The impact of climate change on key operational performance measures

PREPARED FOR ANGLIAN WATER SERVICES LIMTED

PRIVATE AND CONFIDENTIAL

—

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Executive summary (1/3)

Context

This Report presents analysis of the key risk drivers affecting Anglian Water Services' (AWS) operational performance at AMP8, with an emphasis on the impact of exogenous factors such as climate change.

The analysis focusses on AWS's risk exposure in relation to pollution incidents and sewer flooding across AMP8 to inform consideration of regulatory calibration in its Draft Determination (DD) representations.

As the water sector experiences changing climate conditions, exogenous factors such as increased rainfall are expected to have a significant effect on AWS's operational performance.

These factors, which are predominately beyond AWS's control, are in turn likely to exacerbate the impact of risk drivers such as hydraulic overload on operational performance, all else equal leading to more frequent pollution incidents.

A detailed understanding of risk drivers and inter-relationships between these drivers is important for simulating performance across AMP8 and calibrating regulatory mechanisms.

Simulation of core risk drivers and assessment of climate change impact on AMP8 operational performance

01

The Report employs established statistical simulations to evaluate the effects of core risk drivers, for example hydraulic overload and blockages, on AWS's AMP8 operational performance.

02

A neural net is developed to integrate climate change variables into the analysis*. Specifically, the Report provides an assessment of how exogenous factors outside AWS's control in combination are expected to influence AWS's overall risk profile over the AMP8 regulatory period.

03

Analysis of the impact of exogenous factors can be used to stress test DD prescribed performance targets and inform regulatory calibration of Outcome delivery incentive (ODI) and corresponding Totex allowances, in particular to assess whether levels of performance assumed in targets are achievable.

** A neural network is a machine learning model that learns to recognise relationships between variables and uses these relationships to make predictions or decisions based on new information. Detailed description is presented in Step 4 of the Report.*

Executive summary (2/3)

Methodology

The overall approach to carrying out risk simulations for key ODIs over AMP8 is set out below.

01

Identify risk drivers

Identify key risk drivers, which are factors influencing the operational performance risk profile using historical incidents data provide by AWS.

02

Develop risk models

Develop risk models to analyse historical events and understand how changes in these drivers affect operational performance.

The analysis considers a number of statistical algorithms to develop optimised risk models with the highest predictive capability for the simulation.

03

Simulate AMP8 plausible performance

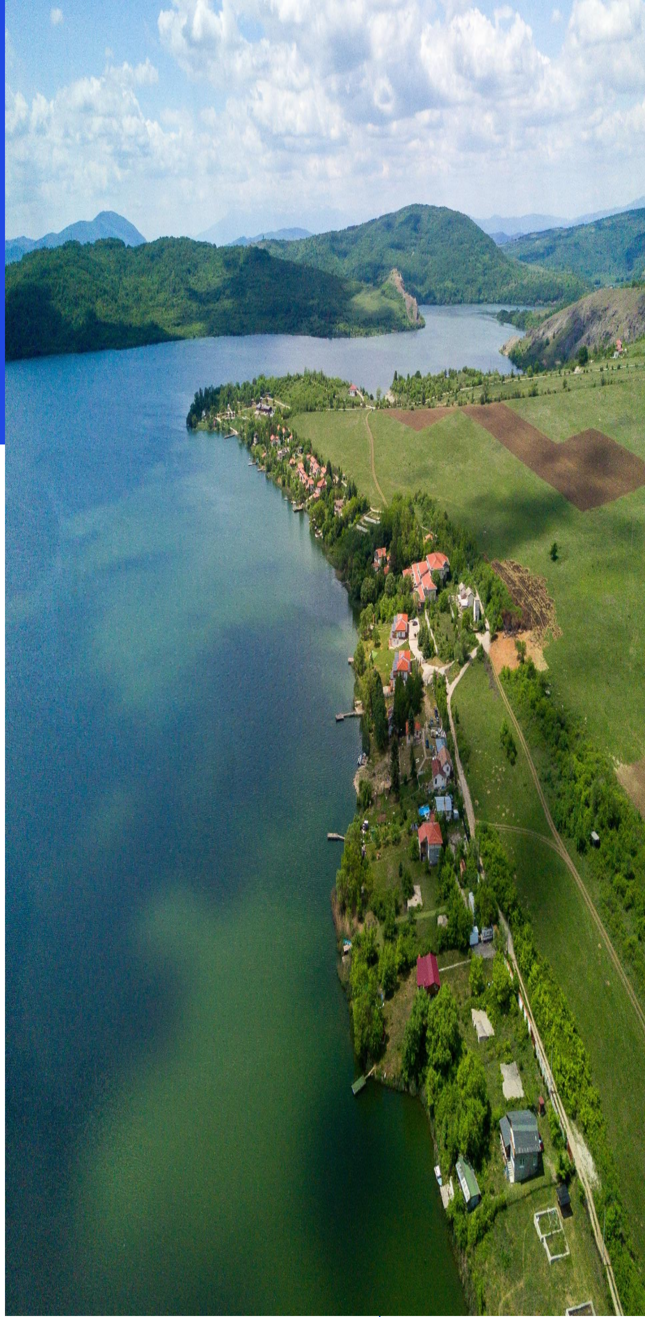
Quantify AMP8 risk exposure by simulating how risk drivers may evolve and the corresponding impact on operational performance.

04

Quantify the potential impact of climate change on AMP8 operational performance

Following step 3, this quantification isolates the impact of climate change on operational performance through a neural network, which is a type of machine learning that can find patterns and relationships based on historical data.

The neural network can quantify how changes in climate change factors, such as monthly rainfall, impact on AMP8 operational performance.



Executive summary (3/3)

Key findings: Risk exposure and climate change impact on AMP8 operational performance

- The analysis suggests that AWS will face materially increased risk exposure at AMP8 relative to historical performance for pollution incidents and sewer flooding, under both base case and downside scenarios.
- Without appropriate risk mitigations, potential performance risk exposure could equate in downside scenarios to **£349m**, **£425m** and **£78m** for pollution incidents, external and internal sewer flooding over AMP8 respectively.
- The implied level of financial exposure emphasises the importance of appropriate calibration of the ODI framework and corresponding Totex allowances to ensure that the price control represents a fair bet and the scale of risk exposure is consistent with returns.

- The neural net has isolated impact of climate change on AWS's operational performance at AMP8. The simulation suggests that climate change risk exposure is increasing at AMP8 and explains up to **24%** of the risk associated with pollution incidents. Similarly **23%** of external flooding incidents can be attributed to increased levels of rainfall.
- This climate-related exposure could result in financial impacts of up to **£84m** and **£101m** for pollution incidents and external flooding under plausible downside scenarios respectively absent changes to calibration of PR24 ODIs and Totex allowances.

Potential implications of the risk simulations

01 *Climate change is affecting core risk drivers and increase risk on pollution incident and sewer flooding ODIs. Therefore, the regulatory framework will need to be carefully specified in order to reflect the increasing risk exposure.* ***Additional investments may be necessary to improve resilience to climate change.***

02 *Alternatively, PR24 targets and ODI rates could be recalibrated to reflect the impact of climate change and ensure that targets are achievable assuming allowance remains unchanged. Adjustments to ODI calibration* ***would refine risk allocation to reflect factors within AWS's control.***

Understanding operational performance and the impact of climate change during AMP8

Understanding the core risk drivers for key ODIs is crucial to address risk at source and to underpin appropriate incentive calibration.

Recent data suggests that climate change poses significant and increasing risk to AMP8 operational performance*.

As a result, the analysis in this Report aims to explore two key areas:

1. **The plausible AMP8 operational performance range based on the evolution of relevant core risk drivers throughout AMP8; and**
2. **The impact of climate change and how this could affect AWS's AMP8 operational performance.**

Given the current rapid changes in climate conditions, it is important to understand how exogenous factors such as weather are expected to impact on the evolution of the core risk drivers during AMP8.

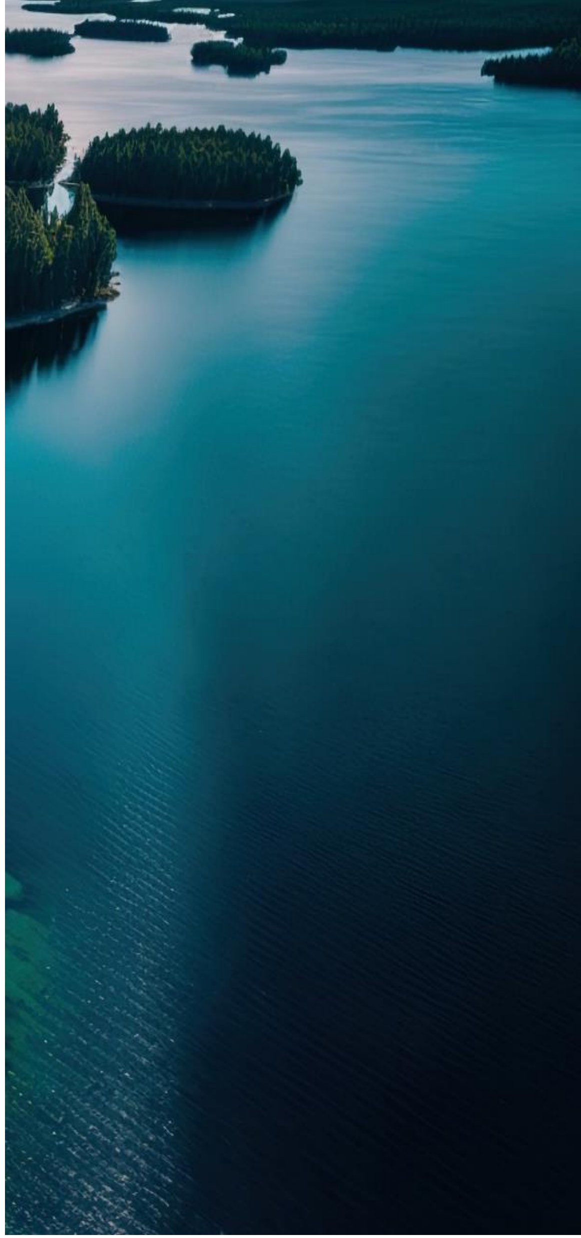
For example, an increase in rainfall can place additional stress on sewage systems, potentially exceeding their designed capacity and leading to hydraulic overload incidents. An increase in expected rainfall would all else equal result in a higher number of forecast pollution incidents and a reduction in water quality.

To achieve these objectives, the Report will:

Identify core risk drivers for key ODIs and quantitatively show how these drivers could evolve over AMP8 and subsequent impact on AWS's potential performance

Link climate measures to these drivers and show how climate change may impact AMP8 performance

Demonstrate the £m value at risk of climate change impacts on key risk drivers.



** Detailed analysis is presented in Step 4 of the Report.*

Potential implications of risk analysis for regulatory calibration

The risk simulation can be used to inform calibration of the regulatory framework proposed in the DD, ensuring the overall package balances risk and return. Risk analysis can support the design of achievable and sustainable targets given trends in exogenous factors outside of company control.

01

Assessing achievability of DD prescribed targets

The analysis provides risk simulations that consider the evolution of relevant risk drivers and their aggregate impact on AMP8 performance.

The simulated AMP8 operational performance can be used to assess whether the DD prescribed targets set by Ofwat are both realistic and achievable given historical trends and relationships between observed drivers.

02

Assessing the level of Totex allowance

The risk simulations provide a robust framework whether additional funding is required to support achievability of targets. These simulations can identify gaps where additional investments may be necessary to address risks at source.

For example, additional allowance may be required to address hydraulic overload issues, which can improve pollution incidents performance throughout AMP8.

03

Informing calibration of regulatory framework

The risk simulations can be used to assess adjustments to ODI targets and penalty rates to inform a more balanced regulatory package. This can ensure that penalties are proportionate and do not penalise companies for factors beyond their control.

Specifically, reduction to ODI targets or the introduction of additional caps and collars could be employed to mitigate the impact of climate change on AMP8 risk exposure.

Methodology to simulate operational performance risk and isolate the impact of climate change on risk exposure

The overall approach to carrying out risk simulations for key ODIs over AMP8 is set out below.

01

Identify risk drivers

- Identify key risk drivers, which are factors influencing the operational performance risk profile using historical incidents data.
- This was undertaken by assessing relative strengths of causal relationships across a large body of data provided to us by AWS.

02

Develop risk models

- Develop risk models to analyse historical events and understand how changes in these drivers affect operational performance.
- The analysis considers a number of statistical algorithms to develop optimised risk models with the highest predictive capability for the simulation.

03

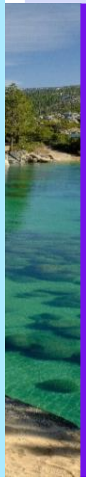
Simulate AMP8 plausible performance

- Quantify AMP8 operational performance risk exposure by simulating how risk drivers will evolve and the corresponding impact on operational performance.
- This step does not isolate climate change common risk driver's impact on performance – see step 4.

04

Quantify the impact of climate change on AMP8 operational performance

- Following step 3, this quantification isolates the impact of climate change on operational performance through a neural network, which is a type of machine learning that can find patterns and relationships based on historical data.
- The neural network can quantify how changes in climate change factors, such as monthly rainfall, impact on AMP8 operational performance.



The methodology adopted for each step is grounded in established statistical models, ensuring that the results from the risk simulations are robust.

A detailed explanation of the methodology is provided at each relevant step of the analysis.

The following sections explore these steps in sequence.

