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Effects of synchronised remote work on office energy use: A three-year field study

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ABSTRACT

Remote work is increasingly recognised as an operational strategy with the potential to reduce office-level energy use. The key idea explored here is that, beyond the amount of remote work adopted, synchronising it across employees may enhance this potential. Synchronised schedules can create predictable low-occupancy days that allow non-essential services in large portions of the building to be reduced or switched off. Against this background, the study contributes field-based evidence on this organisational question under real operating conditions.

The analysis is based on a three-year field study conducted in a fully electric office building in Cagliari, Italy, comparing three operational conditions: no remote work, unsynchronised remote work, and synchronised remote work on a designated day (Friday). High-resolution measurements of building electricity use, occupancy, and outdoor air temperature were analysed using multiple linear regression and climate normalisation. Results show that, in the analysed case, unsynchronised remote work was associated with a 29% reduction in normalised electricity use (95% CI: 25.3–32.6) compared with no remote work. Synchronised remote work was associated with a further reduction of 5.6% (95% CI: 0.7–12.0) relative to the unsynchronised arrangement. On the remote-work day, average savings reached 37.3% (95% CI: 24.4–49.6).

Overall, the findings provide field-based evidence that, within the boundary conditions of the analysed case, synchronising remote work is associated with lower office-level electricity use and that schedule coordination can serve as an operational lever to enhance its energy-saving effectiveness.

1. Introduction

Total final energy consumption in 2024 exceeded 450 EJ, with non-residential buildings accounting for 9% of this total [1]. Over the past decade, building energy use has grown by about 1% per year on average, driven by a rapid increase in electricity demand (2.6% per year), partially offset by efficiency improvements and reductions in fossil fuel use [2]. This growth has occurred almost entirely in emerging markets and developing economies and is expected to continue, with building energy demand projected to increase by around 1.3% per year on average up to 2035 under the International Energy Agency (IEA) Current Policy Scenario [2]. In this context, the Intergovernmental Panel on Climate Change (IPCC) identifies non-technological approaches, such as organisational and behavioural measures, as key strategies to be pursued alongside technological solutions for improving energy efficiency and supporting decarbonisation [3]. Among these approaches, remote work, which alters occupancy patterns and space utilisation, has emerged as a relevant measure for reducing energy use in non-residential buildings [4]. While its potential for overall energy savings and CO_2 reductions is influenced by rebound effects [5], the IEA estimated that remote work could reduce annual global CO_2 emissions by approximately 24 million tonnes [6]. Beyond its environmental implications, remote work has become a firmly established and increasingly widespread labour practice [7], making a return to pre-adoption arrangements no longer conceivable[1] [8]. In the United States, 22.9% of employed individuals teleworked in the first quarter of 2024, up from 19.6% the previous year [9]; while in the European Union (EU-27), around 37% of employees hold "teleworkable" jobs, a level comparable to adoption rates observed during the COVID-19 pandemic [10].

Despite growing interest in remote work as an energy-saving

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[1] An interesting list of remote work advantages and drawbacks is provided by O'Brien et al. [11].

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measure, its actual impacts remain difficult to generalise and highly context-dependent. As stated by both Hook et al. [5] and O'Brien et al. [11], multiple rebound effects, including shifts in energy use between offices and homes, transport, and lifestyle, can erode or even reverse expected savings. These effects act across different domains, including buildings, transport, and lifestyle, making the overall energy balance of remote work inherently complex. Regarding buildings, the rebound mechanism concerns the redistribution of energy demand between offices and houses. Although remote work reduces the number of employees physically present in offices, building systems such as Heating Ventilation and Air Conditioning (HVAC) and lighting typically remain operational to serve the employees still working on-site. At the same time, equivalent services must be provided in multiple households, often with lower energy efficiency [12]. The IEA estimates that remote work may increase household energy demand by between 7% and 23%, depending on climatic conditions, seasonality, and the efficiency of domestic appliances and equipment [13]. Among the indirect rebound effects associated with mobility and lifestyle changes, studies have observed that remote workers may choose to reside farther from their workplace [14] and be engaged in an increased number of non-commuting trips for errands and leisure activities [15]. Consequently, even when commuting is reduced, the expected benefits in terms of transport-related emissions are not guaranteed [16]. Table 1 provides a concise overview of selected studies relevant to remote work, occupancy patterns and building energy implications, highlighting their main findings, strengths and limitations.

