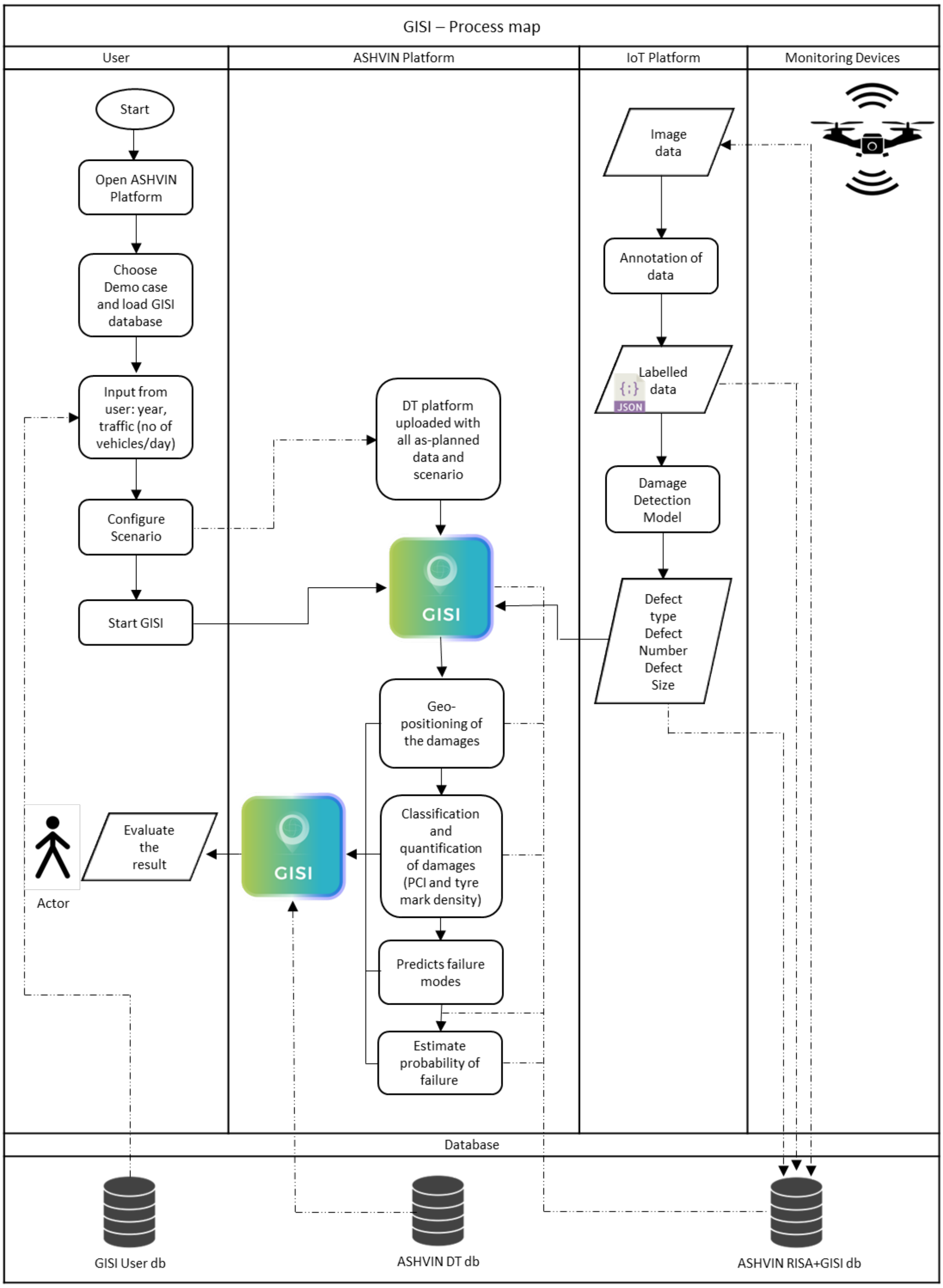

Figure 1 Overall process flow of the GISI tool

2.2 GISI tool applied on Demo case #3: Zadar Airport

2.2.1 Inspection and monitoring procedure

Regular inspection of the airport operating area which includes runways, taxiways, aprons, and other areas where aircrafts move, park, take off and land, is critical to ensure safe and efficient operations. Inspections ensure that the operating area is compliant with regulations and standards set by aviation authorities and can help identify non-compliance issues and ensure that corrective actions are taken promptly. It is performed according to established protocols and frequencies to ensure that all areas are thoroughly examined defined by the provision ADR.OPS.B015 of European Regulation 139/2014 (EU, 2014).

Visual inspections of the airport operating areas are performed on a daily, weekly, quarterly and annual basis, depending on the inspections' objective. There are several constraints that need to be considered when performing these inspections, such as weather conditions, operational constraints, human factors, equipment availability, and restricted areas. Visual inspection of runways requires a high level of concentration and attention to detail, which can be affected by various human factors, such as fatigue, distractions, or stress. Inspectors need to be properly trained and follow established protocols to ensure consistency in their inspections. Operational constraints due to busy flight itinerary require detailed, precise and accurate scheduling of inspections. Time available for accessing the areas such as runway is very limited for any activity that needs to be performed. The aim of the inspections is detection of damages or anomalies that could jeopardize the safety of aircraft landings and take-offs, such as foreign object debris (FOD), contaminants like water, snow, spilled oil or fuel, rubber deposit, etc., cracks in the runway surface, and wildlife on or near the runway. Regular daily inspections are usually performed by car and inspector, who is stopping the car and checking visually when noticing something unusual. Regular inspections focusing on pavement condition are performed quarterly or whenever changes or deviations in the condition are observed, by inspector (operational/infrastructure manager) walking and using digital camera to capture observed damages.

The aim of this demo was the implementation of UAV for the visual inspection of runways, which would replace quarterly visual inspection, using high resolution cameras for capturing images and creating GIS based digital twin model. Digital recording of the damages over time, would not only increase the accuracy and repeatability of the inspection procedures, but it would also enable a development of performance prediction model.

2.2.2 Demo site description– Zadar Airport

Zadar Airport is one of nine international airports in the Republic of Croatia situated in the middle of the Adriatic coast, 7 km east of the City of Zadar. It was opened in 1969 as an addition to the existing military infrastructure, and with the construction of a civilian infrastructure, it became the only airport in Croatia with two runways. The airport is declared as ICAO code 4D and can be categorized as joint civil/military airport. The record year for Zadar Airport is 2022, when they reached a record of over 1 million passengers per year for the first time in their history. As the airport certificate holder, Zadar Airport is responsible for airport operating services, maintenance and to ensure future capacity developments regarding airport infrastructure and technology.

The airport infrastructure related to aircraft and passengers, which includes all operational areas and terminal for passengers and aircraft ground handling, was built, as already stated above, almost 50 years ago. In that period there were several partial renovations of asphalt surfaces, but no major reconstructions. All processes related to inspection and consequently maintenance, are currently performed by non-digital methods.

2.2.3 Defect Detection model

Within WP3 CERTH in collaboration with INFCON has developed Defect Detection method, thoroughly described in D3.1 (Krestenitis & Ioannidis, 2022). The AI-powered solution is developed to detect damages, anomalies and objects on the runway surface and green areas around the runway. The aim is to integrate the automated damage detection into inspection and maintenance planning process, as part of the RISA tool and finally integrated into maintenance management procedures. The primary goal of the approach imbedded into GISI tool is to identify various surface flaws using visual data that was gathered through an UAV scanning of the runway area. Accurate detections are ensured by using cutting-edge deep-learning methods, in particular, a CNN model capable of producing an annotated mask with the identified defects appropriately and semantically segmented the input picture (Zhang et al. 2022, Li et al. 2018, Ni et al. 2019). This approach allows to extract accurate spatial information regarding the location, the shape and the size of the detected defects. An overview of the proposed framework is shown in Figure 2.

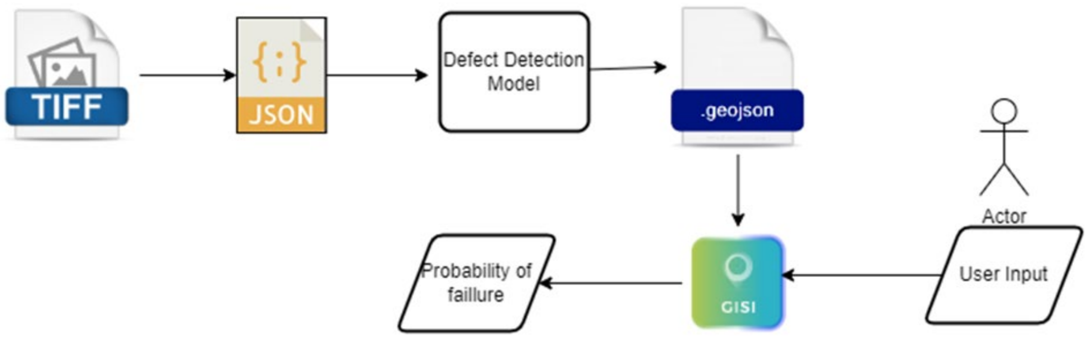

Figure 2 Exchange requirements mapping framework

The developed dataset contains RGB images collected through two different phases. In the first phase, hand-held cameras were utilized to capture a wide variety of defect instances observed on the surface of the airport's runway. The collected data were annotated accordingly, using Make Sense tool used for training the model. Image annotation is a crucial step in training machine learning models, especially in the context of computer vision tasks. Annotation involves labelling or marking specific features or objects within an image, providing the necessary ground truth data for supervised learning. Here's a general process for image annotation:

1. Define Annotation Types:
In our case we have discussed with airport managers to identify the most common problems related to the runways. As well the experts for the asphalt and concrete materials were involved in the selection of the objects or features that we wanted the model to recognize. Four categories were selected: Construction joint; Crack; Repaired crack – so called joint and Tire mark. We have agreed on the annotation types, which were based on polygons.