Step 01

Identification of core risk drivers

Overview of core risk drivers

The risk simulations focus on three key performance measures, based on discussion with AWS, within the water recycling business: Pollution incidents, External sewer flooding, and Internal sewer flooding. A historical database of events that impact these performance measures, along with corresponding root causes, has been provided by AWS to identify core risk drivers for each measure.

By evaluating operational performance at the incident level, the analysis can identify the most material risk drivers for each performance measure, enabling more robust simulations of risk exposure and capturing changing dynamics over time. It also supports the development of targeted risk management strategies and actions to improve AMP8 operational performance.

The tables below outline the relative percentage impact of risk drivers, identified using historical incidents database, for each respective performance measure.

Pollution incidents risk drivers								
% impact on total incidents based on historical data	Blockage	Electrical	Civil/structural	Operator error	Hydraulic overload	Biological	Mechanical	Other / unknown (not significant relationship)
	30.98%	11.09%	20.09%	2.22%	22.05%	5.35%	2.02%	6.20%

Sewer flooding risk drivers									
% impact on total incidents based on historical data	Blockage	Collapse	Equipment Failure	Overloaded	Pumping Station Failure	Pumping Station Failure due to 3rd party	Collapse due to 3rd party	Blockage due to 3rd party	Equipment failure due to 3rd Party
External	80.42%	2.84%	3.37%	1.49%	0.20%	11.52%	0.02%	0.04%	0.11%
Internal	68.03%	5.13%	3.39%	6.23%	0.29%	16.75%	0.00%	0.15%	0.04%

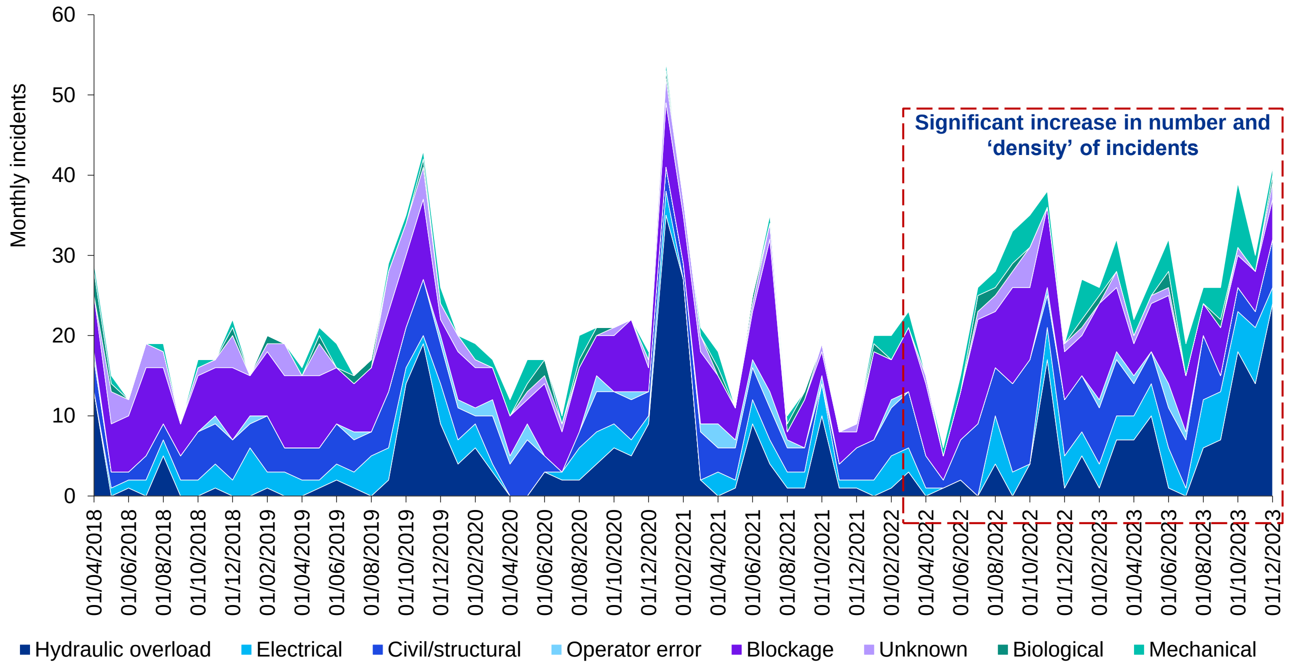
Identifying core risk drivers – Pollution incidents

The risk simulation aims to identify and analyse the evolution of core risk drivers for pollution incidents based on historical data. Emerging trends show that pollution incidents driven by key risk drivers, i.e. hydraulic overload, have increased in both scale and severity in recent years.

The table and figures below decompose key pollution incidents risk drivers and their historical evolution. Definitions of risk drivers and rationale on how these could impact pollution incidents performance are presented in Appendix 1.

Pollution core risk drivers
Hydraulic overload
Electrical
Civil/structural
Operator/interference
Blockage
Biological
Mechanical

Total pollution incidents by drivers (# monthly incidents)



The figures show monthly pollution incidents.

The analysis indicates a significant increase in frequency and severity since mid-2022.

Hydraulic overload and blockages have consistently been the major drivers of pollution incidents.

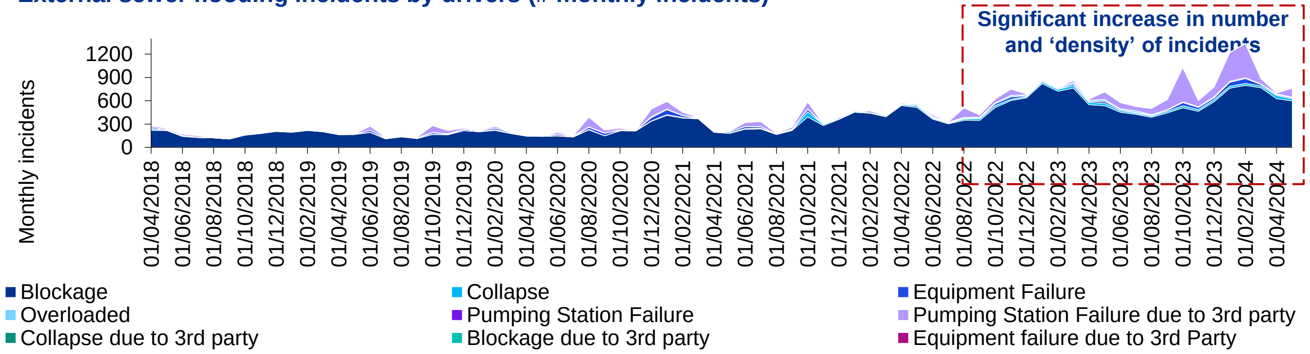
Identifying core risk drivers – Sewer flooding

The risk simulation identifies and examines core risk drivers affecting sewer flooding incidents using historical data at incident level. Recent trends indicate a material increase in the scale and severity of these incidents, primarily attributed to blockages and failures at third-party pumping stations.

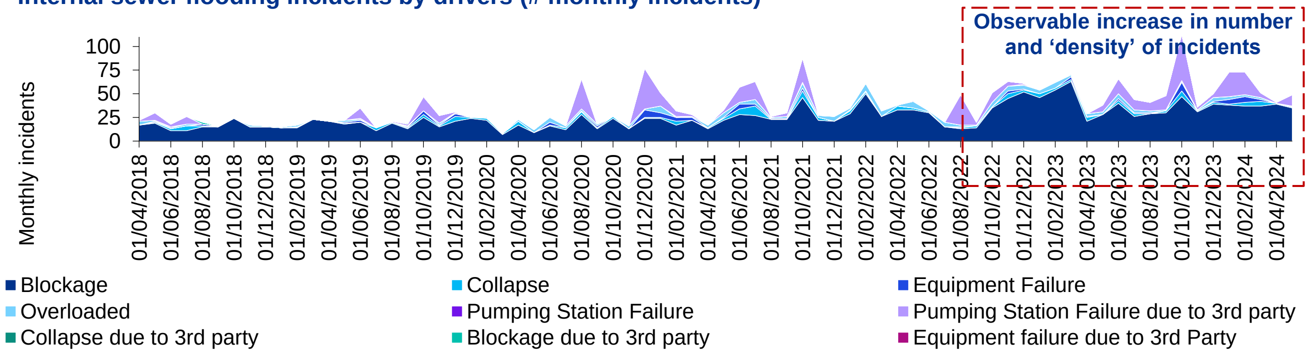
The table and figures below decompose key sewer flooding risk drivers and their historical evolution. Definitions of risk drivers and rationale on how these could impact sewer flooding performance are presented in Appendix 1.

Sewer flooding core risk drivers
Blockage
Collapse
Equipment Failure
Overloaded
Pumping Station Failure
Pumping Station Failure due to 3rd party
Collapse due to 3rd party
Blockage due to 3rd party
Equipment failure due to 3rd Party

External sewer flooding incidents by drivers (# monthly incidents)



Internal sewer flooding incidents by drivers (# monthly incidents)



The figures show monthly sewer flooding incidents.

The analysis indicates a significant increase in frequency and severity since mid-2022.

The main causes are blockages and third-party pumping station failures, both linked to increased rainfall and climate change.

Step 02

Risk model configurations and simulations

Overview of risk models' configurations and simulations (1/2)

A high-level summary of the statistical methodology employed in the simulations is outlined below.

01

Employ 11 distinct statistical models, derived from academic literature, to assess the plausible evolutions of risk drivers over AMP8.

02

Each statistical model uses granular historical data (e.g., daily data at incident level) encompassing thousands of observations.

03

Each model incorporates up to 6 parameters, depending on the specific methodology employed.

These models analyse historical data to generate unique simulation algorithms.

04

Calculate the Akaike Information Criterion (AIC), a metric for assessing model quality, where a lower value indicates better model*.

Select the optimal model for each risk driver based on the lowest AIC.

05

Run each risk driver simulations based on the selected model to generate potential performance paths, enabling the quantification of the plausible operational performance range over AMP8.

Illustrations of these paths are shown on slides 16 and 17.

** AIC balances goodness of fit and model complexity by combining the likelihood of the model (how well it fits the data) with a penalty for the number of parameters used. The best model has the lowest AIC, indicating it explains the data well without being overly complex.*

Overview of risk models' configurations and simulations (1/2)

By simulating each risk driver, the algorithms inherently incorporated embedded information from historical data on capital expenditure and operational parameters, such as spending levels relative to Totex allowances, rates of annualised increase in allowances, and technological changes.

The table below provides an overview of the algorithms used in the simulations and the statistical parameters considered for each algorithm.

Algorithm*	Statistical parameters	AR(1)	AR(2)	MA(1)	MA(2)	ARMA(1,1)	GBM	BMMR	GBM/JD	BMMR/JD	ARCH(1)	GARCH(1,1)
AIC Rank		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Akaike (AIC) Fit		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
# of parameters		*3*	*4*	*3*	*4*	*4*	*2*	*3*	*5*	*6*	*3*	*4*
Parameter #1	µ	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Parameter #2	σ	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Parameter #3	α	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
Parameter #4	λ		✓		✓	✓			✓	✓		✓
Parameter #5	µ Jump								✓	✓		
Parameter #6	σ Jump									✓		

** These algorithms have inherently embedded the impact of climate change in the risk simulations given climate change (i.e. measured as total rainfall) is a common driver influencing all core risks. The impact of climate change will be isolated using a separate neural net model discussed in Step 4 later in the Report.*

AR (Autoregressive) and MA (Moving Average) models capture relationships between current and past values or statistical errors in a time series, respectively. ARMA combines these approaches to model both dynamics. GBM (Geometric Brownian Motion) and its variations, such as GBMJ (with jumps), are used for modelling continuous processes, with possible sudden changes or jumps to capture real-world discontinuities. ARCH and GARCH models are employed to analyse time series data with volatility clustering, allowing for changing variance over time. Detailed description is provided in Appendix 2.

These algorithms provide a comprehensive framework for simulating the evolution of core risk drivers over AMP8.

✓	*Available statistics*

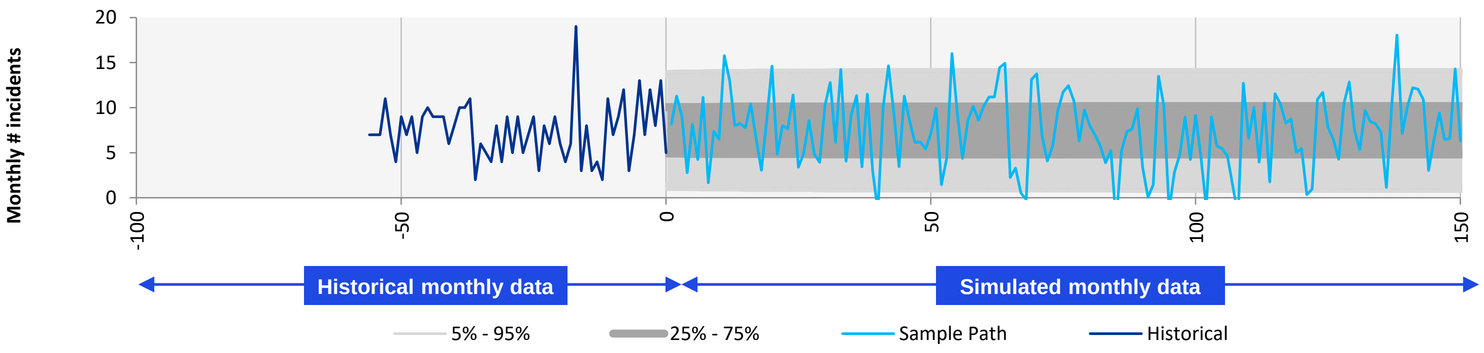
The following slides explore the simulations of core risk drivers for each ODI over AMP8 in more detail.