As summarized in Table 1, existing studies on remote work and energy use have adopted heterogeneous methodological approaches, including review-based syntheses [5,11,16], simulation and scenario analyses [12,17], and survey- or data-driven models [23]. However, much of the literature remains limited either by narrow analytical boundaries or by reliance on modelled rather than measured office-energy evidence [5,11,16].

Beyond these methodological differences, a further challenge in assessing the environmental implications of remote work arises from the growing unpredictability of office occupancy. Human behaviour, which clearly influences energy use [19,20], is inherently stochastic, making it difficult to accurately estimate both the number of occupants and the duration of their presence in specific spaces [21]. Whereas office buildings were traditionally characterised by stable schedules and predictable activity patterns aligned with standard working hours [22], contemporary work practices are increasingly dynamic and heterogeneous. Capturing this variability is particularly challenging for simulation-based analyses, highlighting the first gap addressed in this study: the still limited empirical evidence on the actual energy impacts of remote work.

Considering both rebound effects and the unpredictability of occupancy, Shimoda et al. [17], Kaur et al. [24] and Bezzola et al. [16] agree that only synchronised remote work arrangements are able to fully realise the potential for energy savings, as they combine temporal coordination of remote working schedules with space management measures such as desk sharing and space consolidation. Moreover, synchronised forms of remote work could help mitigate the inefficiencies arising from the structural underutilisation of office spaces (typically 40–50% [12]), which existed even before remote work became widespread. However, despite the evident advantages of synchronised forms of remote work, what emerges from the literature is that the majority of existing studies focus on conventional (unsynchronised) remote work arrangements, in which remote work is adopted individually and asynchronously across employees.

By contrast, only a limited number of studies have explored alternative organisational models, such as co-working or coordinated work schedules, and their implications for workplace energy use. This second literature gap, highlighted by both Bezzola et al. [16] and O'Brien et al. [11], is also addressed in the present study through an explicit focus on a synchronised form of remote work, evaluated against a conventional unsynchronised remote work arrangement as well as a baseline no-remote-work configuration.

The relevance of this research direction is further reinforced by emerging evidence on the evolving role of offices. According to Mantesi et al. [18], the future office is expected to primarily support social interaction, community building, knowledge exchange, and a sense of belonging among employees. Synchronising remote work across employees can therefore serve a dual purpose: it creates full periods of building inactivity, enabling the shutdown of HVAC, lighting, and auxiliary systems, while simultaneously concentrating in-office presence on the same days, thereby enhancing opportunities for collaboration, social interaction, and community building.

Building on these insights and acknowledging that remote work is now an established and largely irreversible practice, the present study aligns with the recent research shift from assessing whether remote work should be adopted to empirically exploring how it may be operationally organised to maximise office-level energy savings, in line with the IEA recommendations [13]. Specifically, the study contributes to the existing empirical literature by examining field-based associations between different organisational remote work arrangements and office-level electricity use, comparing a synchronised remote work scheme (where remote work is concentrated on a designated weekday) with both a conventional, unsynchronised arrangement and a no-remote-work baseline.

The remainder of the paper is structured as follows. Section 2 describes the study design, monitoring system, data sources and the methods adopted to estimate electricity savings, as well as the study limitations. Section 3 presents and discusses the results, including descriptive statistics of the dataset, the performance of the regression models, the observed changes in occupancy patterns, and the corresponding variations in electricity use. Finally, Section 4 draws the conclusions.

2. Methods

This study is based on a three-year field investigation conducted in an office building at the University of Cagliari. Variations in electricity use and occupancy patterns were analysed under three different organisational remote work arrangements, implemented over successive annual periods: a baseline No-Remote-Work arrangement (NO RW), a conventional unsynchronised Remote Work scheme (RW), and a Synchronised Remote Work arrangement (SRW), in which remote work was concentrated on a designated weekday.