2. Select Annotation Tools:
We have used makesense tool for annotation. https://www.makesense.ai/

3. Collect and Organize Data:
We have collected images with drones and handheld cameras. Both images can be used for the annotation and training tasks. The images have to cover a diverse and representative dataset for training, including representative samples for chosen features. The data has to be organized into appropriate training, validation, and test sets.

4. Prepare Annotation Guidelines:
Annotation guidelines has to be prepared and communicated to all persons performing the annotation task to ensure consistency among annotators. Guidelines should cover object boundaries, label definitions, and any specific instructions for complex scenarios.

5. Annotation Process:
Annotators mark or outline objects in the images according to the defined guidelines, in our case using polygons.

6. Quality Control:
Implement a quality control process to ensure the accuracy and consistency of annotations. Use multiple annotators for each image and resolve discrepancies through review and consensus. Include regular checks and feedback loops to maintain annotation quality.

7. Data Splitting:
Split the dataset into training, validation, and test sets. The training set is used to train the model, the validation set helps tune hyperparameters, and the test set evaluates the model's performance on unseen data.

8. Format Conversion:
Convert the annotations into a format compatible with your machine learning framework. We have used COCO JSON format when converting the annotations from makesense tool. The annotated data are then integrated into the machine learning training pipeline.

In the second phase, a camera mounted on a UAV was exploited to collect visual data from a wider area of the runway. Following a similar approach, the collected images were annotated accordingly for the semantic segmentation task. The deployed dataset was utilized to train and test the designed model. In specific, 20% of the drone images was utilized for testing while the rest 80%, combined with the data of the first phase, were employed for training.

In the context of the specific task, a robust AI-based method, named DDCV, for defect detection was employed. Its core element is an efficient CNN model, trained and evaluated on real-world data collected from the demonstration site. Evaluation results implied that the deployed module is capable to detect four different types of defects adequately, see Figure 3, yet highlighted the challenging nature of the defect detection task. More specifically, although the deployed method can detect the depicted crack instances, their shape cannot be perceived in its full complexity. The efficiency of the deployed model is expected to be increased significantly by employing higher number of training data. Towards in this direction, the remaining collected data will be annotated accordingly to create an extended dataset, covering more defect cases. Furthermore, possessing a dataset with higher number of samples, will enable the ability to train deeper architectures which can lead to performance improvements (Krestenitis&Ioannidis, 2022).

Figure 3 Results of the deployed DDCV method. Cracks are highlighted with red, joints with blue, construction joints with yellow and tire marks with green colour, respectively (Krestenitis&Ioannidis, 2022).

2.2.4 Geo-positioning of defects

All images that were captured through UAV survey are geopositioned. Applying defect detection model to the geo positioned images, see Figure 4, provides information about the location and size of each detected defect.

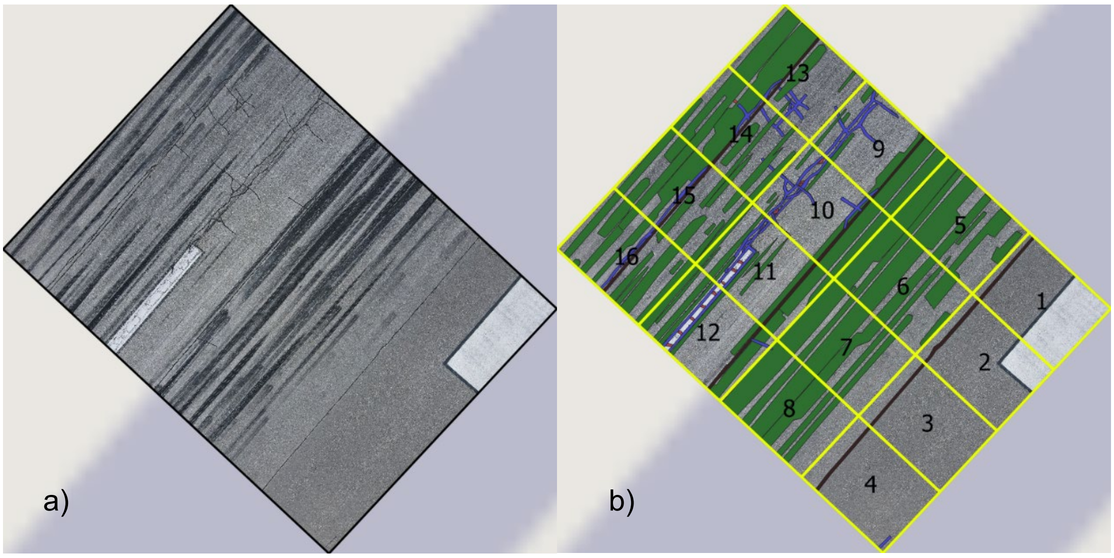

Figure 4 a) Collected data – picture of the runway, b) Qualitative results of the deployed defect detection method. Cracks are highlighted with red, repaired cracks with blue, construction joints with yellow and tire marks with green colour

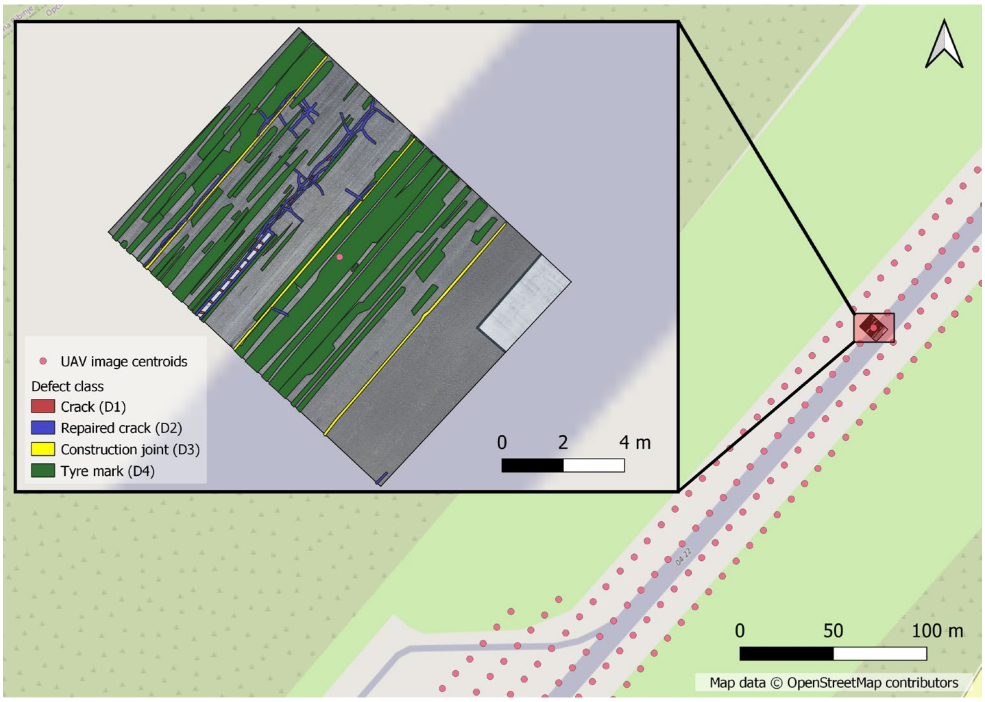

Figure 5 Geo-positioning of damages

The extracted information regarding the location, shape and size of each defect was provided to the developed GISI tool, allowing the estimation of runway condition and the efficient maintenance management, in a fully-automatic manner. The results were encouraging, demonstrating the efficiency of the model and the capabilities for further improvements. All detected defects have been associated with local coordinates, which then were transformed into global coordinates and presented in GIS application, see Figure 5. In the process of development of the GISI tool each analysed image was divided into 16 sample units with approximate area of 13.4 m^2. This enables categorization of parts of the runway surface depicted on an image depending on the quantity of different types of defects per sample unit.

2.2.5 Evaluation & Categorization of the Asset Condition

For the purpose of analysis of the detected damages and visualizing the results in the user-friendly manner, runway surface area was divided into 240 tiles, with the size of each tile of 15mx25m. For Zadar Airport, the main deterioration processes affecting the runway's safety and performance taken further into consideration for risk assessment are cracks and tire marks. The detected defects are represented as crack length and tire mark surface area for each of the 240 tiles. After the quantification of defects per selected unit (in our case tile 15mx25m) in the GISI model, the categorisation is performed according to the degree of deterioration severity and selected threshold values.

2.2.5.1 Evaluation Metrics

The first step in the categorization of the tiles' conditions is the calculation of Pavement Condition Index (PCI) and the percentage of tire mark surface area for each tile. The ASTM D5340 methodology was used to determine condition of the runway pavement defined with PCI value. The PCI value is a numerical indicator that rates the surface condition of the pavement, ranging from 0 to 100, defining the severity and extent of distress observed on a pavement surface with 0 being the worst condition, see Figure 6.