KPMG

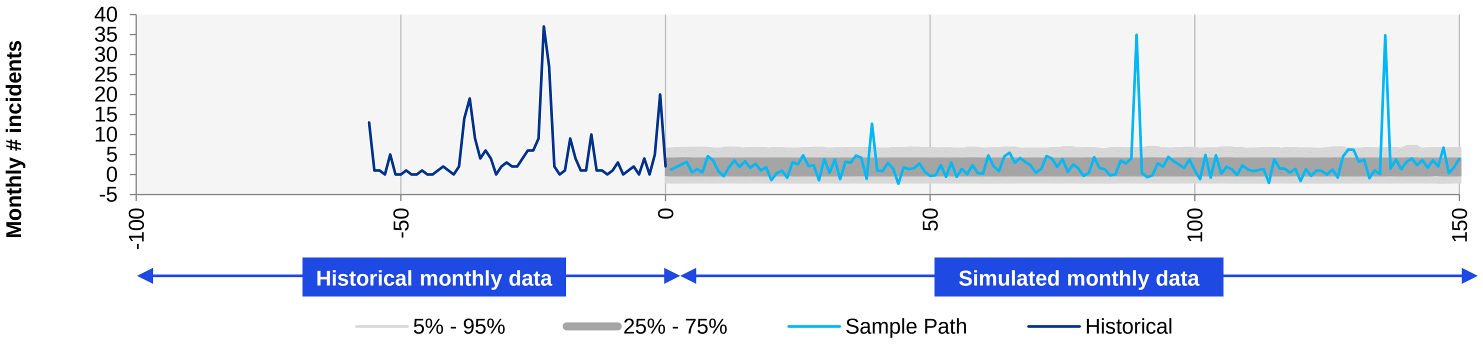
Core risk driver simulations – Pollution incidents

The historical evolution of each risk driver identified in Step 1 is analysed through eleven distinct statistical algorithms, which are outlined in previous slide, to identify the algorithm with the lowest AIC value. This algorithm is used to run the risk simulations for each driver for pollution incidents, which estimate projected performance over AMP8. The figures below illustrate risk simulations for the most significant risk drivers, blockage and hydraulic overload, which contribute 31% and 22%, respectively, to total pollution incidents based on historical data.

Blockage (simulated # monthly incidents)



Hydraulic system overload (simulated # monthly incidents)

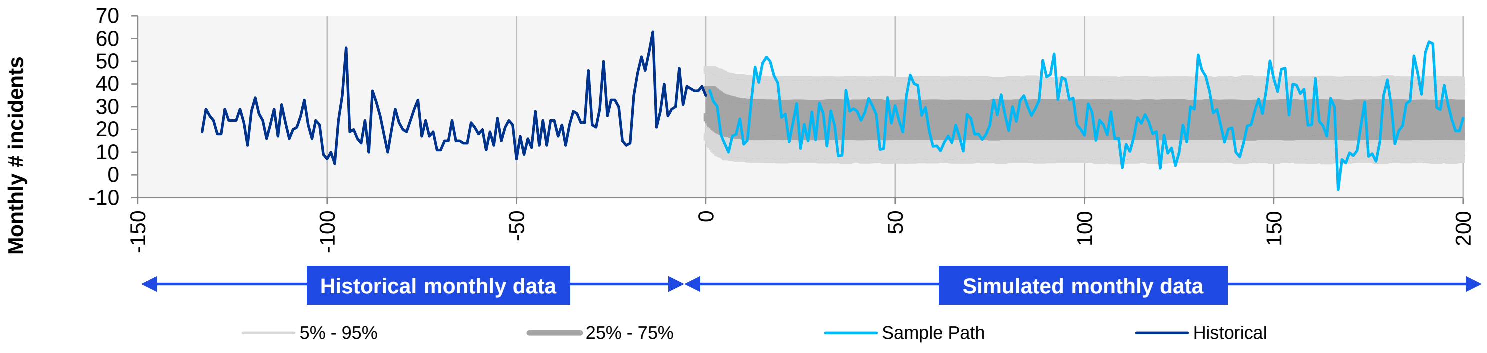


- The blockage simulation results indicate heightened volatility in blockage incidents during AMP8 compared to previous periods, attributed to increased incident variability observed in the most recent two years, as shown in the top graph.
- Incidents caused by hydraulic system overload exhibit statistical seasonality, with a strong positive correlation between incident increases and the rainy season as shown in the bottom graph. Specifically, recent climate trends suggest potential fluctuations in the frequency of extreme weather events, leading to potentially elevated rainfall levels during rainy seasons. This scenario presents an asymmetric risk exposure, with a predisposition toward increased incidents due to rising future rainfall levels. Section 4 of the Report will further explore this dynamic in detail.
- Simulations for the remaining risk drivers were conducted using similar methodology. The results were aggregated, considering the correlations among all risk drivers, to generate a forecast performance for pollution incidents throughout AMP8. This expected position is presented in the following section of the Report.

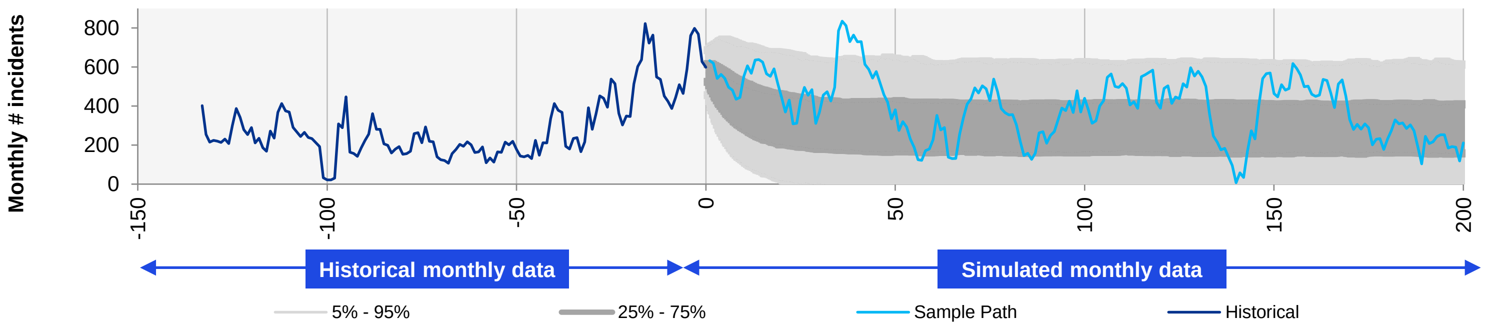
Core risk driver simulations – Sewer flooding

The historical evolution of each risk driver identified in Step 1 is analysed through eleven distinct statistical algorithms, which are outlined in previous slide, to identify the algorithm with the lowest AIC value. This algorithm is used to run the risk simulations for each driver of sewer flooding, which estimate projected performance over AMP8. The figures below illustrate risk simulations for the most significant risk driver – blockage – which contribute 80% and 68% to external and internal sewer flooding incidents, respectively, based on historical data.

Blockage (simulated # monthly incidents) – Internal sewer flooding



Blockage (simulated # monthly incidents) – External sewer flooding



- Blockages have historically been the main risk driver of both external and internal sewer flooding. The historical data shows a significant increase in the number of incidents over the past year, which was the wettest year on record in the UK.
- This indicates a strong positive correlation between rainfall and sewer flooding performance.
- Simulations suggest that sewer flooding incidents are likely to increase over AMP8, with a higher plausible range (25%-75% percentiles) compared to historical data.
- Simulations for the remaining risk drivers were conducted using similar methodology. The results were aggregated, considering the correlations among all risk drivers, to generate a forecast performance for external and internal sewer flooding incidents throughout AMP8. This expected position is presented in the following section of the Report.

Step 03

Simulations of AMP8 operational performance

Simulation of performance across AMP8 - Pollution incidents

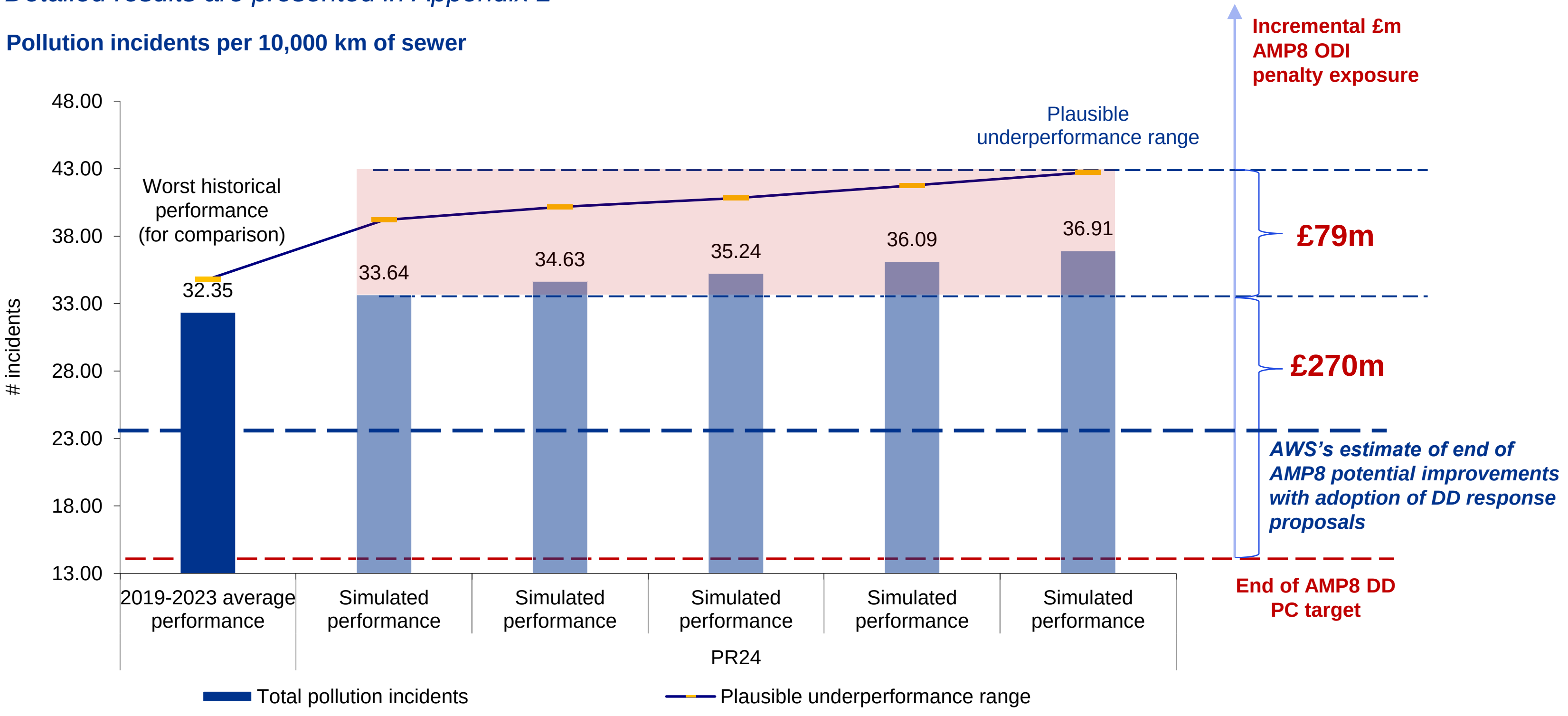
On pollution incidents there is material risk exposure in the base case and plausible downside (P90) scenarios.

- The unmitigated expected position for Anglian performance across AMP8 is estimated to be a £270m ODI penalty.
- This risk exposure increases to £349m over AMP8 in plausible downsides.

AWS has estimated that if its DD representation proposals on Totex and the ODI package are adopted, a proportion of risk asymmetry implied by the pollution incidents ODI would be addressed. Based on the risk simulations using AWS's DD proposed performance target, the mitigated expected risk exposure across AMP8 could be reduced to £81m.

This slide presents a prediction of pollution incidents for AMP8. Predictions are based on simulations for each risk driver discussed in the previous section – i.e., historical relationships assuming no structural breaks in investment or technology.

Detailed results are presented in Appendix 2



Simulation of performance across AMP8 - Sewer flooding

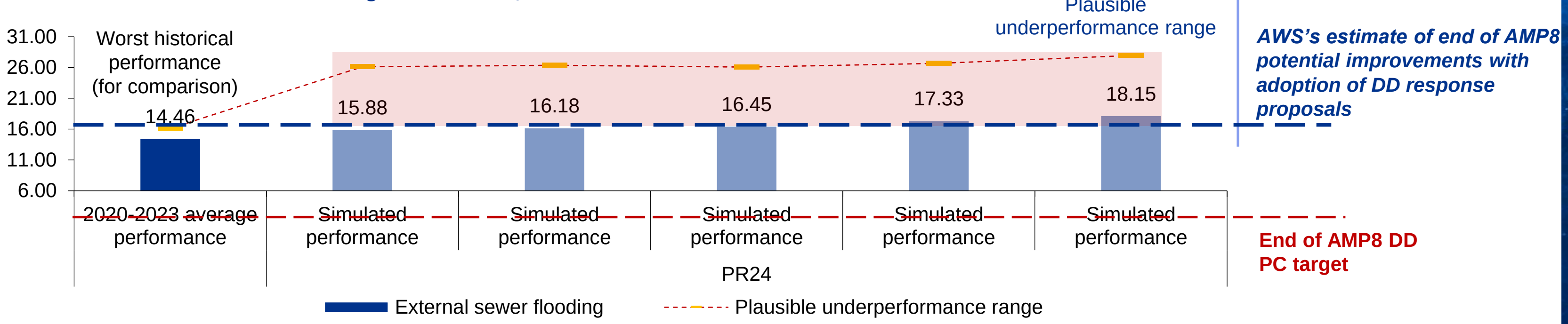
On sewer flooding there is material risk exposure in the base case and plausible downside (P90) scenarios.

