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Research Article

Climate-Informed Schedule Risk Surfaces for Construction Planning in Türkiye: Linking Threshold Operability and Start-Date Optimization

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Abstract

Climate change challenges the stationarity assumptions embedded in construction baseline schedules by shifting temperature and precipitation regimes and, consequently, weather-driven work interruptions. This study presents a gridded, data-driven workflow that links climate forcing to construction schedule outcomes by translating daily temperature/precipitation thresholds into Activity Performance Indices (APIs) for climate-sensitive activities and propagating them into project duration through start-date scanning. Historical baselines are represented using ERA5-Land reanalysis at 0.1° (~9 km) resolution, while future conditions are derived from a bias-corrected and downscaled CMIP6 multi-model ensemble under Shared Socioeconomic Pathways (with emphasis on SSP5-8.5 for end-of-century risk). Single- and multi-hazard operability surfaces are mapped across Türkiye and demonstrated using a 46-activity reinforced-concrete building schedule with a 207-day deterministic baseline. Results show strong seasonal redistribution of workability: warming tends to improve winter operability while degrading summer productivity, producing location- and start-date-dependent optimal windows. Nationally, climate effects increase the schedule mean/median to 255/238 days under historical conditions (+23% mean vs. baseline). Under far-future SSP5-8.5 (2071–2100), optimized outcomes converge to 239 days (+16% vs. baseline). If historical planning start dates are carried forward without climate adaptation, mean/median durations rise to 258/244 days, implying ~19 days (~10% of the baseline) of avoidable delay on average, with substantially larger penalties in some regions. The outputs support climate-aligned planning and provide an auditable basis for contract-ready baselines (e.g., via a Climate–Weather Baseline Report approach).

Keywords: climate change; construction scheduling; operability; start-date optimization; CMIP6

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1 Introduction

Construction planning requires early commitments to baseline schedules, procurement, and resourcing, often months in advance. By contrast, the practical skill of operational weather forecasts degrades rapidly with lead time, leaving a structural gap between short-horizon site decisions and long-horizon programming assumptions.

Weather-driven work interruptions are also a recurring source of time impacts and delay entitlement debates. In both planning and contract administration, separating expected seasonal downtime from exceptional conditions benefits from transparent, location-specific baselines.

This paper proposes a gridded workflow that translates historical reanalysis and future climate projections into day-of-year operability indices for climate-sensitive construction activities and propagates them into schedule outcomes through start-date scanning and schedule emulation.

This paper makes three contributions:

- A threshold-based method to translate climate variables into day-of-year operability for multiple activity groups.
- A schedule-emulation and start-date scanning routine that converts operability into duration distributions and optimal start windows.
- An illustration of the divergence between climate-aligned optimization and historical-practice carryover under future scenarios.

2 Background and Related Work

Construction delay literature consistently identifies adverse weather as an exogenous driver that can reduce productivity, interrupt workability windows, and trigger time- and cost-related claims (Moselhi & El-Rayes, 2002; Nguyen et al., 2010). Reviews of delay causes and delay-conflict linkages also emphasise the breadth of interacting drivers and the analytical challenge of isolating weather impacts from concurrent, project-controlled factors (Durdyev & Hosseini, 2020; Tariq & Gardezi, 2023).

Weather-aware scheduling research has integrated seasonal variability through productivity factors, functional representations (e.g., sine-wave curves), and simulation-based models that propagate weather into activity and project durations (Ballesteros-Pérez et al., 2017, 2018; Jung et al., 2016). However, many practical approaches remain grounded in stationarity assumptions, using historical observations as a proxy for future conditions.

Under non-stationary climate change, weather-related delay assessment and planning baselines require reconsideration (Schuldt et al., 2021). Reanalysis products such as ERA5-Land provide spatially complete historical baselines suitable for gridded engineering applications (Muñoz-Sabater et al., 2021). Future conditions can be explored using CMIP6 ensembles under Shared Socioeconomic Pathways (Eyring et al., 2016; O'Neill et al., 2016), while downscaling and bias correction (e.g., quantile-mapping variants) are commonly used to translate global projections into decision-relevant local signals (Bürger et al., 2012; Cannon et al., 2015).