Standard PCI Rating Scale

Color Designation	PCI Score	Rating
Dark Green	100–85	Good
Light Green	85–70	Satisfactory
Yellow	70–55	Fair
Light Red	55–40	Poor
Medium Red	40–25	Very Poor
Dark Red	25–10	Serious
Dark Grey	10–0	Failed

Figure 6 The standard PCI rating scale (ASTM D5340)

The PCI provides a measure of the present condition of the pavement based on the distress observed on the surface of the pavement which also indicates the structural integrity and surface operational condition. Based on the expert judgment the level of severity of the recorded defects were categorized in three groups, low, medium and high, in order to determine the Deduct Value (DV) and finally PCI for each sample unit, following the ASTM D5340 methodology, as follows:

$$PCI = 100 - DV \qquad (1)$$

The deduct value is calculated according to the distress density curves (Longitudinal - Transverse Cracking from ASTM D5340) shown in Figure 7. In our case cracks are identified as dominant deterioration mechanisms.

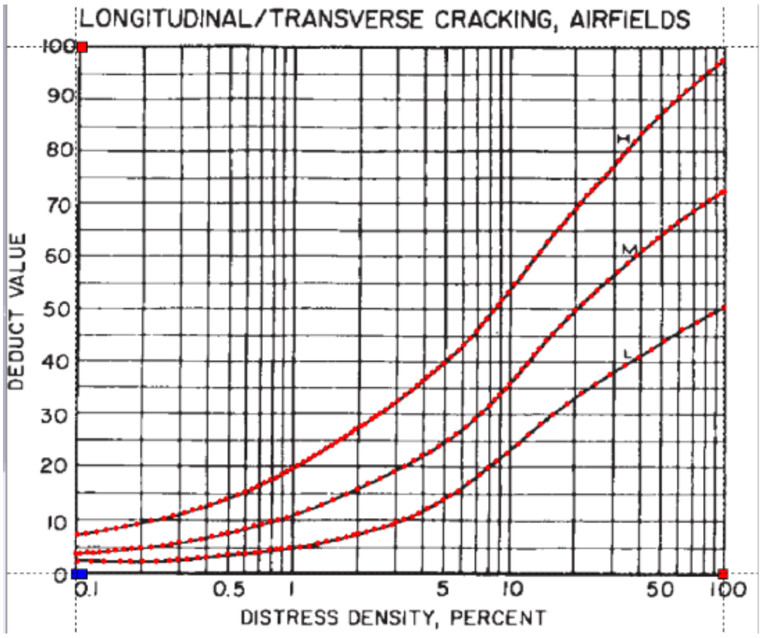

Figure 7 Distress density curves to obtain deduct value (DV) needed to calculate PCI – low, medium, and high severity curves (ASTM D5340)

In order to discretize distress density curves in R, the functions shown below were used to calculate the deduct values where x is the distress density percentage.

High-Severity curve	
IF	x < 15
THEN	19.648 * x^0.4368
ELSE	18.664 * Ln(x) + 12.742
Medium-Severity curve	
IF	x < 25
THEN	-0.000000002 * x^6 + 0.0000007 * x^5 - 0.00009 * x^4 + 0.0062 * x^3 -0.2261 * x^2 + 4.8683 * x + 5.0766
ELSE	0.00002 * x^3 - 0.0072 * x^2 + 0.8312 * x + 37.108
Low-Severity curve	
IF	x < 20
THEN	-0.000003 * x^4 + 0.0008 * x^3 -0.0669 * x^2 + 2.6109 * x + 2.2896
ELSE	0.00002 * x^3 -0.0061 * x^2 + 0.6647 * x + 22.619

2.2.5.2 Categories and Thresholds

For the proof-of-concept of the usage of UAVs and AI defect detection model for determination of pavement condition, we have developed custom based PCI and Tire Mark density (TMD) value, using crack length and tire marks' coverage. PCI and TMD are used as assessment metrics to evaluate and categorize the tiles' conditions. Categories of cracks and tire marks based on the PCI and tire mark surface area coverage (% per tile) are determined based on the literature review (Pieterssen, 2022, ASTM D5340) and in collaboration with airport managers from several airports. Different colour coding was used for visualization of different types of defects, with four categories for cracks and joints and seven for tire marks. Although this custom based PCI cannot be used to directly measure structural capacity, it does provide a logical and objective foundation for selecting the most important maintenance and repair activities. The custom based PCI rating scale, see

Table 1, is used to display the findings in the GIS with each defect class identified for sample units.

Table 1 Runway categorization based on custom based PCI values

	Status	Categorization	PCI Threshold
1	Green	Good	100-85%
2	Yellow	Satisfactory	85-70%
3	Orange	Fair	70-55%
4	Red	Poor	55-0%

The results of the PCI calculations for the 16 sample units used to develop the methodology and colour coded according to the Table 1 are graphically presented in Figure 8.

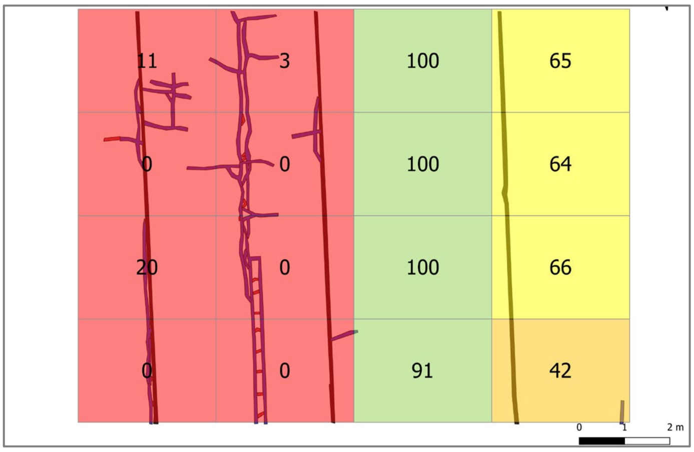

Figure 8 Categorization of runway condition using adopted PCI rating based on detected defects cracks, repaired cracks and construction joints

The study also involved the creation of an automated system to track the accumulation of tire marks on the runway surface. Rubber deposited in the touchdown zone by tires of landing aeroplanes influences the runway friction characteristics and aircraft braking. The ML-model was trained especially for this defect category using the UAV images and expert annotations. Additionally, the goal is to automate this process and use threshold values to connect monitoring data with maintenance action. Prediction of future performance includes analysing different deterioration curves regarding detected failure modes (Anqi et al. 2020, Nguen et al. 2020, Leblouba et al. 2022).

The classification of tire mark density was suggested as shown in Table 2 based on the expert interviews.

Table 2 Categorization of runway surface area based on rubber deposit tire marks density

	Status	Tire mark density categorization (%of surface covered in tire mark)	Categorization
1	Light green	<5%	Very low
2	Green	5-20%	Low
3	Yellow	20-40%	Low to medium
4	Orange	40-60%	Medium
5	Red	60-80%	Medium to high
6	Scarlet	80-95%	High
7	Burgundy	≥95%	Very high

Figure 9 shows how some tiles can have almost no tire marks, while others will have an unsafe amount of tire marks that directly affect the friction coefficient of the pavement and its serviceability.

Tile.ID	Percentage of Surface Area Covered in Tire Marks	Catergory	Landing Tile?
1	0.01	<5%	TRUE
2	0.04	<5%	TRUE
3	0	<5%	FALSE
4	0	<5%	FALSE
5	0	<5%	FALSE
6	0	<5%	FALSE
7	0.05	<5%	TRUE
8	0	<5%	FALSE
9	0	<5%	FALSE
10	0	<5%	FALSE

Tile.ID	Percentage of Surface Area Covered in Tire Marks	Catergory	Landing Tile?
140	56.54	40-60%	TRUE
141	54.2	40-60%	TRUE
142	40.76	40-60%	TRUE
143	60.69	60-80%	TRUE
144	59.58	40-60%	TRUE
145	56.52	40-60%	TRUE
146	59.65	40-60%	TRUE
147	58.19	40-60%	TRUE
148	51.8	40-60%	TRUE
149	55.75	40-60%	TRUE
150	50.61	40-60%	TRUE

Figure 9 Difference between percentage surface covered by tire marks for different tiles

2.2.5.3 Results of condition assessment

Finally, the whole runway area was divided into 240 tiles 15x25m for the calculation and visualization of results in the GIS. Based on the data from the defect detection model built into the GISI tool, the 240 subdivisions of the runway are categorized for cracks and tire marks as shown in Figure 10. On the left side of the figure a histogram with the resulting number of tiles categorized into four categories from good to poor depending on the quantity of cracks per tile. On the right side of the figure a histogram with the resulting number of tiles categorized into seven categories from very low to very high depending on the surface covered by tire marks.

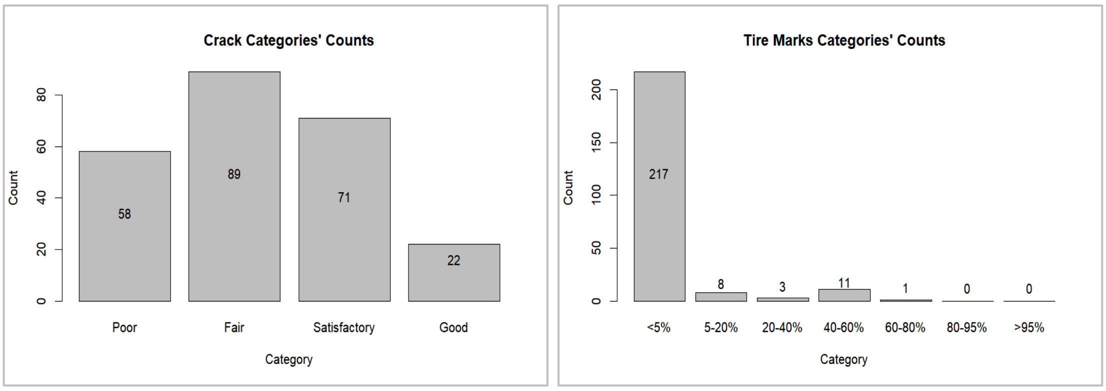

Figure 10 Number of tiles categorized depending on the number of cracks (left) and surface covered by tire marks (right)

The results of tire mark density calculation and categorization of runway shown on a GIS map are presented in Figure 11.