- The unmitigated expected position for Anglian sewer flooding performance across AMP8 is estimated to be a £91m (external) and £36m (internal) ODI penalty.
- This risk exposure increases to £425m (external) and £78m (internal) over AMP8 in plausible downsides.

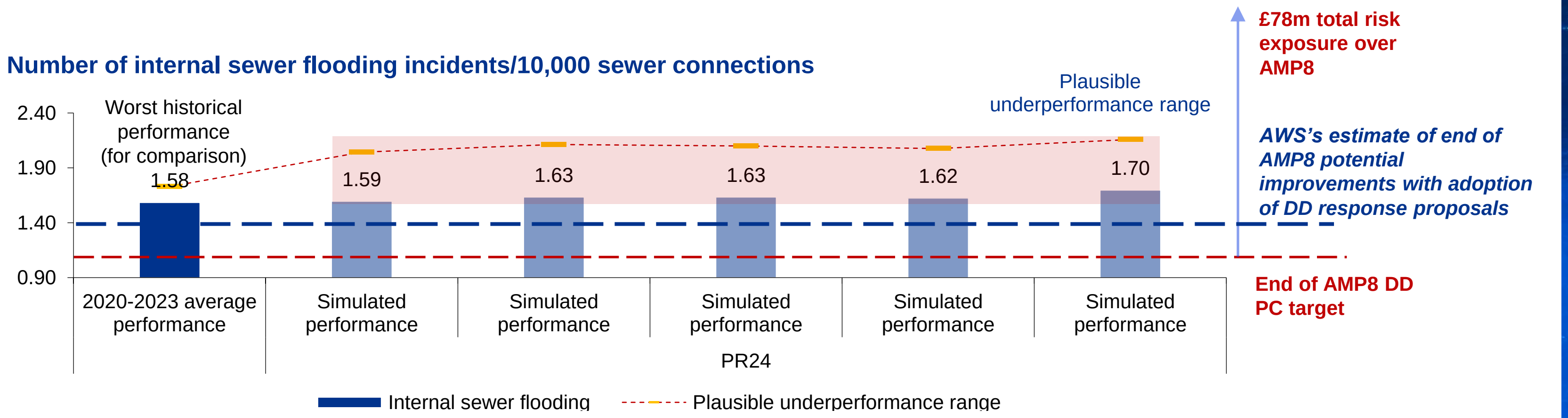
AWS has estimated that if its DD representation proposals on Totex and the ODI package are adopted, a proportion of risk asymmetry implied by the sewer flooding ODI would be addressed. Based on the risk simulations using AWS's DD proposed performance target, the mitigated expected risk exposure across AMP8 could be reduced to £87m (external) and £26m (internal).

This slide presents a prediction of sewer flooding incidents for AMP8. Predictions are based on simulations for each risk driver discussed in the previous section – i.e., historical relationships assuming no structural breaks in investment or technology. *Detailed results are presented in Appendix 2*

Number of external sewer flooding incidents/10,000 sewer connections



Number of internal sewer flooding incidents/10,000 sewer connections

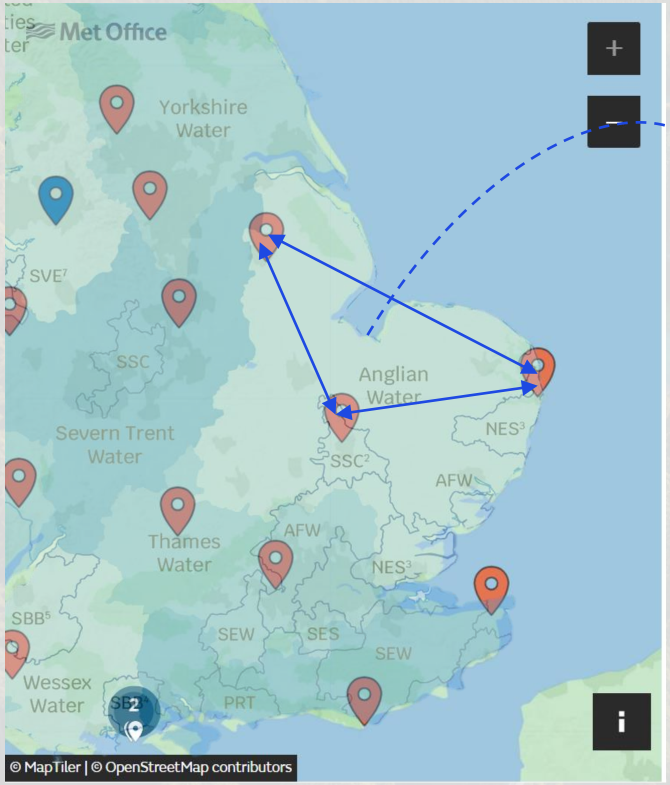


Step 04

Quantification of climate change impacts on AMP8 operational performance

The impact of climate change on key operational performance – climate measures

The climate measures used to quantify the impact of climate change on pollution and sewer flooding incidents are presented below.



Triangulation of climate data taken from different climate stations ensures

Full coverage within AWS's region

By collecting and integrating data from various climate stations strategically located throughout the region, the neural net (see slide 25) can achieve complete spatial coverage. This ensures that microclimatic variations and localised weather patterns are accurately captured. Consequently, this comprehensive data set provides a holistic view of the climate conditions impacting the entire area of AWS's operations.

Robust proxy for climate conditions

The triangulated climate data serves as a proxy for the climate conditions within AWS's operational area. This means that even in areas where direct measurements might be sparse or unavailable, the data from neighbouring stations can be interpolated to give a reliable representation of local climate conditions. This enhances the reliability and accuracy of the data that feeds into the neural net.

01 Given the rapid changes in climate conditions, it is crucial to understand how weather factors, such as regional rainfall, impact the evolution pollution incidents during AMP8.

For example, increased rainfall can put stress on sewage systems, potentially exceeding their capacity and causing hydraulic overload incidents, leading to more pollution incidents for AWS.

Thus, climate conditions must be considered common risk drivers for pollution incidents.

02 Historical station data are taken from MET office, which covers the following parameters*:

1. Mean daily maximum temperature (tmax)
2. Mean daily minimum temperature (tmin)
3. Days of air frost (af)
4. Total rainfall (rain)
5. Total sunshine duration (sun)

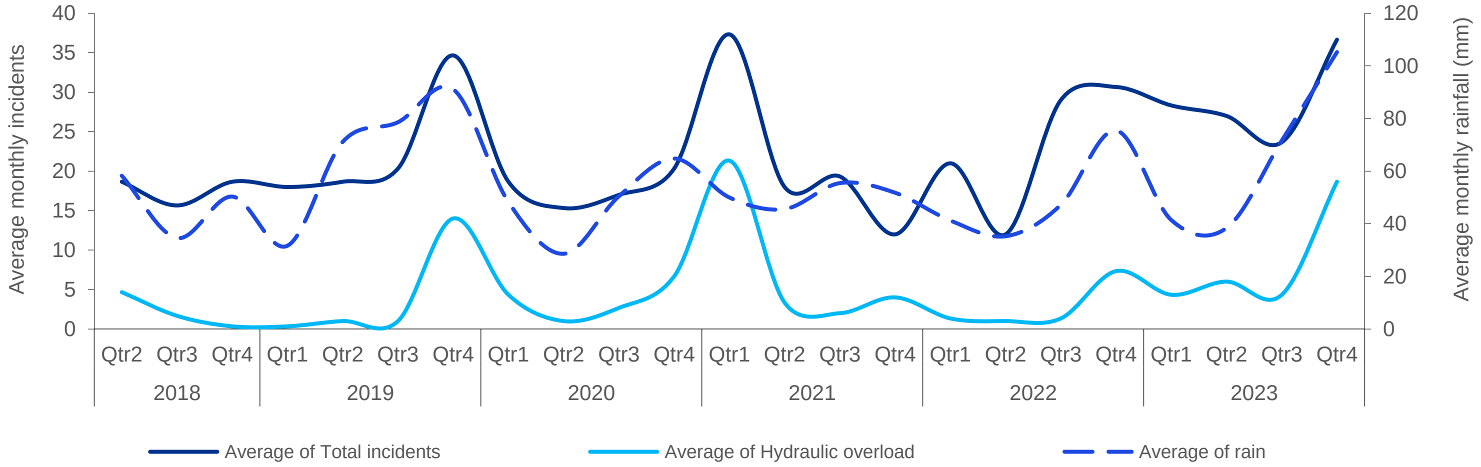
03 The neural net utilises climate data sourced from three stations, as illustrated in the graph to the left.

* https://www.metoffice.gov.uk/research/climate/maps-and-data/historic-station-data

The impact of climate change on key operational performance – Pollution incidents

The dynamic relationship between climate change and pollution incidents is presented below.

Relationship between climate driver – rainfall – and pollution incidents



Implied correlation between rainfall and pollution incident risk drivers (monthly data)								
	Hydraulic overload	**Electrical**	**Civil/structural**	**Operator error**	**Blockage**	**Biological**	**Mechanical**	**Total**
% average impact on total incidents	22.05%	11.09%	20.09%	2.22%	30.98%	5.35%	2.02%	100%
Implied correlation	0.463	0.164	-0.055	-0.170	-0.105	-0.158	0.300	0.383

A correlation measures the relationship between two variables, ranging from -1 to 1. A value of 1 means they move together perfectly, -1 means they move in opposite directions, and 0 means no relationship.

Key observations:

Positive correlation: There is a positive correlation between the peaks in rainfall and the spikes in both total pollution incidents and hydraulic overload incidents. This means that higher rainfall is linked to an increase in these incidents, suggesting that rainfall is a risk driver.

Recent trends: The most recent data shows a material increase in both rainfall and pollution incidents, indicating that the impact of climate change is becoming more pronounced. This rise in incidents correlates with increased rainfall, highlighting the stress placed on the water management infrastructure and therefore deterioration in performance.

The recent trend is consistent with latest findings from the National Climate Projections which suggests (1) winter precipitation is expected to increase significantly and (2) summer rainfall is expect to decrease significantly. But when it rains in summer there may be more intense storms*.

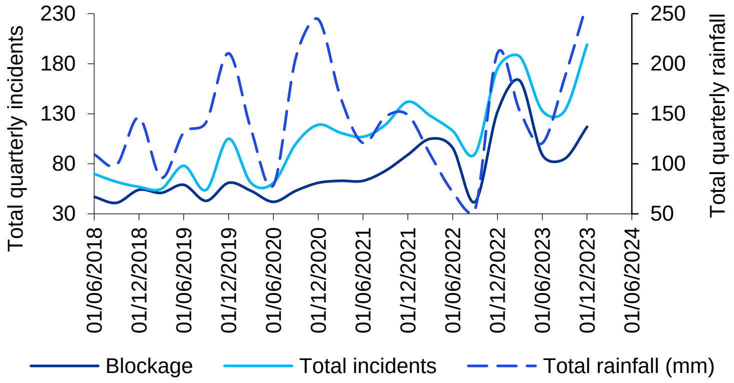
All else being equal, this implies that climate risk exposure is expected to be increasing in future periods.

** pg. 7 https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/research/ukcp/ukcp18-overview-slidepack-march21.pdf*

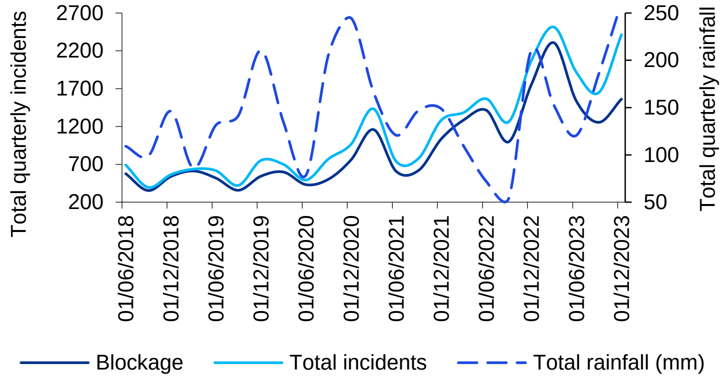
The impact of climate change on key operational performance – Sewer flooding

The dynamic relationship between climate change and sewer flooding incidents is presented below.

Relationship between climate driver – rainfall – and internal sewer flooding incidents



Relationship between climate driver – rainfall – and external sewer flooding incidents



Implied correlation between rainfall and sewer flooding incident risk drivers (monthly data)*

	Blockage	Collapse	Equipment Failure	Overloaded	Pumping Station Failure	Pumping Station Failure due to 3rd party	Total
% average impact on total incidents, external	80.42%	2.84%	3.37%	1.49%	0.20%	11.52%	100%
% average impact on total incidents, internal	68.03%	5.13%	3.39%	6.23%	0.29%	16.75%	100%
Implied correlation, external	0.471	0.275	0.879	0.218	0.214	0.649	0.563
Implied correlation, internal	0.385	0.122	0.548	0.037	*N/A*	0.526	0.544

A correlation measures the relationship between two variables, ranging from -1 to 1. A value of 1 means they move together perfectly, -1 means they move in opposite directions, and 0 means no relationship.

* Collapse due to 3rd party, Blockage due to 3rd party and Equipment failure due to 3rd Party risk driver correlations are not taken into account given immaterial relative impact of these drivers on total flooding incidents

Key observations:

Positive correlation: There is a positive correlation between rainfall peaks and surges in both total sewer flooding incidents and blockage incidents. This pattern indicates that increased rainfall is a critical common driver of these events.