Beyond planning, contract-readiness depends on how risks are allocated and documented. Risk allocation research highlights criteria and fairness considerations in construction contracting (Lam et al., 2007; Bunni, 2009), while contract practice discussions increasingly focus on clarity of baselines

and triggers for external risks. This motivates formal, auditable climate–weather baseline information as an input to both proactive scheduling and dispute-avoidance processes.

In parallel with climate-aware scheduling, recent research has expanded digital planning and BIM-enabled scheduling workflows. Studies comparing conventional and automated schedule creation in 4D BIM show that linking schedules to model objects can improve consistency, traceability, and workflow integration in construction planning (Doukari et al., 2022). Other work has proposed lean-integrated 4D BIM process models for scheduling-intensive settings such as modular construction, highlighting benefits in constructability review, logistics coordination, safety planning, and time control (Mayouf et al., 2024). More recently, systematic review evidence has shown that AI-enabled BIM and 4D BIM research is increasingly focusing on automation, decision support, and workflow optimization, although interoperability and implementation barriers remain significant (Awe et al., 2025). These developments reinforce the relevance of connecting climate-informed scheduling outputs with future BIM-enabled planning environments.

3 Data and Study Context

The study domain is Türkiye, which exhibits strong regional and seasonal contrasts due to coast–inland gradients and complex topography. The workflow is designed to output spatially explicit operability and schedule-risk indicators on a gridded domain (approximately 9 km), enabling nationwide mapping products rather than reliance on a single station time series.

Historical baseline conditions are represented using ERA5-Land reanalysis (Muñoz-Sabater et al., 2021). Future conditions are represented using CMIP6 climate model simulations organised into scenario-based periods (e.g., SSP2-4.5 and SSP5-8.5), with near-, mid-, and far-future windows used to structure comparisons (Eyring et al., 2016; O'Neill et al., 2016).

To obtain locally actionable distributions, projection data are bias-corrected and downscaled. Quantile-based approaches are commonly applied in climate impact studies, but their suitability for preserving changes in quantiles and extremes must be assessed and documented (Cannon et al., 2015). A multi-model ensemble approach is used to reduce dependence on any single model and to capture central tendencies and uncertainty ranges (Ahmed et al., 2019).

4 Methodology

The workflow starts by selecting climate variables and threshold levels that represent stop/go constraints for construction operations. The initial implementation focuses on temperature- and precipitation-based thresholds and maps them to activity groups such as earthworks, concrete works, steelworks, roofing, and pavements. Threshold choices are configurable and should be justified for the local context and project typology. Table 1 summarises the threshold set and its activity mapping used in this implementation. Figure 1 summarises the end-to-end workflow.

The threshold set was fixed before the schedule-emulation stage and should be interpreted as a context-specific workability rule set rather than a universal physical limit. Its selection follows the previous works of the authors, where temperature- and precipitation-based threshold combinations were used to assess the execution and performance of climate-sensitive construction activities over Türkiye at approximately 9 km grid resolution (Oruç et al., 2024). More broadly, prior weather-aware scheduling studies have also shown that construction planning can be linked to threshold-sensitive

weather effects and schedule variation through quantitative planning tools and annual-cycle representations (Ballesteros-Pérez et al., 2017, 2018). Accordingly, the thresholds adopted here reflect a combination of literature precedent, engineering judgement, and the Turkish project-planning context of the case study.

For each grid cell and each day-of-year, threshold exceedance frequencies are computed over the selected analysis years (historical or projected). An impact factor is defined as the complement of exceedance frequency, yielding a [0,1] operability proxy for each parameter and day-of-year.

Activity performance indices (APIs) represent multi-constraint operability for each activity group by combining relevant impact factors (e.g., multiplicative aggregation for independent constraints). APIs can be visualised as annual-cycle curves for a selected location and as spatial maps for selected dates or months. API definitions for the eight activity groups are given in Table 2.

Table 1. Climate thresholds and activity mapping for workability constraints.