Figure 11 Whole runway surface area with visualized results for tire marks density

It is very noticeable that the tiles with less than 5% of their surface area covered in tire marks represent the majority of the runway. However, this does not guarantee that the runway will not need maintenance interventions. In fact, most tiles will have a zero percent of tire mark surface area as they do not have direct contact with aircraft when landing and taking off. It is based solely on the location of the tile.

3 RISK- BASED ASSET MANAGEMENT TOOL – RISA TOOL

Risk-based asset management is an approach to managing assets that takes into account the various risks associated with those assets throughout their lifecycle. This method involves identifying, assessing, and prioritizing risks to make informed decisions about the allocation of resources and efforts to minimize or mitigate those risks. The goal is to optimize the performance, reliability, and value of assets while considering the potential negative impacts that risks can have on these aspects. The first step is to identify potential hazards that could cause harm or damage to the infrastructure. This could include natural hazards but also deterioration and damages due to the increased loading or aging processes. Once the hazards are identified, the next step is to assess the likelihood of occurrence. This involves analysing data on historical events, climate patterns, and other relevant factors to determine the probability of each possible failure mechanism. The following step is to assess the direct and indirect consequences of each hazard, the potential impact on the infrastructure, users and the environment. Based on the probability of failure and consequences of each hazard, the risk associated with the infrastructure is evaluated. This involves comparing the risk level with predefined risk tolerance levels to determine whether the risk is acceptable or not.

Overall, incorporating risk-based asset management into an organization's practices, companies can enhance the overall performance and resilience of their assets. This approach helps to optimize resource allocation, reduce downtime, and improve decision-making processes related to asset management. Additionally, it supports a proactive rather than reactive approach to addressing potential issues with assets.

3.1 Description of the tool

Risk-based asset management tool RISA is used to analyse different maintenance scenarios based on the inspection and monitoring data about assets and end-users preferences. The tool allows end-users to interactively review and utilise specific outputs of the risk assessment and the consequence modelling in risk analysis. The proposed tool enables the end-user a comparison of different maintenance scenarios with given limitations such as budget and time span. Input data are based on the monitoring and condition assessment and/or probability of failure of the asset, which are coming from the GISI tool. Other available data comes partly from asset information, historic data such as previous maintenance works and costs, usage (e.g. traffic intensity), while available budget, total revenue/asset value, estimated available budget per year for regular maintenance, and time available for maintenance works are parameters defined partly by asset owner/infrastructure manager and partly by engineers as specialists responsible for O&M. For each condition state / probability failure class there are certain consequences (planned or unplanned), such as maintenance, costs etc., which are then translated into KPIs, namely safety, costs, productivity and environmental cost (Stipanovic&Skaric Palic, 2023). These KPIs then enable calculation of risk and prioritization based on end-user preferences and development of an optimal maintenance scenario. Schematic overview of RISA tool components is given in Figure 12.

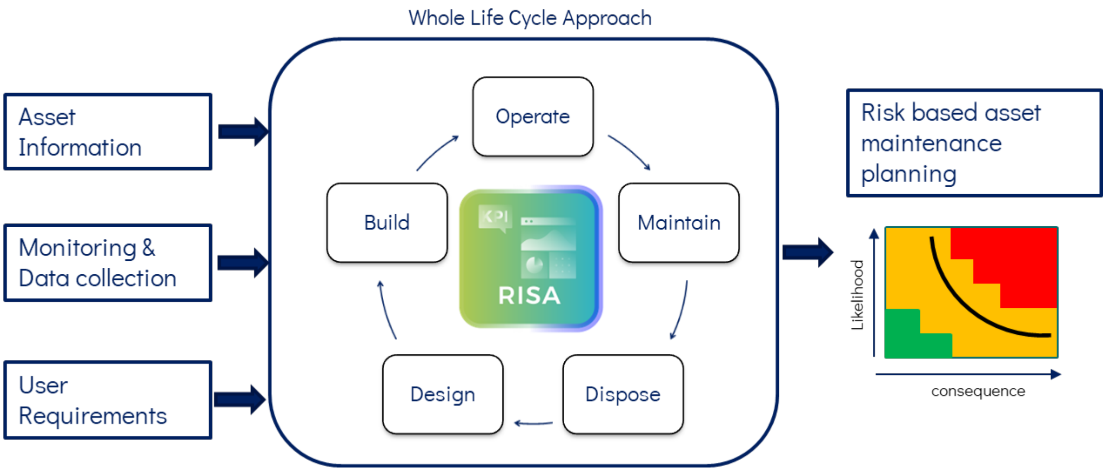

Figure 12 Main component of the RISA tool

Overall tool process sequence of actions, see Figure 13, is as follows:

1. Obtain the probability of failure for the predefined failure mode of the particular asset under study based on monitoring and condition assessment form GISI.
2. Calculate the maintenance cost through time based on the predefined scenarios.
3. Estimate the user delays costs through time based on the predefined scenarios.
4. Estimate environmental costs through time based on the predefined scenarios.
5. Calculate risk through time based on the predefined scenarios.

Pre-conditions for the usage of the RISA tool is that the conditions of the asset under consideration should be monitored and assessed based on the user's requirements. Probability of failure should be calculated before using the RISA tool. When these preconditions are met then the tool can be used for development of well-assessed and condition-based maintenance scenarios for predictive maintenance. The RISA tool is aimed to be used throughout the whole life cycle of the asset, especially during its O&M cycle.

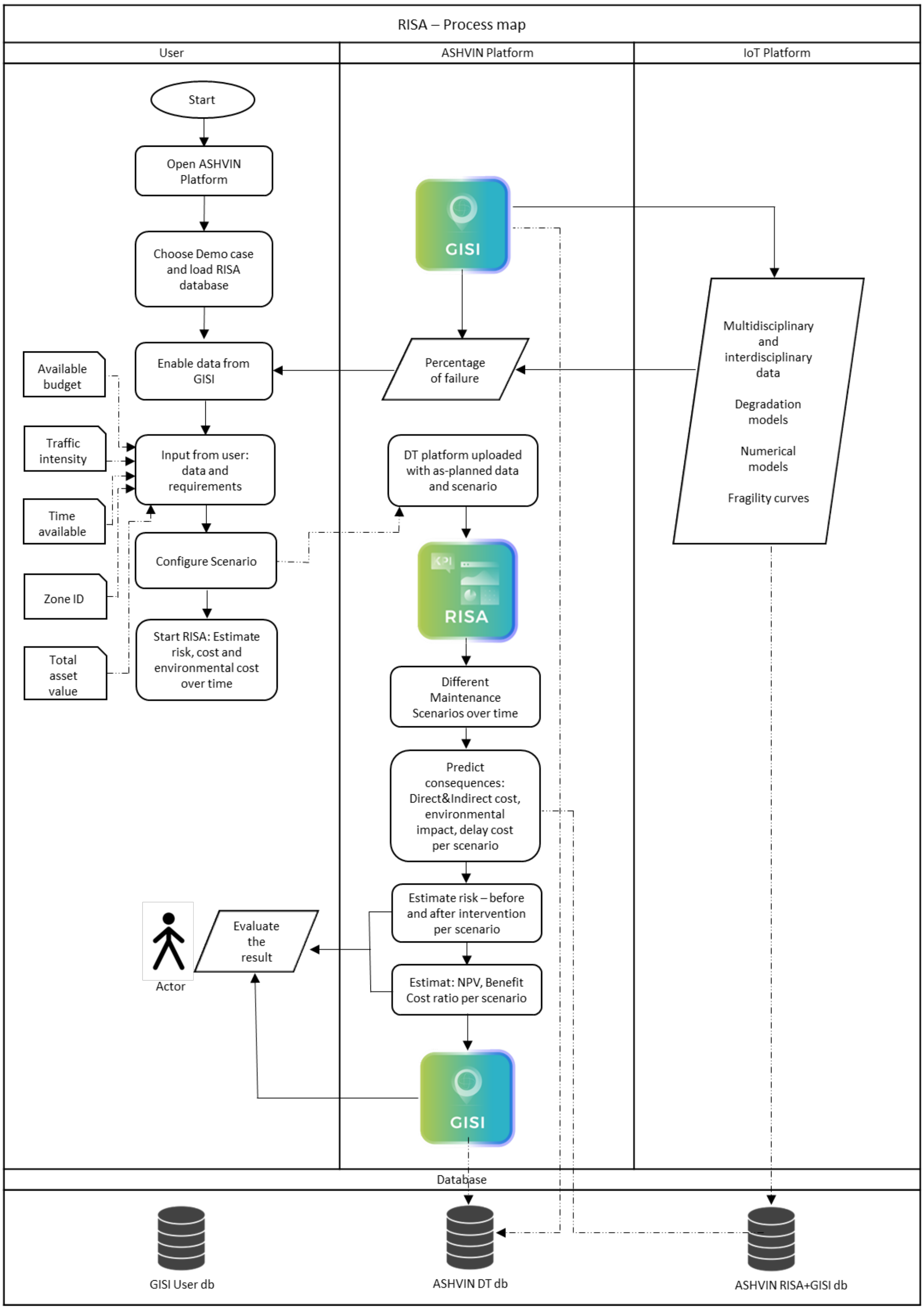

Figure 13 Overall process flow of the RISA tool

3.2 RISA tool applied on Demo case #3: Zadar Airport

Infrastructure managers are faced with a range of decisions when it comes to managing risks associated with their infrastructure assets. One of the most important considerations in this regard is how to balance risk and budget constraints and the user/manager decides on the risk approach.