The implied correlation between rainfall and external sewer flooding incidents caused by blockages is higher than that for internal incidents. This suggests that external sewer systems are more susceptible to blockage-related flooding during periods of increased rainfall. This is because heavy rainfall can increase inflow and infiltration in external sewer systems, where groundwater and surface water enter the sewers, compounding the risk of blockages.

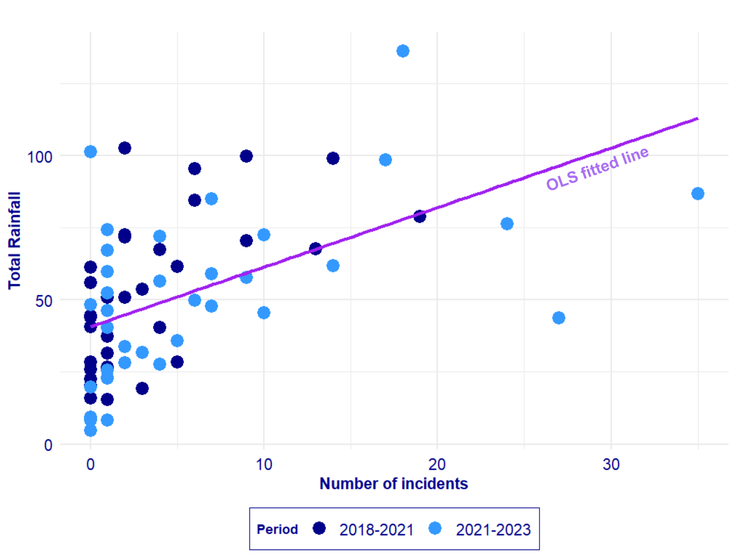
Recent trends: Recent data suggests a significant increase in both rainfall and sewer flooding incidents, underscoring the more pronounced impact of climate change. This upward trend in incidents aligns with increased rainfall, emphasising the strain on water management infrastructure and its respective decline in performance.

Understanding the impact of climate change on AMP8 operational performance

The methodology used to quantify the climate change impact on operational performance is presented below.

Case study – The dynamic relationship of hydraulic overload risk driver and rainfall.

The graph below illustrates the relationship between monthly hydraulic overload incidents and rainfall – presented by the Ordinary Least Squares (OLS) fitted line, with light blue dots representing the most recent incidents since 2021.



There has been a significant increase in the number of hydraulic overload incidents in recent years. The data suggests that pollution incidents driven by hydraulic overload are increasingly linked to elevated level of rainfall, which serves as a proxy for climate change.

This pattern has already become evident during AMP7, indicating that the impacts of changing climate conditions may be actively shaping operational risks.

Non-linear and interrelated relationships: The case study indicates that hydraulic overload and total pollution incidents are linked to climate change, as measured by rainfall. However, the impact of climate change on operational performance is not linear and is also contingent on various factors such as the time of year and specific temperature conditions at the time of the incidents.

To account for these complexities, this Report employs a neural network configuration – a type of machine learning consisting of interconnected layers of nodes (or "neurons") that work together to recognise patterns and relationships within data. This model can be used to handle complex, non-linear interactions between multiple variables.

By using a neural network, the model can learn from the data and adapt to uncover statistical patterns, enabling it to better estimate how increases in rainfall might affect operational performance on an annualised mean expected basis. This approach allows for a more robust quantification that integrates variables above, providing a more accurate and unbiased estimate based on the available data.

Neural net configurations: The neural network is configured as follows:

- **Step 1: Selection of optimal neural network configuration**

The first step involves identifying the best-performing neural network (based on the available data for each performance measure) using Linear, Generalised Regression Neural Network (GRNN), and Multilayer Feedforward Network (MLFN) configurations, which are the most established models. This ensures that the model is well-suited to capture the complex relationships between climate variables and operational performance.

- **Step 2: Ensuring robustness and stability**

The selected neural network is then run six times, each time with different node configurations, to explore different architectures and select the most effective one. This process can help in identifying a configuration that balances performance and complexity, resulting in a more reliable model.

- **Step 3: Quantification of climate change impact**

The configured neural network is used to quantify the impact of climate change on operational performance.

Results of impact of climate change on operational performance is presented in subsequent slides.

Estimating the impact of climate change on AMP8 – Pollution incidents

The neural network derives a non-linear plausible marginal impact curve, which shows how a one-unit increase in rainfall risk exposure (mm) affects pollution incidents performance as illustrated in the top graph. Detailed methodology is presented in Appendix 3. This is then compared to the total forecast for performance (bottom graph).

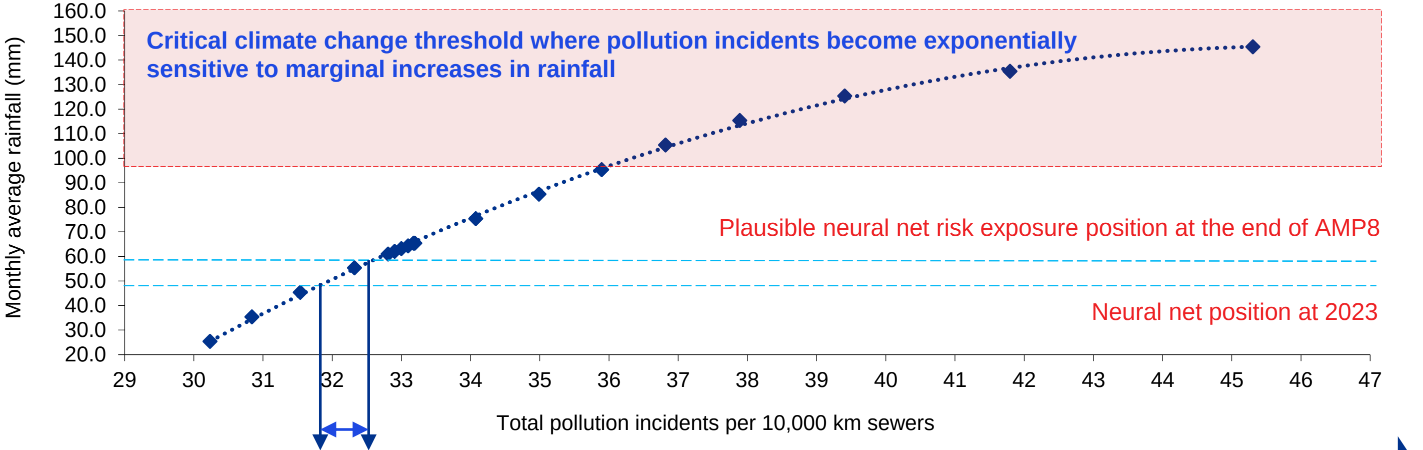
How climate change drives AMP8 financial exposure on pollution incidents

The neural net indicates that **24%** of pollution incidents in AMP8 are driven by climate change, as proxied by rainfall, and hence are outside of AWS's control.

This translates to a AMP8 total financial exposure of £65m under the P50 scenario and £84m under the P90 scenario due to climate change.

The dynamic relationship between climate change and pollution incidents was estimated using neural network and is presented below

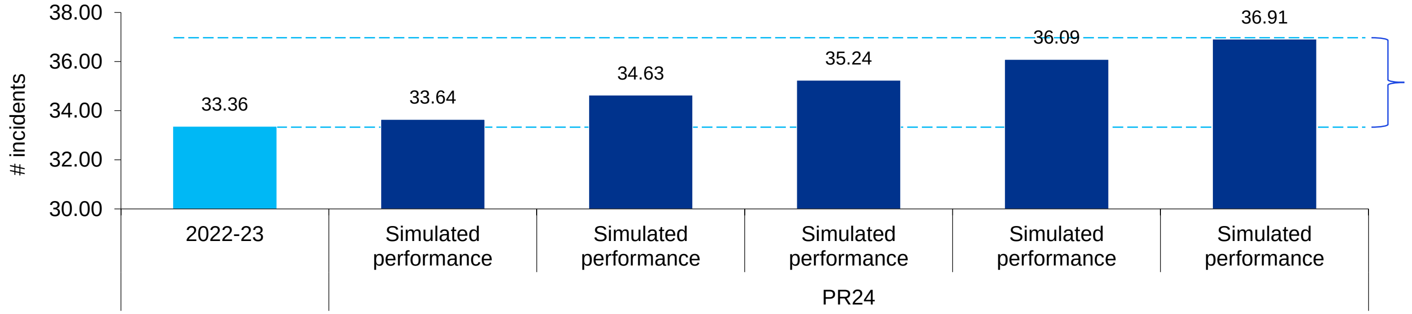
Total pollution incidents vs monthly total rainfall – plausible marginal impact curve



Plausible annualised risk impact on AMP8 Total pollution incidents (per 10,000km) = **0.30** relative to 2023 position

24% **of the AMP8 total pollution risk exposure (0.3/1.24) is driven by the climate change measure rainfall.**

Pollution incidents per 10,000 km of sewer



An average expected increase of **1.24** annually over AMP8 relative to 2023 position

Estimating the impact of climate change on AMP8 – Sewer flooding

The non-linear plausible marginal impact curves illustrated in the top graphs are derived using the same methodology adopted for pollution incidents.

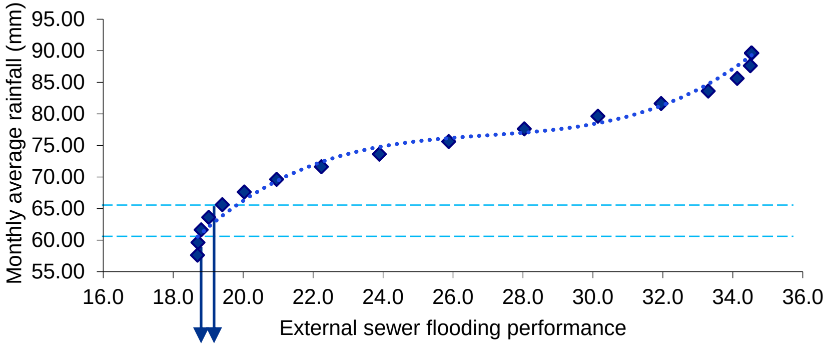
How climate change drives AMP8 financial exposure on pollution incidents

The neural net indicates that **23% and 13%** of external and internal flooding incidents in AMP8, respectively, are driven by climate change, as proxied by rainfall, and hence are outside of AWS's control.

This translates to a AMP8 total financial exposure of: £22m (external flooding) and £5m (internal flooding) under the P50 scenario, £101m (external flooding) and £11m (internal flooding) under the P90 scenario due to climate change.

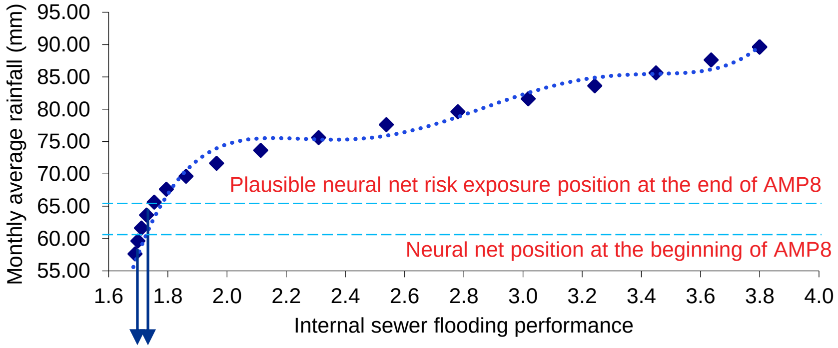
The dynamic relationship between climate change and pollution incidents was estimated using neural network and is presented below

Total external sewer flooding vs monthly total rainfall – plausible marginal impact curve



Plausible risk impact of **0.54** due to increased in rainfall level during AMP8

Total internal sewer flooding vs monthly total rainfall – plausible marginal impact curve

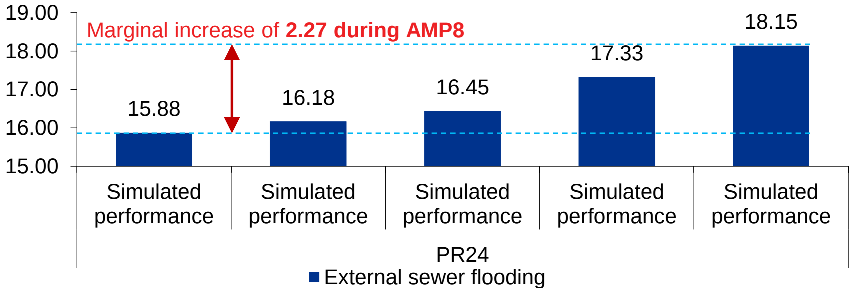


Plausible risk impact of **0.015** due to increased in rainfall level during AMP8

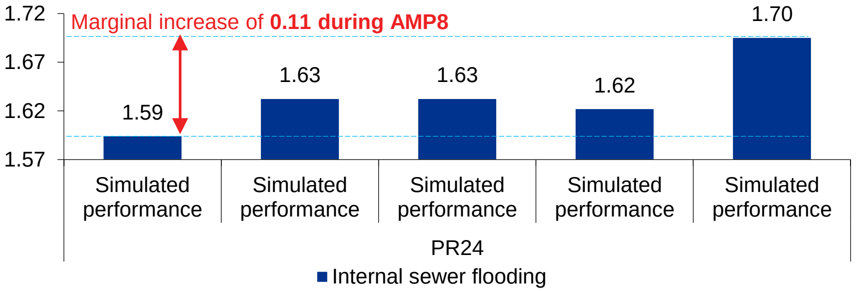
This implies that **<u>23%</u>** (=0.54/2.27) **of the AMP8 external flooding risk exposure is driven by rainfall**.