Impact factor (threshold)	Affected activity groups
Tmin0 (Tmin ≤ 0 °C)	Concrete (C), Pavements (P)
Tmax0 (Tmax ≤ 0 °C)	Formworks (F), Roof (R)
Tmean0 (Tmean ≤ 0 °C)	Earthworks (E), Steelworks (S), Exterior finishes (EV), Landscape (L)
Tmax40 (Tmax ≥ 40 °C)	Concrete (C), Pavements (P), Steelworks (S)
Pr1 (Precipitation ≥ 1 mm/day)	Pavements (P), Exterior finishes (EV)
Pr10 (Precipitation ≥ 10 mm/day)	Earthworks (E), Concrete (C), Roof (R), Landscape (L)
Pr30 (Precipitation ≥ 30 mm/day)	Formworks (F), Steelworks (S)

Table 2. Activity performance index (API) definitions (multiplicative combination of impact factors).

Activity group	API definition
Earthworks (E)	$E = T_{mean0} \times Pr_{10}$
Formworks (F)	$F = T_{max0} \times Pr_{30}$
Concrete (C)	$C = T_{min0} \times T_{max40} \times Pr_{10}$
Pavements (P)	$P = T_{min0} \times T_{max40} \times Pr_1$
Exterior finishes / Envelope (EV)	$EV = T_{mean0} \times Pr_1$
Steelworks (S)	$S = T_{mean0} \times T_{max40} \times Pr_{30}$
Roof (R)	$R = T_{max0} \times Pr_{10}$
Landscape (L)	$L = T_{mean0} \times Pr_{10}$

Schedule impacts are evaluated through a day-by-day schedule emulation. Each activity in the baseline schedule is tagged with an API (or left untagged if climate-insensitive). For a candidate start day-of-year, the schedule is progressed in time while applying day-specific operability indices to climate-sensitive activities. Repeating the emulation across a full set of candidate start dates produces a duration–start-date response curve and identifies optimal start windows.

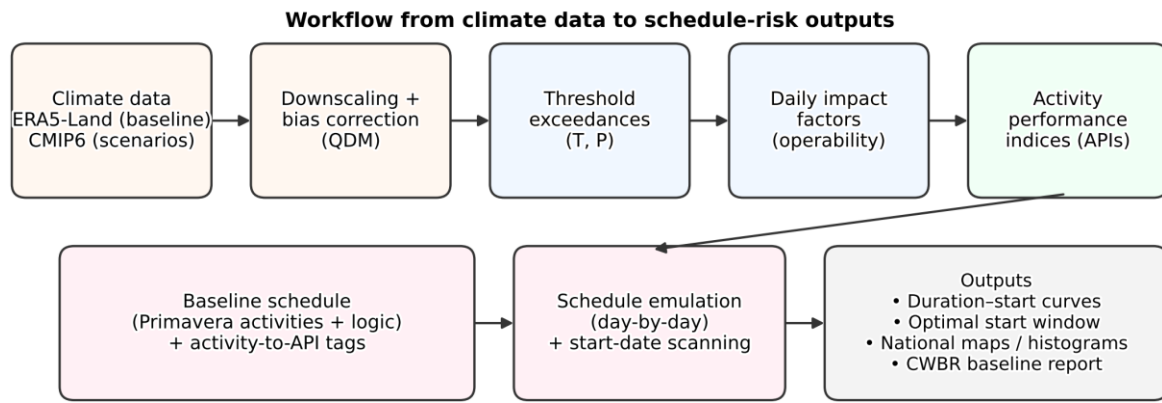


Figure 1. Workflow overview from climate data to schedule risk outputs.

Algorithm 1 summarises the start-date scanning procedure.

1. Input: baseline schedule (activities, logic, baseline durations), activity-to-API tags, daily API series for a grid cell, candidate start dates.
2. For each candidate start date s : initialise project day $d = s$ and set all activities to 'not started'.
3. Progress the schedule day-by-day; for each active climate-sensitive activity a , advance effective work by $API_a(d)$.
4. Apply precedence logic; start successor activities when predecessors complete; continue until project completion.
5. Record total duration $D(s)$. Output: $D(s)$ curve, optimal start date s^* , and optimal duration $D(s^*)$.

5 Case Study

A reinforced concrete building schedule prepared in Oracle Primavera is used to demonstrate the workflow. The case study represents a five-storey building in Ankara with 46 activities and a deterministic baseline duration of 207 days.