If an infrastructure manager has a limited budget, they will probably postpone interventions for as long as it goes and in that way be more prone to risk while keeping the infrastructure at acceptable level. This means investing only in necessary reactive measures over the service life and finally have major investment at the end of service life of structure components.

With a higher budget available, infrastructure managers invest regularly in monitoring, inspections and preventive maintenance interventions to ensure that infrastructure assets are in excellent condition, while avoiding the risk over the whole life cycle and overall having more consideration about socio-economic impacts (i.e. reducing greenhouse gas emissions or improving public safety).

Overall, the risk preferences of infrastructure managers depend on a range of factors, including the specific nature of the infrastructure assets in question, the goals and priorities of the organization, and the available budget.

The RISA tool allows the user/manager to choose the risk approach from smaller to larger investments, considering the available budget for a certain period, per year, or per investment period. For transport infrastructure such as airports different traffic growth scenarios are taken into account, see Figure 14. Higher traffic increase in the future leads to accelerated degradation of the structure, a larger number of users, and the need for more frequent inspections and maintenance activities.

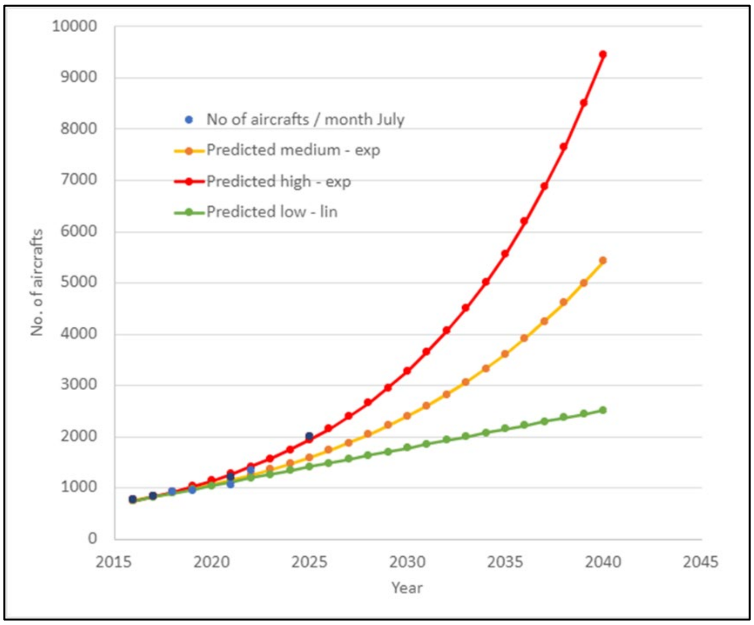

Figure 14 Estimated traffic scenarios for the peak month (July) for Zadar airport until 2040 – low, medium, and high traffic growth[1]

[1] https://www.zadar-airport.hr/en/aci-zadar-airport-among-top-5-terms-traffic-growth

RISA includes the development of different maintenance scenarios for defects detected and visualized in the GISI. The type and frequency of maintenance required can vary depending on the condition of the infrastructure and the type of defects. The level of maintenance can vary from routine maintenance such as regular inspections, cleaning, and minor repairs to more significant maintenance such as rehabilitation and reconstruction, or even urgent and extensive maintenance such as full reconstruction or replacement, see Figure 15. Overall, infrastructure managers need to develop specific maintenance scenarios depending on the condition of the asset, its age, the materials used, and the level of usage. A proactive approach to maintenance can help prevent more serious issues from developing, extend the life of infrastructure assets, and ensure the safety and efficiency of transport systems. Also, optimal planning with performing multiple maintenance activities in a coordinated and efficient manner saves time and resources by minimizing traffic disruptions.

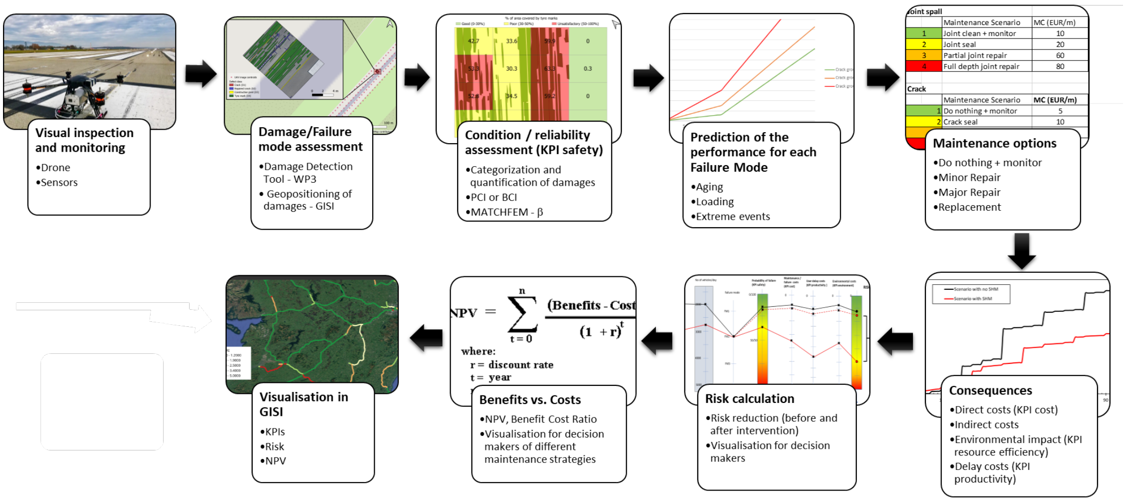

Figure 15 RISA Process flow

As the RISA tool heavily depends on input from airport management, an interactive and automated process is necessary to allow for seamless integration with the GISI tool and the airport's facility management system. Consequently, a model of RISA was implemented using R, a programming language and environment primarily used for statistical analysis, data visualization, and data manipulation. The outputs of the model include forecasts of the runway condition, associated costs, and risks which all directly depend on the client's thresholds and spending preferences. In the next chapters two use cases related to runways will be presented: i) accumulation of tire marks, which influence the friction and therefore need to be removed, ii) pavement cracking, causing potentially FODs and bigger delamination in the runway pavement.

3.2.1 Tire marks

3.2.1.1 User Inputs

In the case of tire marks the user will be asked a few questions that will influence the results of the deterioration forecast. As there is a direct relationship between the number of operations per year and the speed at which the system deteriorates, the first question inquiries about the current number of aircraft operations per year. Then, the second question is to know an estimated percentage of increase in operations in the upcoming years. These values are unique to every airport and should be collected form historic data. In the case of Zadar Airport, the inputs for the first and second questions are 30,000 operations and 2% respectively. Finally, the last input from the user will be a threshold of the percentage of tire marks per tile at which a maintenance intervention will be prompted. The threshold is a value between 0 and 100%, where the latter is the worst and will be set at 60% for this scenario. Input data are shown in Figure 16.

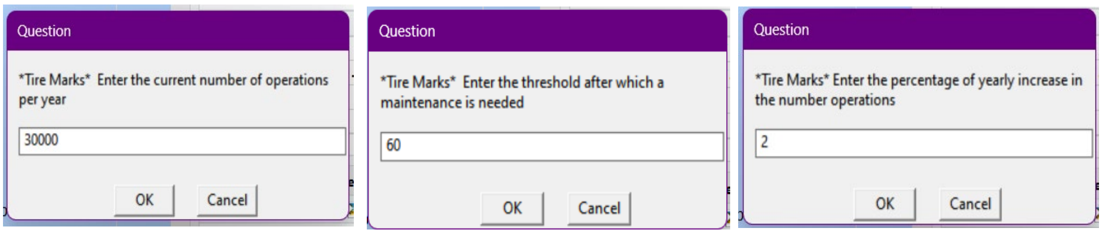

Figure 16 Input data for Use Case 1: Tire Marks

3.2.1.2 Calculation of Operations

As the number of yearly operations and the percentage of increase are stored, the next step is to calculate the number of yearly operations for the period selected for analysis. In this case, the selected period is 30 years. The equation (1) demonstrates how the future yearly operations are calculated. The calculation of the number of operations is important because according to historic data, every 600 operations increase the percentage of tire marks by 1% in tiles subjected to take-off and landing. The chart below, Figure 17, represents the results of the calculation of operation numbers over 30 years.

*No. of operations [i, j] = Initial No. of operations * ((1 + (Percentage of yearly increase / 100)) ^j)* [Eq. 1]

Where *i* is the tile id and *j* is the year.

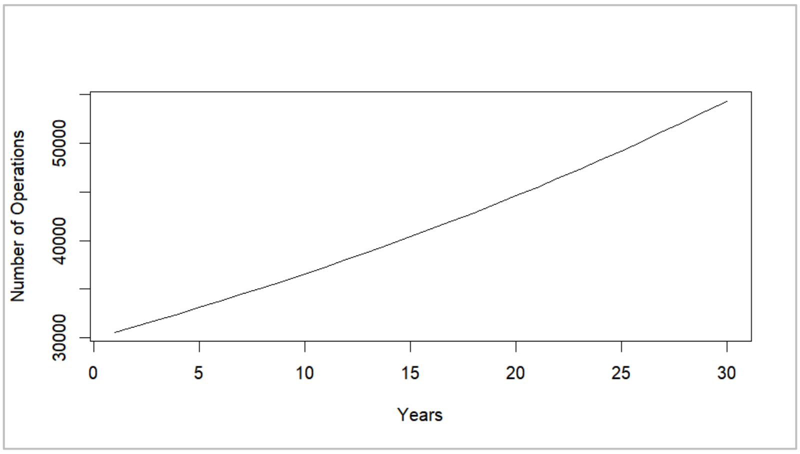

Figure 17 Increase of airport operation numbers for the case study

3.2.1.3 Tire Mark Forecast

Because of the gap in the deterioration rate of different tiles due to location, when forecasting, a linear increase in tire mark percentage for all tiles will not be realistic. Instead, a rule is created to forecast the increase in tire marks over the years so that tiles that are not subject to landing and take-off will deteriorate much slower than tiles that are subject to a greater amount of friction with the operating aircraft.