This implies that **<u>13%</u>** (=0.015/0.11) **of the AMP8 internal flooding risk exposure is driven by rainfall**.

External sewer flooding incidents per 10,000 sewer connections



Internal sewer flooding incidents per 10,000 sewer connections



Key implications of climate risk assessment

Given the potential impact of climate change on key operational performance throughout AMP8, regulatory mechanisms need to be calibrated such that there is an appropriate risk allocation to companies based on factors within company's control.

The table below outlines potential adjustments to regulatory calibration that Ofwat could adopt to mitigate company exposure to climate change.

01	**Allowance for additional investment to mitigate climate change risk exposure** The risk simulations indicate that additional investments may be required to respond to increasing climate change risks. For example, additional investments addressing hydraulic overload issues to improve pollution incident performance during periods of high rainfall. This could help mitigate the impact of climate change on wastewater infrastructure and enhance service quality for PR24 customers.
02	**Adjusting PR24 targets and ODI rates** The risk simulations indicate that PR24 targets and ODI rates may need to be adjusted to ensure that the targets are achievable based on historical trend analysis for pollution incidents and sewer flooding. This would affect AWS's risk exposure both on a P50 and a P10/P90 basis. For example, with climate change estimated to drive 24% of plausible pollution incident performance during AMP8, decreasing the DD prescribed target and reducing the ODI penalty rate by 24% would offset this underlying impact and therefore mitigate the climate change-related risk exposure at base and P90 positions respectively.

Appendix 1
Methodology to identify core risk drivers

Pollution incidents risk drivers

The table below sets out the bottom-up risk drivers and the rationale behind how they could impact total pollution incidents.

Pollution incidents core risk drivers	
Hydraulic overload	Hydraulic overload can lead to the excessive flow that exceeds system capacity, resulting in untreated or partially treated wastewater being discharged.
Electrical	Electrical failures can disable pumping stations or treatment plants, leading to the overflow of untreated sewage or the halt of essential treatment processes.
Civil/structural	Structural failures, such as breaches in containment structures or pipeline integrity, can result in the direct release of contaminants into the environment.
Operator/interference	Human error or unplanned interference can cause operational failures, leading to incorrect processing or the accidental release of pollutants.
Blockage	Blockages in pipes or sewage lines can cause backflows or overflows, leading to the discharge of untreated wastewater into the environment.
Biological	Biological imbalances, such as excessive growth of harmful microorganisms, can compromise water quality, leading to pollution incidents if not adequately managed.
Mechanical	Mechanical failures in equipment such as pumps, valves, or treatment systems can lead to the interruption of normal wastewater treatment processes, resulting in pollution.

% impact on total incidents based on historical data	Blockage	Electrical	Civil/structural	Operator error	Hydraulic overload	Biological	Mechanical
	30.98%	11.09%	20.09%	2.22%	22.05%	5.35%	2.02%

Sewer flooding risk drivers

The table below sets out the bottom-up risk drivers and the rationale behind how they could impact total sewer flooding incidents.

Sewer flooding core risk drivers	
Blockage	Blockages in the sewer system can prevent the normal flow of wastewater, leading to backups and overflows, causing flooding. Common causes include the accumulation of grease, debris, and inappropriate materials flushed into the system during heavy rainfall.
Collapse	Structural failure or collapse of sewer pipes can obstruct the flow of wastewater, resulting in backups and subsequent flooding. This can be due to ageing infrastructure, ground movement, or external damage.
Equipment Failure	Failures in critical equipment such as pumps, valves, or control systems can disrupt the proper functioning of the sewer network, leading to flooding incidents.
Overloaded	Excessive inflow during heavy rainfall or increased wastewater discharge can exceed the capacity of the sewer system, causing overflows and flooding.
Pumping Station Failure	A failure at these stations can halt wastewater transport, resulting in overflows and flooding.
Pumping Station Failure due to 3rd party	External factors such as power outages or third-party construction activities can lead to pumping station failures, thereby increasing the risk of sewer flooding.
Collapse due to 3rd party	Activities such as nearby construction, heavy traffic, or other external impacts can cause sewer pipes to collapse, leading to flooding.
Blockage due to 3rd party	3rd party actions, such as improper disposal of waste or construction debris entering the sewer system, can cause blockages and result in flooding.
Equipment failure due to 3rd Party	External influences like accidental damage during construction or utility works can cause equipment failures in the sewer system, leading to flooding.

% impact on total incidents based on historical data	Blockage	Collapse	Equipment Failure	Overloaded	Pumping Station Failure	Pumping Station Failure due to 3rd party	Collapse due to 3rd party	Blockage due to 3rd party	Equipment failure due to 3rd Party
External	80.42%	2.84%	3.37%	1.49%	0.20%	11.52%	0.02%	0.04%	0.11%
Internal	68.03%	5.13%	3.39%	6.23%	0.29%	16.75%	0.00%	0.15%	0.04%

Appendix 2
Simulation of AMP8 plausible performance

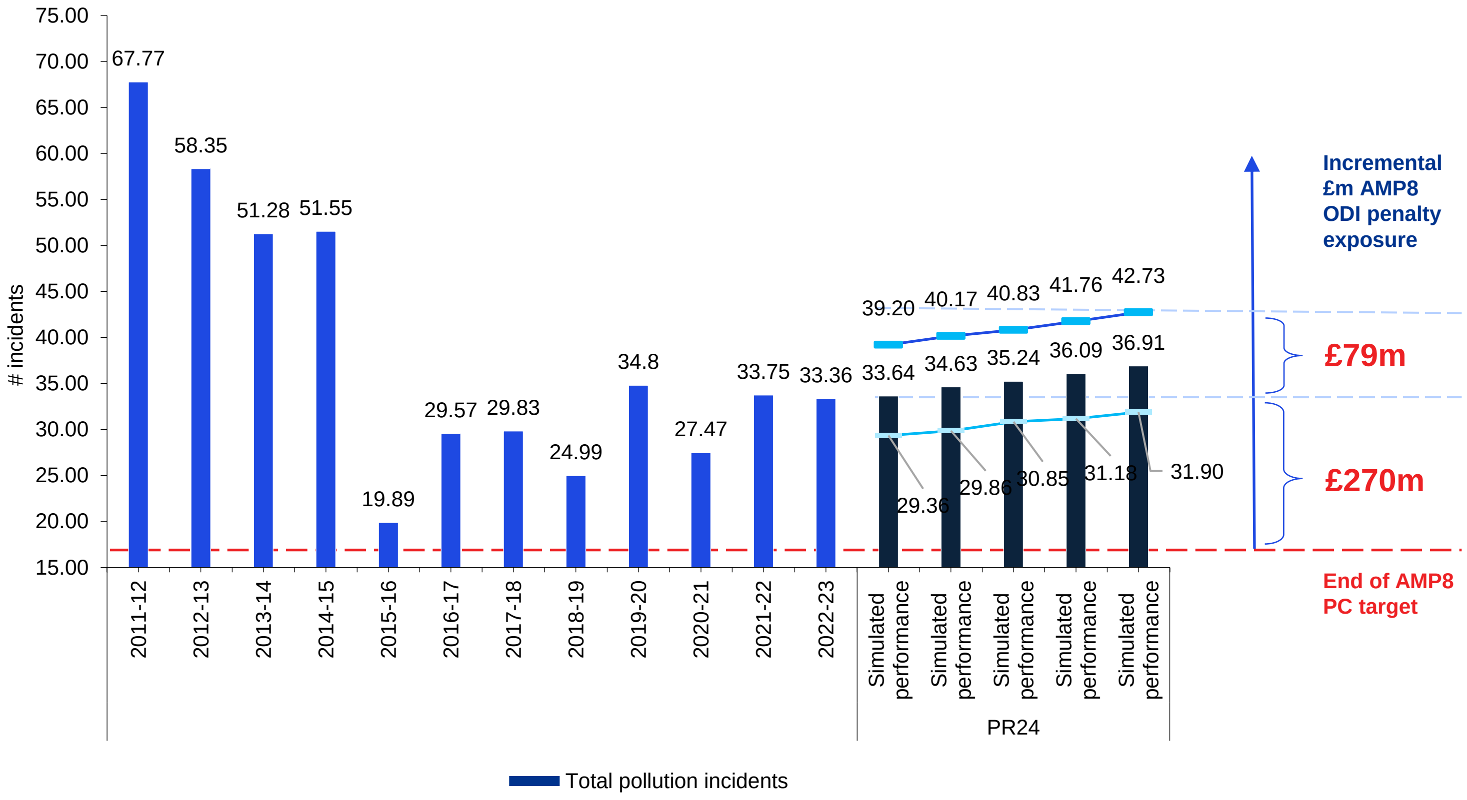
Risk models' configurations and simulations

The table below provides a detailed descriptions of the algorithms used in the simulations.	
Algorithm	**Description**
AR(1)	Autoregressive Model of order 1, where the current value of the time series is a linear function of its immediately preceding value. This model captures short-term temporal dependencies.
AR(2)	Autoregressive Model of order 2, extending AR(1) by including the two most recent past values to predict the current value, allowing for more complex dependency structures.
MA(1)	Moving Average Model of order 1, where the current value is a linear combination of the past forecast error. It helps to model short-term shocks or noise in the time series.
MA(2)	Moving Average Model of order 2, incorporating the past two forecast errors, which provides a more refined correction for short-term fluctuations in the data.
ARMA(1,1)	Autoregressive Moving Average Model of orders 1 and 1, combining the AR(1) and MA(1) models to capture both temporal dependencies and short-term shocks in the time series.
GBM	Geometric Brownian Motion, a model often used to describe the stochastic process, assuming a constant drift and volatility in the log returns.
BMMR	Bounded Mean Reverting Model, which describes a process that tends to revert towards a long-term mean within certain bounds, often used for mean-reverting processes.
GBM/JD	Geometric Brownian Motion with Jumps, extending the GBM model by including sudden, random jumps, capturing the occurrence of unexpected large changes.
BMMR/JD	Bounded Mean Reverting Model with Jumps, combining mean reversion within bounds with occasional random jumps, useful for modeling more complex simulations.
ARCH(1)	Autoregressive Conditional Heteroskedasticity Model of order 1, where the variance of the current error term is dependent on the previous period's error term, used for modeling time series with volatility clustering.
GARCH(1,1)	Generalised Autoregressive Conditional Heteroskedasticity Model of orders 1 and 1, generalising ARCH by allowing both past variances and past errors to influence the current period's variance, often used in volatility modeling.

Simulated AMP8 pollution incidents expected performance

The simulations of expected AMP8 pollution incidents performance are presented below

Pollution incidents per 10,000 km of sewer



01 The simulations for each risk driver are performed while accounting for the inherent correlations between the drivers. These simulations are aggregated to quantify the expected pollution incidents performance for AMP8.

02 The simulation shows that there is an annual average performance shortfall of 19.31 incidents per 10,000km of sewer to reach PR24 Performance commitment (PC) level as demonstrated on the graph.

03 Given the current assumptions on PR24 PC, there is material risk exposure at both P50 and P90 levels.

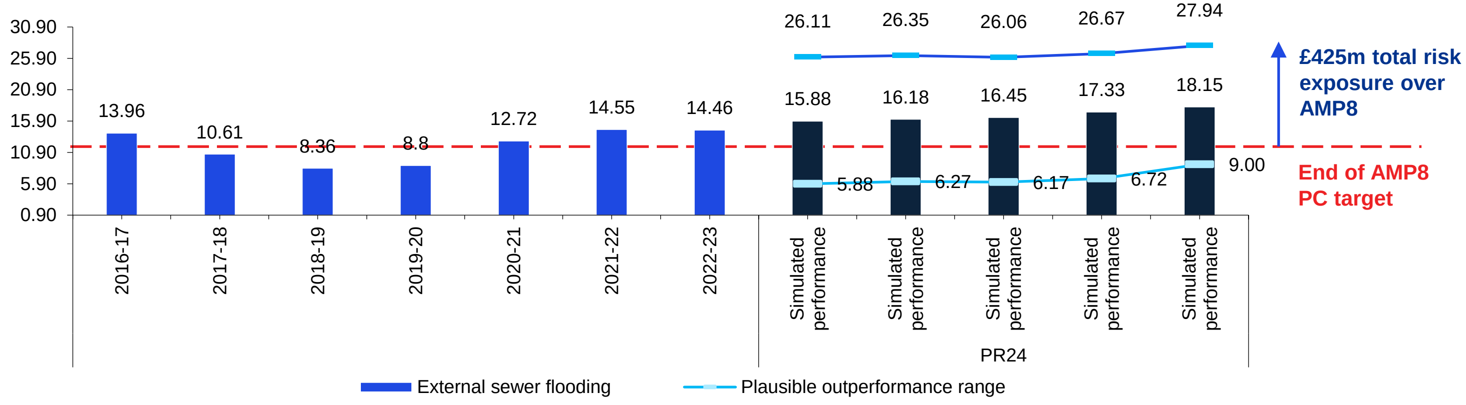
04 Specifically, the mean-expected position for AWS pollution incidents performance during AMP8 is estimated to be £270m ODI penalty.

This penalty increases by £79m when considering the P90 position, resulting in £349m total risk exposure over AMP8.