The schedule is first emulated without climate effects to confirm that the logic and baseline durations reproduce the original deterministic completion time. Climate-aligned simulations then evaluate how operability modifies realised duration across start dates and climate periods/scenarios.

6 Results

Annual-cycle operability curves highlight distinct seasonal drivers. In many inland locations, low temperatures and precipitation constrain winter operations, while high-temperature thresholds can reduce summer operability for selected activities. Spatial outputs indicate that the same activity group can exhibit markedly different seasonal patterns across Türkiye.

For the Ankara coordinate, Figure 4 provides a compact annual-cycle comparison of historical and SSP5-8.5 Activity Performance Indices for the same eight activity groups, allowing the timing and direction of seasonal change to be read directly from the curves.

Start-date scanning demonstrates that, even for an unchanged baseline schedule, achievable duration can vary substantially with start timing. This positions start-date selection—and related seasonal strategy—as a controllable lever in climate-aware planning (Figure 2).

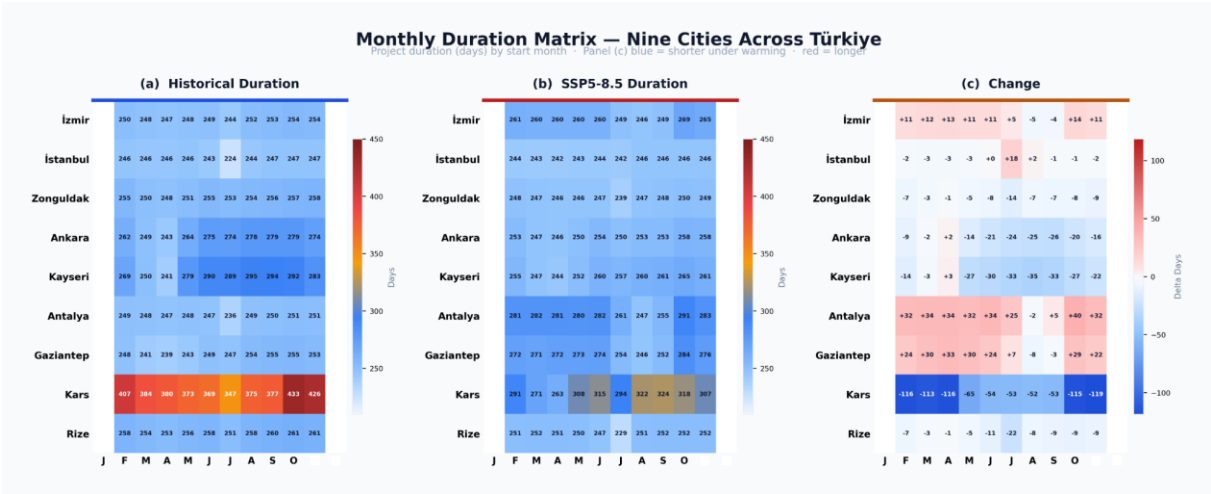


Figure 2. Monthly start-month duration matrix for nine representative Turkish cities: (a) historical period (1961–2014), (b) SSP5-8.5 far-future (2071–2100), and (c) change (future – historical). Values show expected project duration (days); blue indicates shorter durations under warming, red indicates longer. Start months shown Jan–Oct (Nov–Dec omitted for readability).

For the Ankara case schedule, climate-aligned scheduling shifts duration expectations materially relative to the deterministic baseline. Under historical conditions, optimised outcomes shift to a mean of 255 days and a median of 238 days. Under far-future SSP5-8.5, optimised mean/median converge to approximately 239 days. If historical planning practices are carried forward without climate adaptation, far-future mean/median durations increase to 258/244 days, indicating avoidable delay exposure when planning remains anchored to historical seasonality. National maps are provided in Figure 3, Figure 4 compares the historical and far-future annual-cycle operability profiles of the Ankara case across eight activity groups, and Figure 5 decomposes the Ankara results into daily variability, interannual variance, climate-shift benefits, and practice carryover penalties.

Table 3 summarises key duration metrics reported for the case study under different planning assumptions.