Now, based on the number of operations in each particular year and as long as the tire mark percentage remains lower than the predetermined acceptable threshold specified by the client, the percentage is calculated per each tile according to the following rules.

Procedure is as follows:

Initial Percentage of tire marks = 0%

The percentage remains zero.

0% < Initial Percentage of tire marks <= 2%

x.forecast [i, j] = initial tire mark percentage + (No. of operations [i, j] / 600)) * 0.05

Where i is the tile id, j is the year and x.forecast is the forecasted tire mark percentage

2% < Initial Percentage of tire marks <= 10%

x.forecast [i, j] = initial tire mark percentage + (No. of operations [i, j] / 600)) * 0.2

Where i is the tile id, j is the year and x.forecast is the forecasted tire mark percentage

10% < Initial Percentage of tire marks <= 30%

x.forecast [i, j] = initial tire mark percentage + (No. of operations [i, j] / 600)) * 0.5

Where i is the tile id, j is the year and x.forecast is the forecasted tire mark percentage

30% < Initial Percentage of tire marks <= 100%

x.forecast [i, j] = initial tire mark percentage + (No. of operations [i, j] / 600))

Where i is the tile id, j is the year and x.forecast is the forecasted tire mark percentage

3.2.1.4 Planning Maintenance Interventions

If, at any year, the forecasted tire mark percentage surpasses the predetermined threshold, a maintenance intervention is then triggered, calculating the associated costs. In that case, it is assumed that the maintenance intervention will leave only 5% of the tire marks behind. The following Table 3 demonstrates the maintenance interventions with respect to the percentage of tire marks.

Table 3 Different maintenance scenarios associated with cost, triggering values and rule after performance of scenario

	Maintenance Scenario	Cost (EUR/m2)	Tire mark density	Rule after maintenance TMI
1	Do nothing + monitor		0-30	
2	Remove tire marks	2	> 30	5

The following chart, Figure 18, plots the number of tiles (out of 240, it is on average 5%) that surpass the predetermined threshold and will consequently need maintenance intervention with respect to the year number in the forecast. As observed, the number of tiles in need of maintenance intervention remains the same through the years as it is mainly governed by the tiles subject to friction from take-off and landing.

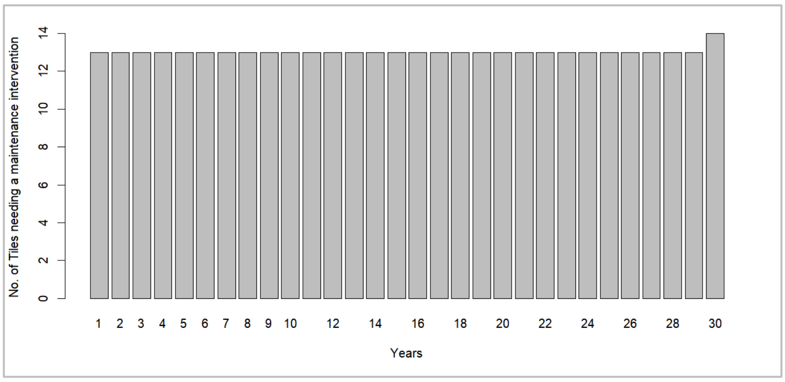

Figure 18 Number of tiles needing a maintenance intervention in a certain year

3.2.1.5 Maintenance Costs

To calculate the total cost of maintenance for each tile, the surface area of tire marks on the tile is multiplied by the unit price of the process of tire mark removal. As presented in Table 3, for this analysis the assumed cost of removing 1 square meter of tire marks is 2 euros. Consequently, a list is returned showing the maintenance costs per tile per year. The equation (2) is used for the calculation of the maintenance interventions' costs, as follows:

$$\textit{Maintenance cost } [i, j] = (\textit{x.forecast } [i, j] * \textit{Total Tile Surface Area}) * \textit{Tire Mark Removal Unit Cost} \qquad \text{[Eq.2]}$$

Where *i* is the tile id, *j* is the year and *x.forecast* is the forecasted tire mark percentage.

Based on the built in deterioration forecast and given the initial inputs mentioned in the user inputs section, Figure 19 shows the tire marks maintenance costs over the span of 30 years with a minimum of 7,296 euros in the first year and a maximum of 10,306 euros on the 30th year.

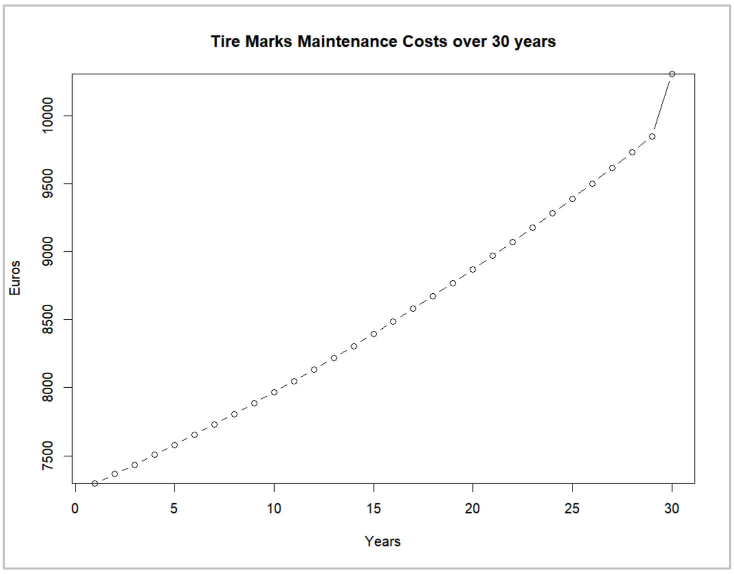

Figure 19 Maintenance cost for removal of rubber from runway surface over 30-year span

3.2.1.6 Risk Calculation for Tire Marks

Tire marks reduce friction on the runway, which can cause aircraft excursions and other fatal and costly consequences. Therefore, the risk is calculated taking into account several factors like friction coefficient, direct and indirect costs of failure, and their probabilities. The following equation demonstrates how risk is calculated for tire marks.

$$R = p_{FM}\ x\ Consequences = p_{FM}\ x\ (DC + IC) \qquad \text{[Eq. 3]}$$

Where p_{FM} is the probability of an asset failure mode given the threat scenario magnitude. *DC +IC* are the direct and indirect consequences i.e., monetized losses due to the failure mode for certain elements/objects/systems.

As a performance metric, the friction coefficient is used to determine the probability of failure. Table 4 demonstrates ranges of tire mark percentages and their respective friction coefficients. The final probability of failure per tile is calculated to be 1 minus the friction coefficient.

Table 4 Correlation between percentage of surface covered with tire marks and friction coefficient

Percentage of Tire Marks	Average value of friction coefficient
<5%	>= 0.65
5-20%	0.55 - 0.64
20-40%	0.50 - 0.54
40-60%	0.40 - 0.49
60-80%	0.30 - 0.39
80-95%	0.20 - 0.29
≥95%	<= 0.19

As different tiles are treated differently according to their location with respect to the aircraft landing positions, calculating the risk for all tiles together will not be a good representation of the overall state of the structure. For this reason, the following graphs in Figure 20 display the risk calculations for the landing zone and the non-landing zone.

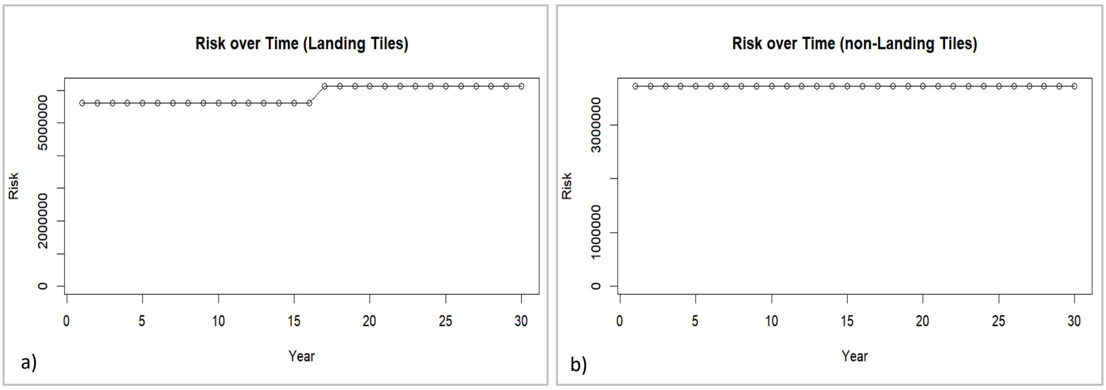

Figure 20 Risk values for a) landing and b) non-landing zone

3.2.2 Cracks

Cracks in the asphalt of an airport runway can pose several dangers and risks including FOD Hazards. This can create gaps where debris, such as loose asphalt, stones, or vegetation, can accumulate. This debris can be ingested by aircraft engines or damaged tires, leading to potential accidents or equipment malfunctions. Unlike tire marks, the categorization of the tiles according to their respective PCI does not show a clear trend. This is because cracks mostly happen due to environmental factors rather than being directly related to the number of operations.