This section outlines the methodological framework adopted to examine the relationships between the three organisational arrangements and office-level electricity use. The methods are structured into three parts: first, the study design, monitoring system, and data sources are described (Section 2.1); second, the modelling approach, statistical analyses, and procedures used to quantify and compare electricity use across arrangements are presented (Section 2.2); third, the main methodological limitations are discussed (Section 2.3).

2.1. Study design, monitoring system, and data sources

The case study building (main characteristics summarized in Table 2) is fully electric and has an average annual electricity consumption of approximately 100 MWh, mainly associated with HVAC systems, lighting, and office equipment. Throughout the three-year investigation, no substantial physical modifications were made to the installed building systems, HVAC equipment, lighting system, or set points.

The building hosts administrative offices with 200 employees working under a 36-h weekly contract with heterogeneous schedules. Some employees work from 8:00 a.m. to 2:00 p.m. with additional 3-h afternoon shifts on Tuesdays and Thursdays, while others follow a continuous schedule from 8:00 a.m. to 3:30 p.m. The building operates

Table 1
Overview of selected studies on remote work and energy implications.

Type of analysis	Study focus	Main findings	Strengths	Limitations	Ref.
Review	Energy and environmental impacts of remote work	Remote work savings are uncertain once rebound effects are included.	Broad synthesis of mechanisms, rebound effects and methodological weaknesses.	Limited measured office-energy evidence, no distinction between synchronised and unsynchronised remote-work schedules.	[5] [11]
Review	Location, time and space flexibilisation and their energy pathways.	Energy savings are most likely when telework is combined with space management, desk sharing and occupancy-responsive office operation.	Maps multiple working models, mediators and organisational/ contextual factors.	Few studies on space/time flexibilisation; lack of robust evidence on measured office electricity and occupancy-related effects.	[16]
Review	Remote work as an organisational practice involving multiple aspects.	Remote and hybrid work reshape temporal, structural, technological and social coordination; adoption is influenced by technological, organisational and environmental conditions.	Frames remote work as a structured organisational and multilevel arrangement rather than only an individual preference.	Limited attention to energy-related implications; limited empirical evidence on synchronised and unsynchronised remote-work schedules.	[7] [8]
Simulation	Energy-use shifts between homes and offices under remote work.	Remote work generally increases home energy use and can reduce office energy use; net impacts depend on office-space reduction, occupancy-adaptive building systems, climate, and energy/emission factors.	Scenario-based approach captures home–office trade-offs under different remote work, occupancy, building-stock and adaptability assumptions.	Simulation-based; relies on modelled occupancy schedules rather than badge-derived occupancy data; no explicit synchronised and unsynchronised comparison, although adaptable vs inadaptable systems are considered.	[17] [12]
Simulation	Post-pandemic office design, activity-based workspaces and hybrid utilisation.	Hybrid working and activity-based workspace design can reduce office energy.	Evaluates alternative office futures and identifies key operational variables.	Scenario assumptions; no measured long-term office electricity or badge-derived occupancy.	[18]
Simulation	Occupancy, behaviour, modelling complexity and the energy performance gap.	Occupant presence and actions strongly affect energy use; measured or fit-for-purpose behavioural data reduce uncertainty in building energy analysis.	Provides mechanisms linking occupancy, behaviour and building operation.	Mostly residential or simulation-oriented; limited direct evidence on office remote-work scheduling.	[19] [20] [21] [22]
Carbon footprint	Life-cycle carbon and cost impacts of moving education, work and conferences online.	Virtual formats reduce carbon footprints mainly by reducing travel, but home energy and other rebound components must be included.	Broader environmental comparison across activity modes and scopes.	Carbon-footprint rather than office electricity focus; occupancy not measured through badge data; climate normalisation limited.	[4]
Data-driven modelling	Data-driven prediction of office electricity using dynamic and static data.	Office electricity prediction improves when measured consumption is combined with operational, occupancy-related and seasonal information.	Empirical benchmark value; high-resolution office electricity prediction and performance metrics.	Prediction focus; no remote-work arrangements or synchronised distinction.	[23]

Table 2
Main characteristics of the case-study building.