Table 3. Duration summary for the Ankara case study.

Scenario / Planning assumption	Mean duration (days)	Median duration (days)
Deterministic baseline (no climate effects)	207	207
Historical period (climate-aligned optimum)	255	238
Far-future SSP5-8.5 (climate-aligned optimum)	239	239
Far-future (historical-practice carryover)	258	244

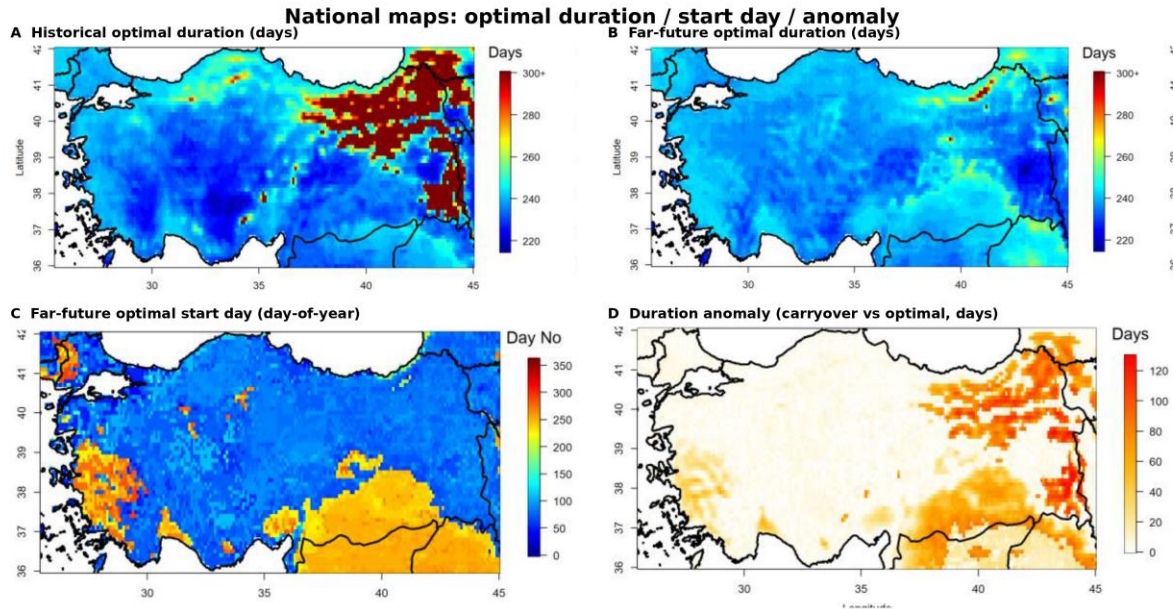


Figure 3. Spatial analysis over Türkiye (≈ 9 km grid) from start-date scanning: (a) historical optimal duration, (b) far-future SSP5-8.5 optimal duration, (c) far-future optimal start day, and (d) schedule anomaly (carryover – optimized) quantifying avoidable delay if historical practice is not updated.