3.2.2.1 User Input

As a client decision-based model, the RISA tool allows the user/manager to choose the risk approach from smaller to larger investments, considering the available budget for a certain period, per year, or per investment period. In that sense, the model starts by asking the user about the preferred threshold after which a maintenance intervention is scheduled, and its costs calculated. After that, to capture the spending preference of the user, he/she is asked if maintenance interventions should restore the pavement to its optimal state or only commence partial maintenance. This will create two completely different maintenance scenarios; however, the model can accommodate more maintenance scenarios if demanded by the airport management. In this context, typing TRUE will assume full repairs, which corresponds to scenario 1. On the other hand, typing FALSE will assume partial repairs, which is scenario 2.

For the purpose of this study, a threshold of PCI=40 is chosen, see Figure 21, and a comparison will be made between the two provided scenarios in every section.

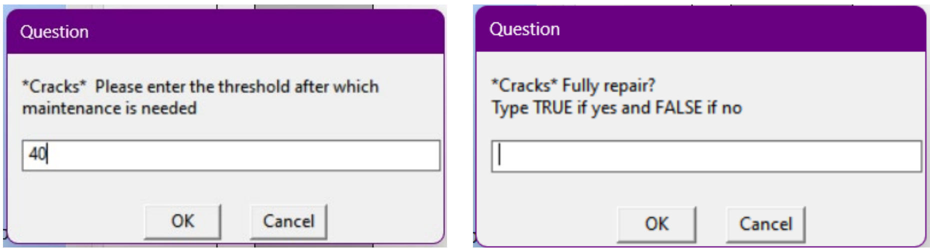

Figure 21 User inputs for threshold regarding cracks

3.2.2.2 PCI forecast

Since cracks are not directly related to the number of operations, a look into historic data implied that the PCI increase by 2.5 every year resulting in a linear deterioration behaviour. For the demo case of Zadar Airport, the calculated PCI values are represented in the normal distribution curve shown in the Figure 22 below with a mean of 65.64, a minimum of 32.72, and a maximum value of 95.48.

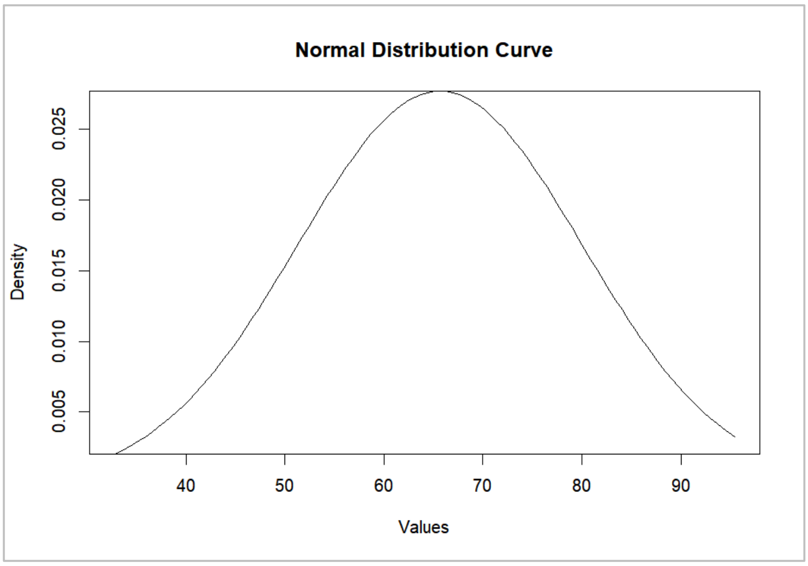

Figure 22 Normal distribution curve for PCI values for demo case

3.2.2.3 Planning Maintenance Interventions

The first step in planning maintenance interventions is predefining maintenance options for crack repair, their costs and and how much they improve the state of the pavement.

Table 5 and Table 6 display the predefined input data (developed in collaboration with airport managers) and highlight the differences between scenarios 1 and 2.

Table 5 Maintenance scenario 1 – different maintenance activities associated with cost and difference of PCI value before and after maintenance

	Category	PCI	Maintenance Activity	Maintenance Cost (EUR/m)	PCI value after maintenance
1	Good	100 – 85	Do nothing + monitor	0	
2	Satisfactory	85 – 70	Crack seal	200	99
3	Fair	70 – 55	Partial crack repair	500	99
4	Poor	55 – 0	Full-depth crack repair	1500	99

Table 6 Maintenance scenario 2 – different maintenance activities associated with cost and difference of PCI value before and after maintenance

	Category	PCI	Maintenance Activity	Maintenance Cost (EUR/m)	PCI value after maintenance
1	Good	100 – 85	Do nothing + monitor	0	
2	Satisfactory	85 – 70	Crack seal	200	PCI + 15
3	Fair	70 – 55	Crack Seal	200	PCI + 15
4	Poor	55 – 0	Partial Crack Repair	500	PCI + 30

Figure 23 and Figure 24 display the number of tiles in need of maintenance in both scenarios 1 and 2. It is important to note the importance of the chosen PCI threshold on the amount of needed maintenance. If this number increased, the number of needed maintenance interventions will also increase. The charts also show that choosing to maintain only partially (scenario 2) results in a higher amount of maintenance interventions, where the total amount of maintained tiles for scenario 1 is 311 whereas it is 516 for scenario 2.

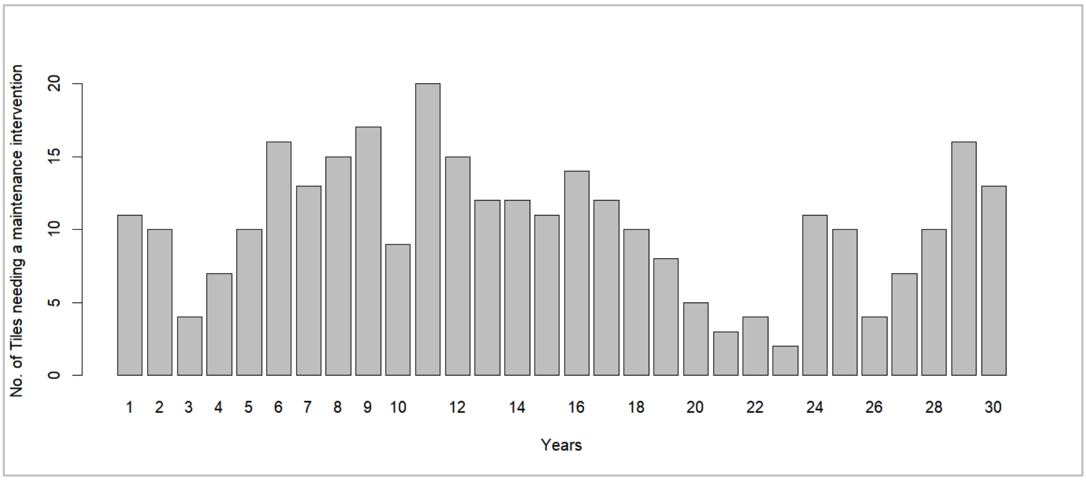

Figure 23 Number of tiles needing a maintenance intervention for scenario 1

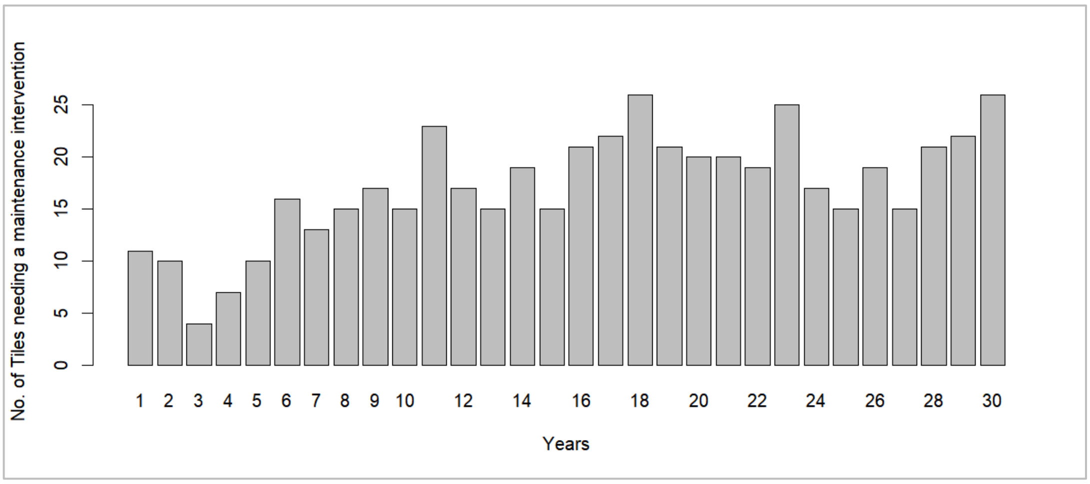

Figure 24 Number of tiles needing a maintenance intervention for scenario 2

3.2.2.4 Maintenance Costs

To calculate the total cost of maintenance for each tile, the length of the crack is multiplied by the unit price of the respective maintenance activity, mentioned in the table above. However, a step is added to estimate the length of the crack from the forecasted PCI. Consequently, a list is returned showing the maintenance costs per tile per year. The equations used are as follows:

If PCI threshold > 35
Then Length of Crack [i, j] = ((100 – PCI [i, j]) / 19.648) ^ (1/0.4368) * (375 / 100)
Else Length of Crack [i, j] = exp ((100 - PCI [i, j] - 12.742) / 18.664) * (375 / 100)

$$Maintenance\ cost\ [i, j] = Length\ of\ Crack\ [i, j] * Unit\ Cost\ of\ Chosen\ Treatment \quad \text{[Eq. 4]}$$

Where *i* is the tile id, *j* is the year.