Characteristic	Description/Value
Geographic coordinates	39.217° N, 9.114° E
Year of construction	1778
Gross floor area/net floor area	7900 m^2/6800 m^2
Net floor area by function	Administrative functions: 2800 m^2 Auxiliary functions (corridors, staircases, archives, restrooms): 4000 m^2
Building floors	Basement (1500 m^2); Ground floor (1850 m^2); First floor (1160 m^2); Second floor (2250 m^2); Third floor (1140 m^2)
Structural system	Load-bearing masonry structure
Building envelope	Limestone masonry walls and traditional timber roof with clay tile covering
Windows	Timber-framed double-casement with single or double glazing
HVAC system	VRF system with a nominal heating capacity of 50 kW and a cooling capacity of 40 kW, with decentralised control at the individual unit level, combined with numerous single- and multi-split units, operating within the periods prescribed for Italian climate zone C. Fixed set-point temperatures of 20 and 24 °C.
Lighting system	LED lighting installation with a total installed electrical capacity ≈30 kW
Elevators	2 units

from 7:00 a.m. to 8:00 p.m. from Monday to Friday.

Following standard practice in energy savings assessments, each work arrangement (NO RW, RW, SRW) was monitored for one year. In the NO RW arrangement, all employees worked entirely on-site. In the RW arrangement, employees worked remotely on selected days upon agreement with their supervisors, without coordination among staff. In the SRW arrangement, remote work was synchronised by concentrating remote activities on a specific weekday (Friday), while maintaining on-site presence during the remaining working days. The SRW arrangement was introduced as a straightforward temporal reorganisation of remote work, concentrating remote activities on a single coordinated weekday rather than distributing them asynchronously across the week. Indeed, under the RW arrangement, some offices and building areas remained in use due to the presence of a limited number of employees, and therefore their systems could not be fully deactivated; by contrast, under the SRW arrangement, the consolidation of remote work on a single day allowed the majority of spaces to remain inactive. Operationally, this enabled the deactivation of non-essential HVAC systems, lighting, and auxiliary services in those areas on the designated remote-work day. In this sense, SRW can be interpreted as an organisational energy-management measure.

To enable a consistent comparison across the three arrangements, electricity use and its main drivers, namely occupancy and weather (outdoor air temperature) [23], were systematically monitored.[2] Electricity consumption data were obtained from the metering system of the local electricity distributor, e-distribuzione. The data were downloaded from the distributor's web portal at 15-min resolution and represent the total electricity consumption of the building. Occupancy was reconstructed from the clock-in and clock-out records of each employee. For each working day, the timestamped entry and exit records were processed to define individual presence intervals within the building. Each employee was considered present between the corresponding clock-in

[2] The dataset is available in Mendeley Data [30].

and clock-out events. Outdoor air temperature was measured at hourly resolution using a meteorological station located in the building.

Before the data analysis, a common preprocessing procedure was applied to all three data streams. Electricity use, occupancy, and outdoor air temperature were temporally aligned, restricted to working days, and evaluated over the office-opening period from 7:00 a.m. to 8:00 p.m. Weekends, Italian public holidays, and extraordinary closures were excluded. The resulting variables were then aggregated at the daily level for model fitting. Hereafter, the term "filtered" refers to this common preprocessing procedure.

To make the data structure and processing workflow explicit, Table 3 summarises the monitored variables used to construct the filtered daily regression dataset.