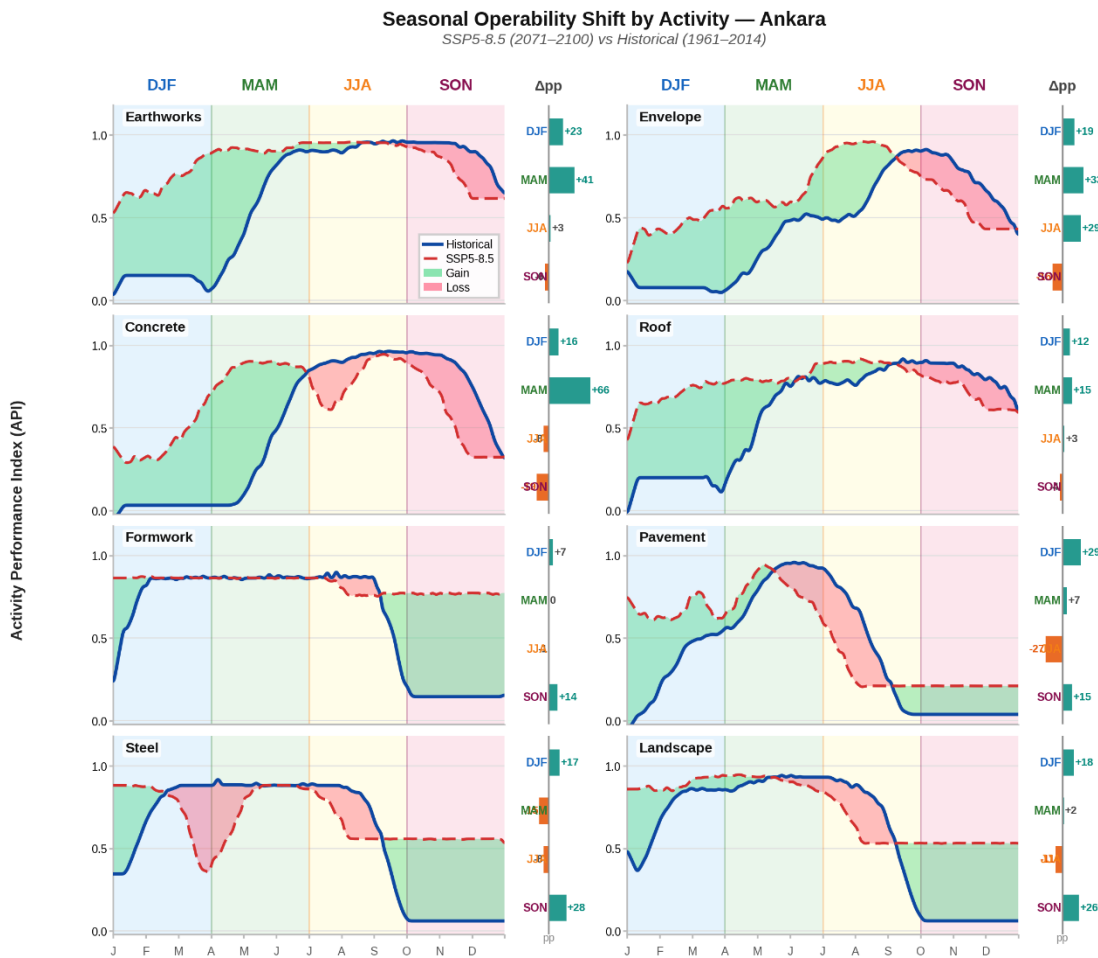


Figure 4. Historical (1961–2014) and SSP5-8.5 (2071–2100) annual-cycle Activity Performance Indices for eight climate-sensitive construction activity groups at the Ankara coordinate. Solid blue lines denote historical conditions and dashed red lines denote far-future SSP5-8.5 conditions, showing how warming redistributes operability across the year.