Based on the built deterioration forecast and given the initial inputs mentioned in the user inputs section, the following graphs in Figure 25 and Figure 26 show the cracks maintenance costs for both scenarios over the span of 30 years. It is worth noting that for scenario 1, the cumulative amount of money needed to be spent on maintenance is forecasted to be 22.5 Mil while for scenario 2 it is close to 12.5 Mil.

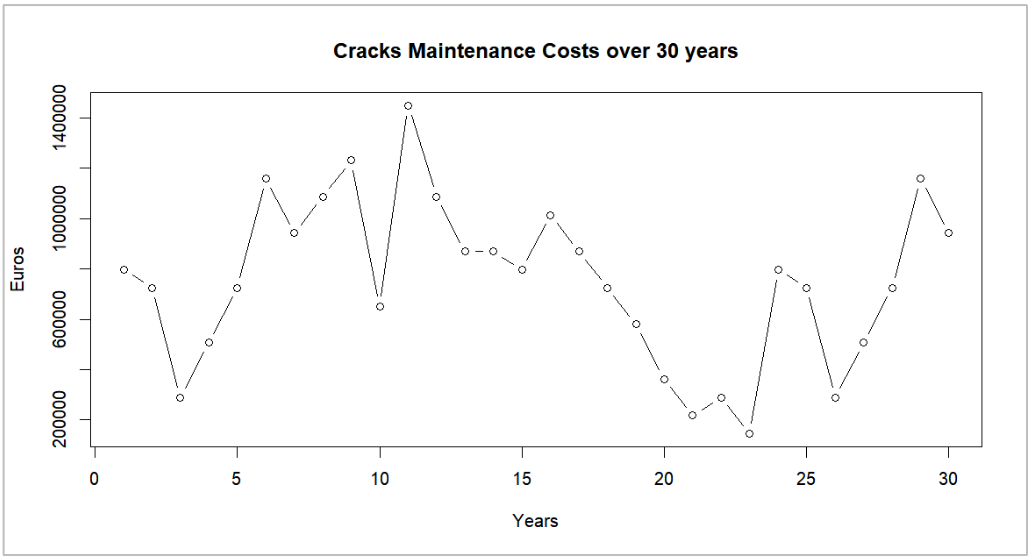

Figure 25 Maintenance costs for scenario 1

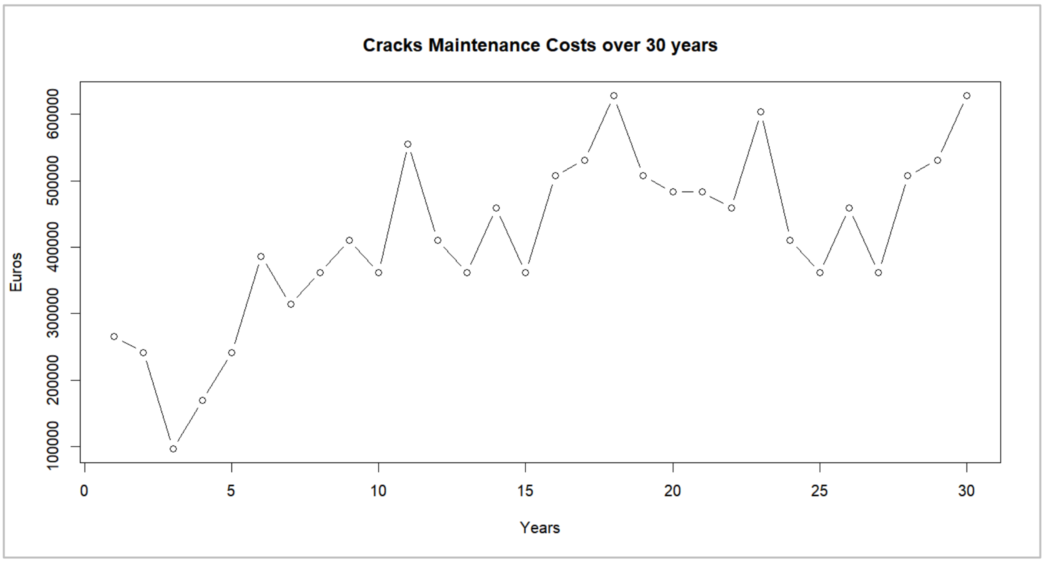

Figure 26 Maintenance costs for scenario 2

3.2.2.5 Risk Calculation for Cracks

Given a PCI threshold of 40, it is safe to assume that all tiles will need maintenance interventions at least once over the span of 30 years. However, the closer a tile is to the threshold without being maintained, the more risk it is to the whole system. As in the tire marks, the equation to calculate risk is as follows.

$$R = p_{FM}\ x\ Consequences = p_{FM}\ x\ (DC + IC) \qquad \text{[Eq. 5]}$$

Where p_{FM} is the probability of an asset failure mode given the threat scenario magnitude. *DC +IC* are the direct and indirect consequences i.e., monetized losses due to the failure mode for certain elements/objects/systems.

The calculation of consequences included aircraft damage due to FODs, airport closure costs, costs of runway excursions, and total runway replacement costs. Meanwhile, the probability of failure due to runway cracks is inversely proportional to the respective tile's PCI. The following table is an example of PCIs and their respective failure probabilities.

Table 7 Correlation between PCI, probability of failure and FOD hazard probability

PCI	Probability of failure	FOD hazard probability
99	0.01	0.001
70	0.30	0.030
55	0.45	0.056
30	0.70	0.175
0	1.00	0.333

Depending on the investment patterns of the airport's management, the risk will be affected. One way to keep the risk low is to choose a high PCI value as the threshold that triggers a maintenance intervention. Another way that affects risk is the choice to either fully or partially repair the tiles. In our demo case, the difference between scenarios 1 and 2 is in the choice to fully repair or not. The following graphs, see Figure 27 demonstrate the calculation of risk over the span of the next 30 years comparing scenarios 1 and 2.

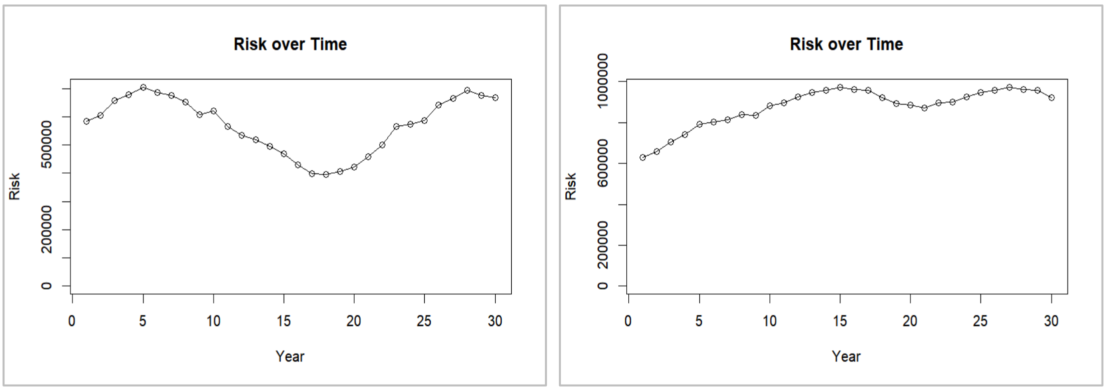

Figure 27 Risk values through time for scenario 1 (left) and scenario 2 (right)

Even though the threshold is the same for both scenarios, the choice to spend less money on maintenance interventions still leads to a higher risk. Scenario 1 has an average risk of ca. 571k euros over the span of 30 years while scenario 2 has more than 50% higher average risk (ca. 877k euros). This is illustrative example why preventive maintenance should be preferred (Scenario 1) over reactive maintenance (Scenario 2).

4 CONCLUSION

The integration of monitoring, condition assessment, and maintenance of infrastructure into GIS tool enables creation of a comprehensive database of infrastructure assets. Various information through all life cycle phases of a structure is collected, stored and processed for improved maintenance and operations planning. The condition of infrastructure assets is visualized in the GIS system and can be further used to establish trends and patterns. Asset managers are provided with a tool that enables detecting possible issues on time and planning of maintenance and repair works appropriately. According to condition assessment, this entails identifying specific areas that need attention and prioritizing work according to the degree of risk connected to each asset or component of an asset. Finally, the use of GISI tool can assist asset managers in communicating to stakeholders the state of the infrastructure and in making data-driven decisions for maintenance and repair activities.

Infrastructure managers must make various decisions in managing risks related to their infrastructure assets. A critical consideration in this context involves finding the right balance between risk and budget constraints, with the user/manager determining the preferred risk approach. The risk based asset management tool (RISA) has embedded those considerations and constrains and in that way empowers the end-user to select the preferred risk approach, considering the scale of investments, while ensuring certain safety, taking into account the available budget and considering the wider socio-economic impacts. In this way the tool enables end users to interactively review and make use of certain outcomes from risk assessment and consequence modelling. The goal of the proposed tool is to enable comparison of various maintenance scenarios based on asset monitoring and condition assessments, considering predefined KPIs like safety, costs, productivity, and environmental costs, in order to identify the best maintenance scenarios to carry out within the certain time frame. The tools can be used for both short term and long term planning under budget and maintenance constraints and different environmental and social preferences.

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