2.2. Energy modelling and climate-normalised analysis

For each period $P \in \{NO\,RW, RW, SRW\}$ corresponding to an organisational arrangement, a multiple linear regression model was developed in MATLAB R2024b [25] using the filtered dataset described in Section 2.1. The model was used to examine the association between electricity use, occupancy, and climatic variables (Heating and Cooling Degree Days, HDD and CDD). Separate models were estimated for each arrangement to account for potential structural differences in energy-use dynamics across organisational settings. For each period P, filtered daily observations were indexed by $t = 1,\dots,n_P$, where n_P is the number of days of that period. The regression models were formulated as:

$$E_{t,P} = \beta_{0,P} + \beta_{1,P}O_{t,P} + \beta_{2,P}HDD_{t,P} + \beta_{3,P}CDD_{t,P} + \epsilon_{t,P} \tag{1}$$

where $E_{t,P}$, $O_{t,P}$, $HDD_{t,P}$ and $CDD_{t,P}$ denote, respectively, the daily electricity use, occupancy, Heating and Cooling Degree Days; $\beta_{0,P}$ is the baseline component of daily electricity use, not directly explained by occupancy or weather conditions; $\beta_{1,P}, \beta_{2,P}, \beta_{3,P}$ are the regression coefficients associated with each energy driver, and $\epsilon_{t,P}$ is the residual term, capturing remaining variability not explained by the model.

Equivalently, for each period P, the model can be written in matrix form as:

$$\mathrm{y}_P = \mathrm{X}_P\beta_P + \varepsilon_P \tag{2}$$

where $\mathbf{y}_P$ is the $n_P \times 1$ vector of daily electricity use, X_P is the $n_P \times 4$ design matrix including the intercept, occupancy, HDD, and CDD terms, β_P is the vector of regression coefficients, and $\boldsymbol{\varepsilon}_P$ is the residual vector.

Occupancy was expressed as man-hours of on-site presence and was calculated as:

$$O_{t,P} = \sum_{i=1}^{N_e} h_{i,t,P} \tag{3}$$

Where N_e is the number of employees (unchanged among periods) and $h_{i,t,P}$ is the duration between the clock-in and clock-out records of employee i on day t in period P.

Following degree-day-based building energy analytics [26], $HDD_{t,P}$ and $CDD_{t,P}$ were adopted as proxy indicators of heating and cooling demand, and were defined according to Mehregan et al. [27] as:

$$HDD_{t,P} = \begin{cases} \max\left(0, T_{set,H} - \overline{T}_{out,t,P}\right), & \text{heating season} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

$$CDD_{t,P} = \begin{cases} \max\left(0, \overline{T}_{out,t,P} - T_{set,C}\right), & \text{cooling season} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

where $T_{set,H}$ and $T_{set,C}$ are heating and cooling set-point temperatures, and $\overline{T}_{out,t,P}$ is the daily mean outdoor temperature from the filtered dataset. A specification based directly on daily mean outdoor temperature was also tested; however, the HDD/CDD formulation was retained because it better captured the weather-related variability in daily electricity.[3]

Model coefficients were estimated using robust linear regression to reduce the influence of outlying daily observations without manually removing data. Formally, for each period P, the coefficient vector was obtained by solving the following M-estimation problem:

$$\widehat{\beta}_P = \underset{\beta_P}{\operatorname{argmin}} \sum_{t=1}^{n_P} \rho\left(\frac{E_{t,P} - \mathrm{x}_{t,P}^\top \beta_P}{\widehat{\sigma}_P}\right) \tag{6}$$

where $\mathrm{x}_{t,P}$ is the predictor vector for day t in period P, $\widehat{\sigma}_P$ is an estimate of the residual scale, and $\rho(\cdot)$ is the loss function associated with the iteratively reweighted least-squares procedure. To account for heteroscedasticity and serial correlation in residuals, inference was based on Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors computed using a Newey–West approach, with autocovariances included up to the maximum lag $L_P = \left\lfloor n_P^{1/4} \right\rfloor$ and Bartlett weights applied across lags. The HAC covariance matrix was computed in sandwich form as:

$$\widehat{\mathrm{Var}}_{\mathrm{HAC}}\left(\widehat{\beta}_P\right) = \left(\mathrm{X}_P^\top \mathrm{X}_P\right)^{-1} \mathrm{S}_P \left(\mathrm{X}_P^\top \mathrm{X}_P\right)^{-1} \tag{7}$$

where S_P includes contemporaneous residual cross-products and lagged autocovariances up to lag L_P, weighted using the Bartlett kernel. Residual serial dependence was additionally inspected using the Durbin–Watson statistic computed from the raw residuals of the robust fit. Statistical significance was evaluated using HAC-adjusted t-statistics and corresponding two-sided p-values, computed with $n_P - k_P$ degrees of freedom, where $k_P = 4$ is the number of estimated regression parameters in period P. Model performance was assessed through the coefficient of determination (R^2) and adjusted R^2.