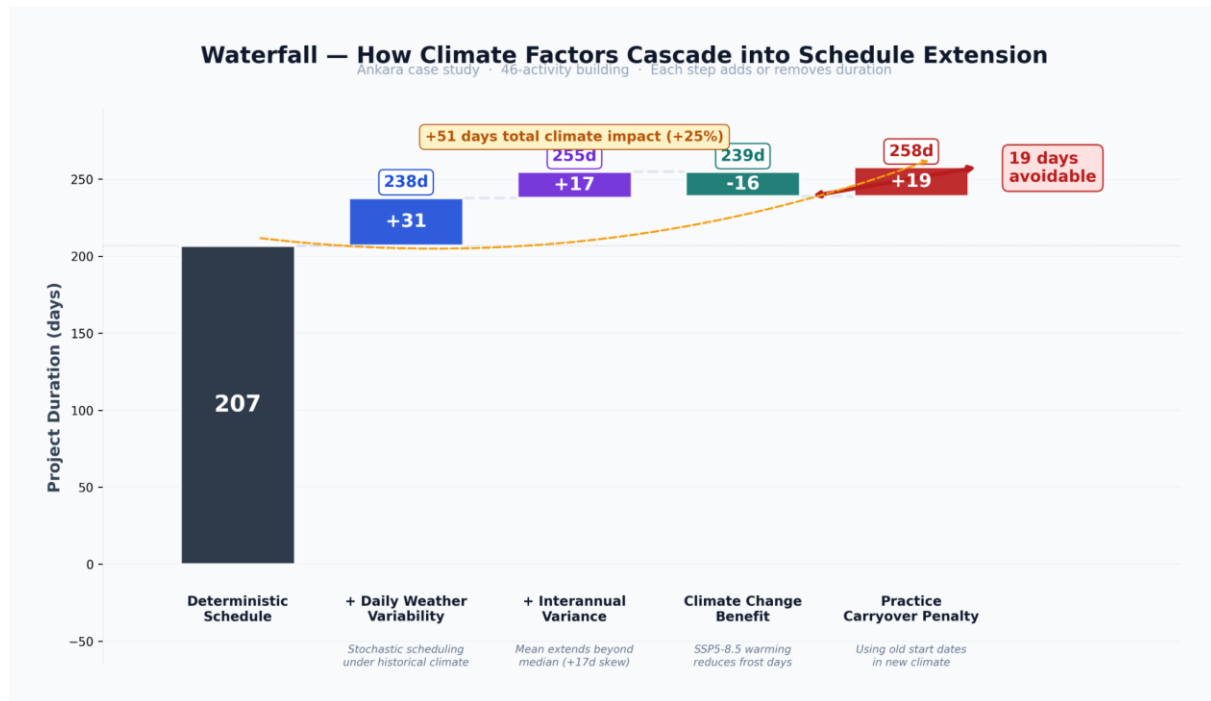


Figure 5. Waterfall decomposition of the Ankara case (46-activity building): deterministic baseline (207 days) extended by daily weather variability and interannual variance, partially offset by SSP5-8.5 warming (fewer frost days), and increased by practice carryover. This visualizes the avoidable delay recovered through climate-adjusted start-date selection.

7 Discussion and Practical Implications

The results suggest that climate-aligned scheduling should be framed as a schedule-risk surface problem: climate variables translate into day-of-year operability, which in turn reshapes expected durations through the seasonal placement of climate-sensitive activities.

Warming can produce a redistribution of constraints across seasons—improving winter operability while degrading summer operability for selected thresholds—so net schedule outcomes depend on the baseline sequence and the selected start window. Start-date scanning makes this dependency explicit and provides an objective basis for comparing alternatives.

Beyond planning, the same analytics can support more transparent baseline documentation for weather-related delay evaluation. A practical implementation is a Climate–Weather Baseline Report (CWBR) that documents datasets, thresholds, operability expectations, and agreed exceedance logic as a common reference for project parties. Supplementary Material S1 provides a contract-ready one-page CWBR baseline summary sheet aligned with this workflow.

8 Limitations and Future Work

Key limitations include:

- Dependence on reliable baseline datasets and careful post-processing of climate model outputs (downscaling and bias correction).
- Computational intensity for nationwide, daily, gridded products and multi-scenario ensembles.
- Limited representation of microclimates at ~9 km resolution and the need for contextual adjustments on complex sites.

- Schedule impacts are only one driver of project outcomes; resources, economics, safety, and policy constraints also shape realised performance.

The reported duration shifts are schedule-specific and activity-mix dependent; infrastructure and civil engineering projects with different sequencing logics, exposure profiles, and climate-sensitive work packages may therefore exhibit materially different responses under the same climate regime.

Future work includes expanding the variable set (e.g., wind), validating outputs against realised project delay records, and integrating the workflow with BIM and automated planning tools for repeatable decision support.

9 Conclusions

This paper presents a gridded, data-driven workflow that converts reanalysis and climate projections into day-of-year operability indices for climate-sensitive construction activities and propagates them into schedule outcomes through start-date scanning.

The case study demonstrates that climate-aligned planning can materially shift expected durations relative to deterministic baselines and that historical-practice carryover under future climate can introduce avoidable time impacts. The proposed outputs support actionable decisions on location and start-window selection and provide an auditable evidence base for climate-related delay assessment. A contract-ready CWBR one-page baseline summary sheet is provided as Supplementary Material S1.

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Data Availability Statement

ERA5-Land reanalysis and CMIP6 climate model outputs used in this study are publicly available. Processed datasets and code supporting the findings can be provided by the authors upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

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