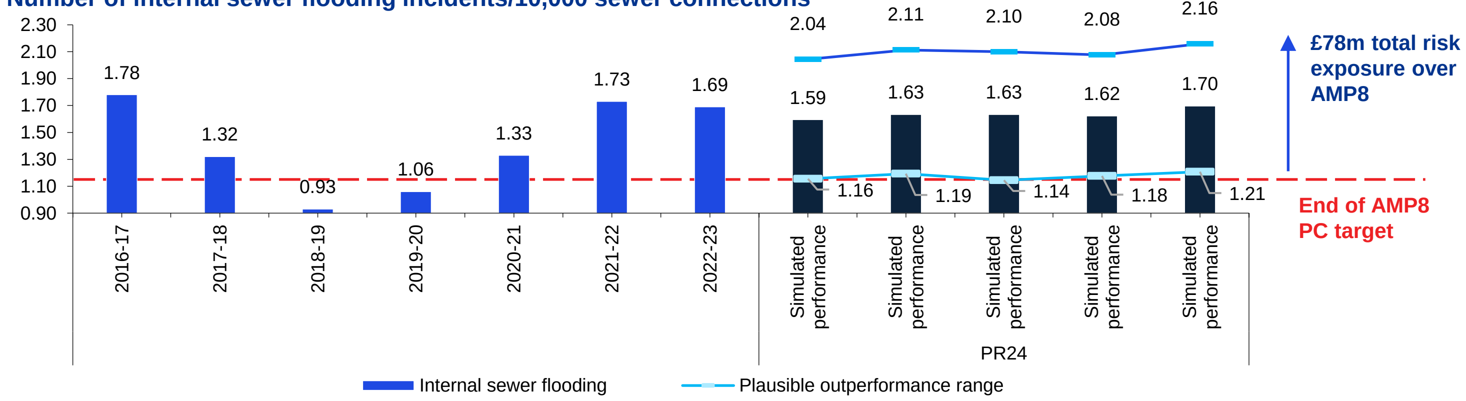
Simulated AMP8 sewer flooding expected performance

The simulations of expected AMP8 sewer flooding performance are presented below

Number of external sewer flooding incidents/10,000 sewer connections



Number of internal sewer flooding incidents/10,000 sewer connections



01 The simulations for each risk driver are performed while accounting for the inherent correlations between the drivers. These simulations are aggregated to quantify the expected sewer flooding incidents performance for AMP8.

02 The simulation shows that there are annual average performance shortfalls of 2.68 and 0.40 incidents per 10,000km of sewer to reach PR24 Performance commitment (PC) level for external and internal flooding respectively, as demonstrated on the graphs.

03 Given the current assumptions on PR24 PCs, there is material risk exposure at both P50 and P90 levels.

04 Specifically, the mean-expected position for AWS sewer flooding performance during AMP8 is estimated to be £91m (external) and £36m (internal) ODI penalty.

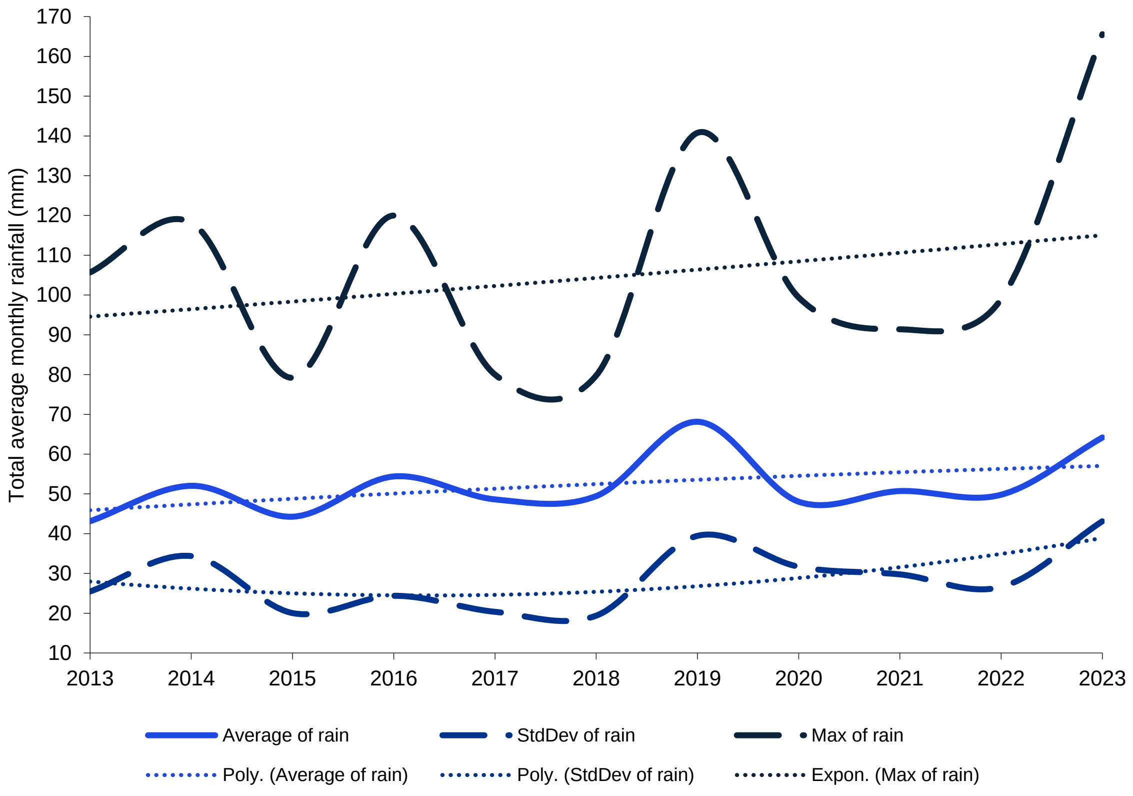
This penalty increases by £334m (external) and £42m (internal) when considering the P90 position, resulting in £425m (external) and £78m (internal) total risk exposure over AMP8.

Appendix 3
The relative impact of climate change on operational performance – neural net specification

The impact of climate change – historical evolution of climate measures

The historical evolution of climate measures is presented below

Historical evolution of total rainfall (mm) within AWS's region



01 Among all climate parameters, total rainfall has the most statistically significant impact on sewer flooding and pollution incidents.

02 The graph to the left presents historical data for three key rainfall metrics:

1. **Annual average monthly rainfall**: This represents the mean rainfall for each month, averaged over the year, providing insight into long-term precipitation trends.
2. **Annual standard deviation of monthly rainfall**: This measures the variability in monthly rainfall within each year, highlighting the unpredictability of weather patterns.
3. **Annual maximum of monthly rainfall**: This indicates the highest monthly rainfall recorded each year, pointing to extreme weather events.

03 The analysis shows a material increase in the mean-expected rainfall, the maximum recorded rainfall, and the risk exposure (as measured by the standard deviation). These trends suggest that the impact of climate change has increased over the years, characterised by:

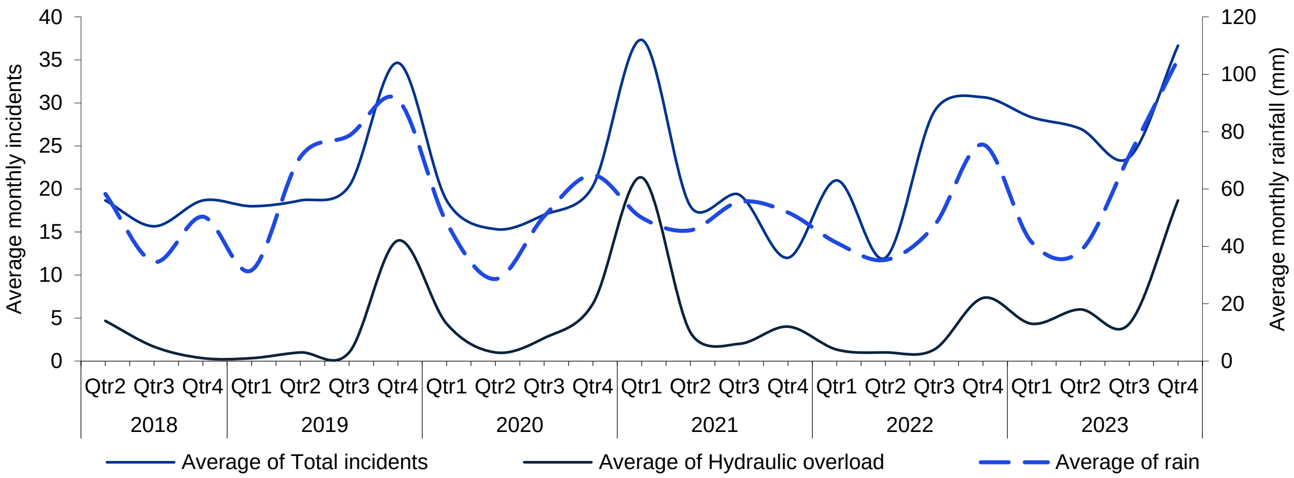
1. **Increased mean and maximum rainfall**: These increases indicate that both average and peak rainfall levels have risen, reflecting a greater volume of water entering the sewage and drainage systems, which can lead to more frequent and severe hydraulic overloads, sewer flooding and pollution incidents.
2. **Higher variability in rainfall**: The rise in standard deviation suggests more unpredictable rainfall patterns. This unpredictability could impact water management efforts, as it becomes harder to anticipate and prepare for extreme weather events, thus leads to deterioration in operational performance.

04 **The following slide suggests that part of sewer flooding and pollution incidents performance is driven by weather factors which are outside of AWS's control.**

Relationship between climate change and pollution incidents core risk drivers

The dynamic relationship between climate change and pollution incidents is presented below

Relationship between climate driver – rainfall – and pollution incidents



Implied correlation between rainfall and pollution incident risk drivers (monthly data)

	Hydraulic overload	Electrical	Civil/ structural	Operator error	Blockage	Biological	Mechanical	Total incidents
% average impact on total incidents	22.05%	11.09%	20.09%	2.22%	30.98%	5.35%	2.02%	100%
Implied correlation	0.463	0.164	-0.055	-0.170	-0.105	-0.158	0.300	0.383

01 The graph illustrates the relationship between rainfall and pollution incidents, with the left y-axis representing the average monthly incidents (both total pollution incidents and hydraulic overload incidents), and the right y-axis representing the average monthly rainfall.

Key observations

02 **Strong correlation:** There is a clear correlation between the peaks in rainfall and the spikes in both total pollution incidents and hydraulic overload incidents. This suggests that higher rainfall is a significant driver of these incidents.

03 **Emerging trends**: The most recent data shows a material increase in both rainfall and pollution incidents, indicating that the impact of climate change is becoming more pronounced. This rise in incidents correlates with increased rainfall, highlighting the stress placed on the water management infrastructure and therefore deterioration in performance.

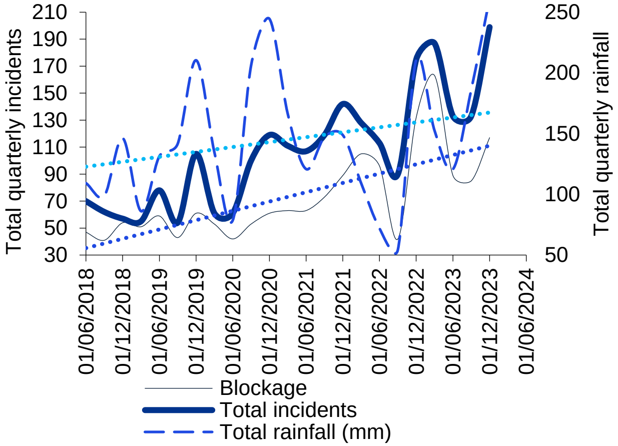
04 The table provides the implied correlation coefficients between rainfall and pollution incident risk drivers. There is a strong positive correlation between rainfall and hydraulic overload incidents (0.463). This indicates that as rainfall increases, the likelihood of hydraulic overload incidents also rises significantly, underscoring the direct impact of increased precipitation on system capacity.

Similarly, the total number of total pollution incidents shows a strong positive correlation with rainfall (0.383), suggesting that higher rainfall generally leads to a greater number of pollution incidents, reflecting the broad impact of increased rainfall on water infrastructure that drives pollution incidents.

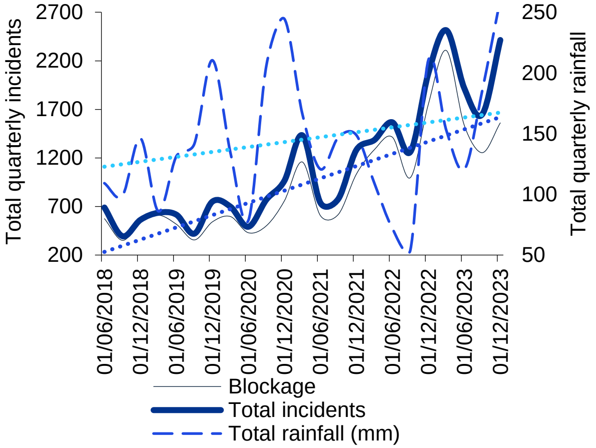
Relationship between climate change and sewer flooding core risk drivers

The dynamic relationship between climate change and sewer flooding incidents is presented below

Relationship between climate driver – rainfall – and internal sewer flooding incidents



Relationship between climate driver – rainfall – and external sewer flooding incidents



Implied correlation between rainfall and sewer flooding incident risk drivers (monthly data)*

	Blockage	Collapse	Equipment Failure	Overloaded	Pumping Station Failure	Pumping Station Failure due to 3rd party	Total
External	0.471	0.275	0.879	0.218	0.214	0.649	0.563
Internal	0.385	0.122	0.548	0.037	*N/A*	0.526	0.544

* Collapse due to 3rd party, Blockage due to 3rd party and Equipment failure due to 3rd Party risk driver correlations are not taken into account given immaterial relative impact of these drivers on total flooding incidents

01 The graph illustrates the relationship between rainfall and sewer flooding incidents, with the left y-axis representing the quarterly incidents (both total sewer flooding incidents and blockage incidents), and the right y-axis representing the total rainfall.