To further examine the appropriateness of modelling the periods separately rather than jointly, an interaction model was also fitted including all three periods with interaction terms. The interaction model was used as a diagnostic specification and enabled an assessment of whether the relationships between occupancy, weather, and electricity differed structurally across periods. The interaction model was specified with the SRW period as the reference baseline:

$$\begin{aligned} E_t = {} & \beta_0 + \beta_1 O_t + \beta_2 HDD_t + \beta_3 CDD_t + \beta_4 D_{RW,t} + \beta_5 D_{NO\ RW,t} \\ & + \beta_6 \left(O_t \cdot D_{RW,t}\right) + \beta_7 \left(O_t \cdot D_{NO\ RW,t}\right) + \beta_8 \left(HDD_t \cdot D_{RW,t}\right) \\ & + \beta_9 \left(HDD_t \cdot D_{NO\ RW,t}\right) + \beta_{10} \left(CDD_t \cdot D_{RW,t}\right) + \beta_{11} \left(CDD_t \cdot D_{NO\ RW,t}\right) + \epsilon_t \end{aligned} \tag{8}$$

where $D_{NO\ RW,t}$ and $D_{RW,t}$ are dummy variables equal to 1 when observation t belongs to the NO RW and RW periods, respectively, and

Table 3
Data sources and preprocessing procedure.

Variable	Unit	Source	Native resolution	Filtered daily aggregation
Electricity use	kWh	Electricity meter	15-min readings	Sum of 15-min electricity use
Occupancy	man-hours	Clock-in/ clock-out records	timestamped events	Sum of presence intervals
Outdoor air temperature	°C	On-site weather station	hourly records	Mean outdoor temperature

Note: Filtered daily aggregation refers to valid working days and to the office-opening period from 7:00 a.m. to 8:00 p.m.

[3] Replacing HDD and CDD with daily mean outdoor temperature reduced the model explanatory power from $R^2 = 0.755$ to 0.303 in NO RW, from 0.767 to 0.289 in RW, and from 0.842 to 0.569 in SRW.

0 otherwise.

Once both the appropriateness of modelling each period separately and the overall adequacy of the individual models were established, daily electricity use for each period was normalised to a common climatic reference to reduce the influence of weather variability when comparing organisational arrangements. Normalisation was performed considering the SRW period as the common climatic reference,[4] following an IPMVP-based forecasting approach [28]. Specifically, the normalised daily electricity use ($E_{norm,t,P}$) was calculated by keeping the regression coefficients unchanged and replacing $HDD_{t,P}$ and $CDD_{t,P}$ with the monthly averages from the common climatic period:

$$E_{norm,t,P} = \widehat{\beta}_{0,P} + \widehat{\beta}_{1,P} O_{t,P} + \widehat{\beta}_{2,P} \overline{HDD}^{SRW}_{m(t)} + \widehat{\beta}_{3,P} \overline{CDD}^{SRW}_{m(t)} \tag{9}$$

where $m(t)$ denotes the month of day t, and $\overline{HDD}^{SRW}_{m(t)}$ and $\overline{CDD}^{SRW}_{m(t)}$ are the monthly average HDD and CDD values computed over the SRW climatic reference period.

To examine the robustness and statistical uncertainty of differences in occupancy and electricity use among arrangements, non-parametric tests were conducted. Pairwise comparisons between NO RW and RW, and between RW and SRW, were performed using the Mann–Whitney U test (Wilcoxon rank-sum). Tests were conducted on both weekly aggregates and daily values to capture intra-week variability, with statistical significance evaluated at $\alpha = 0.05$.