Key observations

02 **Strong correlation:** There is a strong correlation between rainfall peaks and surges in both total sewer flooding incidents and blockage incidents. This pattern indicates that increased rainfall is a critical common driver of these events.

The implied correlation between rainfall and external sewer flooding incidents caused by blockages is higher than that for internal incidents. This suggests that external sewer systems are more susceptible to blockage-related flooding during periods of increased rainfall. This is because heavy rainfall can increase inflow and infiltration in external sewer systems, where groundwater and surface water enter the sewers, compounding the risk of blockages. Internal systems are less affected by direct rainwater inflows.

03 **Emerging trends**: Recent data suggests a significant increase in both rainfall and sewer flooding incidents, underscoring the more pronounced impact of climate change. This upward trend in incidents aligns with increased rainfall, emphasising the strain on water management infrastructure and its respective decline in performance.

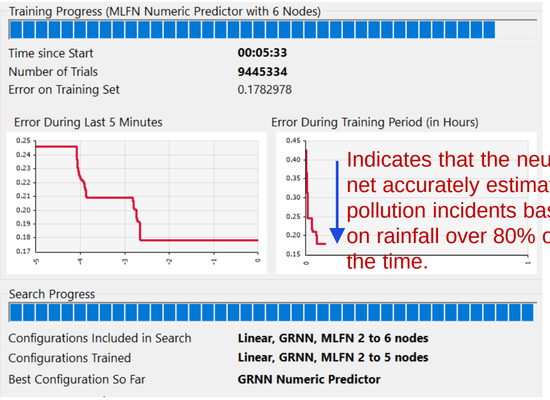
04 The table presents the implied correlation coefficients between rainfall and sewer flooding incident risk drivers. A strong positive correlation is evident between rainfall and blockage incidents, with coefficients of 0.471 for external flooding and 0.385 for internal flooding. This indicates that as rainfall intensifies, the likelihood of blockage incidents happening significantly increases, underscoring the direct impact of increased precipitation on system performance.

Additionally, the total number of sewer flooding incidents also exhibits a robust positive correlation with rainfall, with coefficients of 0.563 for external flooding and 0.544 for internal flooding. These figures suggest that higher rainfall typically results in a greater frequency of sewer flooding incidents, demonstrating the impact of increased precipitation on water infrastructure and its significant contribution to overall flooding events.

Estimating the impact of climate change on AMP8 pollution incidents performance

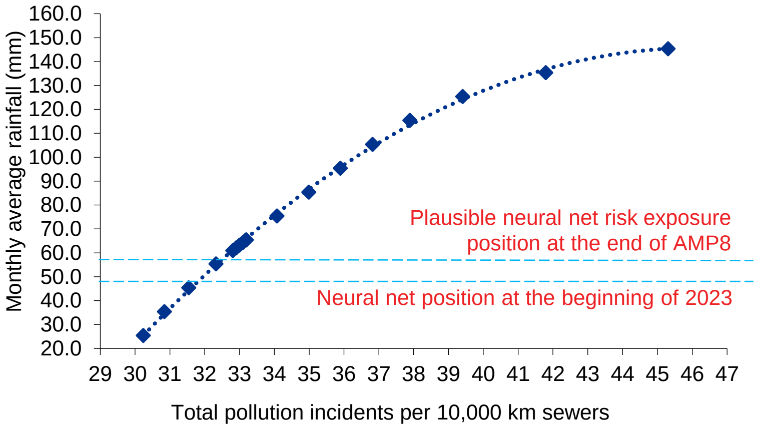
The plausible marginal impact of climate change on AMP8 pollution incidents performance is presented below

Neural net configurations on rainfall impact on total pollution incidents (per 10,000 km sewers)



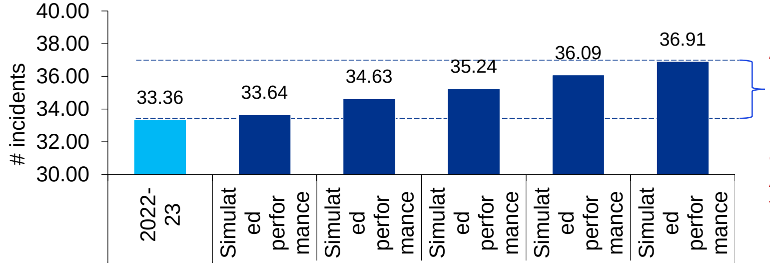
The neural net estimated average monthly rainfall (mm) would increase by **1.1mm annually over AMP8,** as demonstrated in the graph to the right

Total pollution incidents vs monthly total rainfall – marginal impact curve



Plausible annual average risk impact on AMP8 Total pollution incidents (per 10,000km) = **0.30** relative to 2023 position

Pollution incidents per 10,000 km of sewer



An average increase of **1.24** (equivalent to 9 incidents) annually over AMP8 relative to 2023 position

All else being equal, this implies that **24.19%** (=0.30/1.24) **of the AMP8 total pollution risk exposure is driven by the climate change measure rainfall**.

01 A neural net has been constructed to quantify the relationship between climate change, measured as total monthly rainfall, and total pollution incidents.

As shown in the top left figure, over 9,500,000 trials were run using historical pollution incidents and rainfall data to understand the quantitative interaction between these two parameters.

02 The neural network derives a non-linear plausible marginal impact curve, which shows how a one-unit increase in rainfall risk exposure (mm) affects performance in the top right graph.

The neural net suggests that average monthly rainfall will increase by a plausible range of within 1.1mm annually over AMP8, driven by recent climate trends discussed in previous slides. This translates into an annual average increase of 0.30 pollution incidents (per 10,000 km of sewers) over AMP8, relative to the 2023 baseline, as depicted in top right graph.

How climate change drives AMP8 financial exposure on pollution incidents

03 The neural net indicates that 24.19% of pollution incidents in AMP8 are driven by climate change, as proxied by rainfall, and are outside of AWS's control.

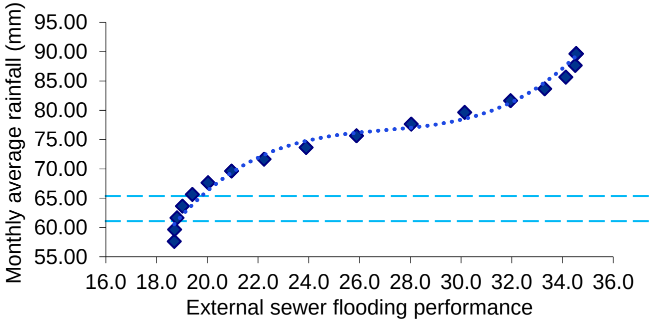
04 **This translates to a total financial exposure of £65m under the P50 scenario and £84m under the P90 scenario due to climate change.**

(The total AMP8 exposure is £270 million under P50 and £349 million under P90 position).

Estimating the impact of climate change on AMP8 sewer flooding performance

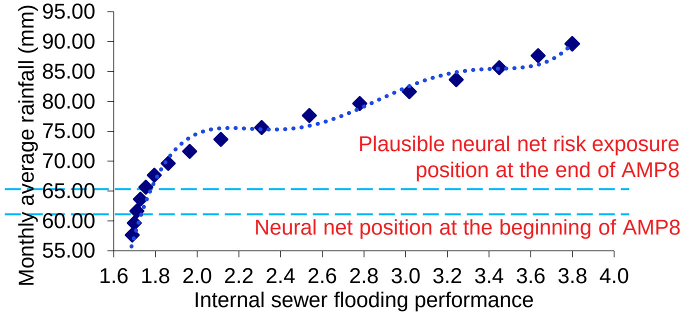
The plausible marginal impact of climate change on AMP8 sewer flooding performance is presented below

Total external sewer flooding vs monthly total rainfall – marginal impact curve



Plausible risk impact of **0.54** due to increased in rainfall level during AMP8

Total internal sewer flooding vs monthly total rainfall – marginal impact curve

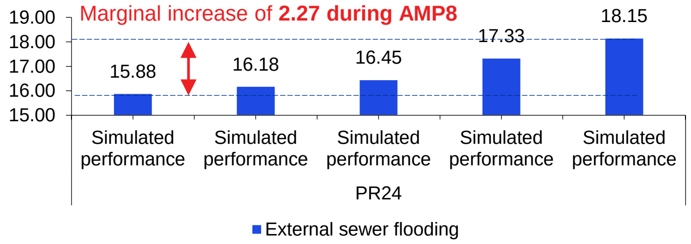


Plausible risk impact of **0.015** due to increased in rainfall level during AMP8

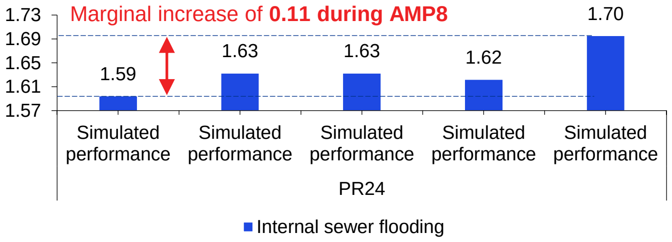
This implies that **23.78%** (=0.54/2.27) **of the AMP8 external flooding risk exposure is driven by rainfall**.

This implies that **13.64%** (=0.015/0.11) **of the AMP8 internal flooding risk exposure is driven by rainfall**.

Number of external sewer flooding incidents/ 10,000 sewer connections



Number of internal sewer flooding incidents/ 10,000 sewer connections



01 A neural net has been constructed to quantify the relationship between climate change, measured as total monthly rainfall, and sewer flooding incidents.

The neural net were run using historical sewer flooding incidents and rainfall data to understand the quantitative interaction between these two parameters.

02 The neural network derives a non-linear plausible marginal impact curve, which shows how a one-unit increase in rainfall risk exposure (mm) affects performance in the top graphs. The neural net suggests that average monthly rainfall will increase by a plausible range of within 1.1mm annually over AMP8, driven by recent climate trends discussed in previous slides. This translates into an impact over AMP8 of 0.54 and 0.015 external and internal flooding incidents (per 10,000 km of sewers), respectively.

How climate change drives AMP8 financial exposure on Sewer flooding incidents

03 The neural net indicates that **23.78%** and **13.64%** of external and internal sewer flooding incidents, respectively, in AMP8 are driven by climate change, as proxied by rainfall, and are outside of AWS's control.

04 **This translates to a AMP8 total financial exposure of:**

£22m (external flooding) and £5m (internal flooding) under the P50 scenario, £101m (external flooding) and £11m (internal flooding) under the P90 scenario due to climate change.

(The total risk exposure is £425m (external flooding) and £78m (internal flooding) over AMP8 under P90).

Important notice

This Report has been prepared for Anglian Water Services Limited by KPMG LLP under a private contract, set out in our Engagement Letter and should be read in conjunction with the Engagement Letter.

Anglian Water Services Limited has commissioned KPMG to develop the Report to understand the expected performance of key ODIs and climate change impact for the PR24 price control. In preparing this Report we have not taken into account the interests, needs or circumstances of anyone apart from Anglian Water Services Limited even though we may have been aware that others might read this Report. We have prepared this Report for the benefit of Anglian Water Services Limited alone.

In preparing the Report, we have relied upon and assumed, without independent verification, the accuracy and completeness of any information on historical operational performance and associated root-cause provided by Anglian Water Services Limited. Nothing in this Report constitutes a valuation or legal advice.

Although we endeavour to provide accurate and timely information, there can be no guarantee that such information is accurate as of the date it is received or that it will continue to be accurate in the future.

This Report is not suitable to be relied on by any party wishing to acquire rights against KPMG LLP for any purpose or in any context. Any party other than Anglian Water Services Limited that obtains access to this Report or a copy (under the Freedom of Information Act 2000 or the Freedom of Information (Scotland) Act 2002) and chooses to rely on this Report (or any part of it) does so at its own risk. To the fullest extent permitted by law, KPMG LLP does not assume any responsibility and will not accept any liability in respect of this Report to any party other than Anglian Water Services Limited.

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Anglian Water Services Ltd
Lancaster House
Lancaster Way
Ermine Business Park
Huntingdon
PE29 6XU

Tel 01480 323000
www.anglianwater.co.uk

Private & confidential

Water Services Regulation Authority
Centre City Tower
7 Hill Street
Birmingham
B5 4UA

27 August 2024

Dear Director,

Report on Impact of climate change on key operational performance measures for PR24

We attach a copy of the above confidential report dated August 2024 the ("Final Report") prepared by KPMG LLP ("KPMG"). The Final Report was solely prepared for Anglian Water Services Limited ("the Company").

KPMG has agreed that we may disclose the attached Final Report to you, on the basis set out in this letter, to enable you to verify that a report has been commissioned by us and issued by KPMG in connection with the estimation of required cost of equity for the PR24 price control, and to facilitate the discharge by you of your regulatory functions subject to the remaining paragraphs of this letter to which your attention is drawn. KPMG has also agreed that you may publish the Final Report (in full only) on your website pages.

KPMG's work was designed to meet our agreed requirements and the engagement activities were determined by our needs at the time. The Final Report should not be regarded as suitable to be used or relied on by any party other than us for any purpose or in any context.

In consenting to the disclosure of the Final Report to you, KPMG does not assume any responsibility to you in respect of its work for us or for the Final Report. To the fullest extent permitted by law, KPMG accepts no liability in respect of any such matters to you. If you rely on the Final Report or any part of any of them, you do so at your own risk.

Yours faithfully

D Rice
Regulation Director