Electricity savings (ES) associated with the transition from one organisational arrangement (period) P_1 to another P_2 were quantified as the relative difference in the average daily climate-normalised electricity use over the considered subset of days $\mathscr{T}$:

$$ES_{P_2 \ vs \ P_1}(\mathscr{T}) = \frac{\overline{E}_{norm,P_1}(\mathscr{T}) - \overline{E}_{norm,P_2}(\mathscr{T})}{\overline{E}_{norm,P_1}(\mathscr{T})} \tag{10}$$

where $P_1, P_2 \in \{\text{NO RW}, \text{RW}, \text{SRW}\}$ are the periods being compared, $\mathscr{T}$ denotes the subset of days considered (e.g., individual weekdays, or longer periods), $\overline{E}_{norm,P}(\mathscr{T})$ is the mean daily climate-normalised electricity use in period P over the days $\mathscr{T}$. Uncertainty in estimated ES was quantified using non-parametric bootstrap resampling (1000 iterations). Bootstrap samples were drawn with replacement from daily observations within each period, and 95% confidence intervals were obtained using the percentile method.

2.3. Limitations

Several limitations should be acknowledged. First, the study follows a sequential quasi-experimental design, in which the three organisational arrangements were observed over three consecutive annual periods rather than through a concurrent control group or a randomised crossover. This approach reflected the real-world implementation of the remote-work arrangements at the organisational level, where frequent randomisation or reversal of work arrangements would have been difficult to apply operationally. Because the arrangements were implemented sequentially, the possible influence of historical factors cannot be fully excluded. Climate normalisation was adopted to reduce weather-related differences across periods, and no structural changes were made to the building systems during the monitored years. Nevertheless, non-weather factors, such as equipment ageing, staff turnover, minor operational changes, or gradual behavioural adaptation, may have partly influenced electricity use.

Second, the study was conducted in a single office building with specific technical, climatic, and organisational characteristics. Therefore, the study results are most directly transferable to office buildings with comparable boundary conditions, while buildings with different HVAC systems, control strategies, occupancy densities, climates, or organisational practices may respond differently.

Third, electricity use was measured at the whole-building level because no end-use sub-metering data were available. This allowed a consistent assessment of the overall electricity response of the building but did not allow the relative contribution of individual end uses, such as HVAC, lighting, office equipment, elevators, and auxiliary loads, to be directly quantified.

In light of these limitations, the results should be interpreted as empirical associations observed under real operating conditions, rather than as strong causal estimates in the sense of a randomised experiment.

3. Results and discussion

This section first presents the structure and descriptive statistics of the dataset (Section 3.1), then the performance of the regression models (Section 3.2), then the variations in daily occupancy that occurred across the three arrangements (Section 3.3), and finally the observed differences in energy use associated with the RW and SRW arrangements (Section 3.4).

3.1. Dataset description and descriptive statistics

Table 4 reports descriptive statistics for the observed, filtered, daily variables. The dataset included a similar number of valid working days for the three arrangements, thus providing a balanced empirical basis for comparison. The descriptive statistics show a clear reduction in daily occupancy following the introduction of remote work, with mean occupancy decreasing from 1125 man-hours/day in the NO RW period to 798 and 784 man-hours/day in the RW and SRW periods, respectively. A corresponding decrease was observed in raw electricity use, whose mean value declined from 575 kWh/day in NO RW to 412 kWh/day in RW and 364 kWh/day in SRW.

During the monitored periods, heating and cooling needs varied significantly. HDD and CDD were calculated for the local heating season (November 15–March 31) and cooling season (June 1–September 30). The resulting values are reported in Fig. 1.

3.2. Performance of regression models and interaction effects

The regression models for the three arrangements were statistically meaningful and exhibited good explanatory capability. A concise summary of the estimated coefficients and diagnostic indicators is reported in Table 5. In all arrangements, occupancy and climatic variables emerged as statistically significant predictors of electricity use. The explanatory power of the models was comparable ($R^2 \approx 0.75$–0.84). Durbin–Watson statistics (between approximately 1.0 and 1.3) indicated the expected positive serial correlation of residuals, supporting the use of HAC-adjusted inference.

Following the estimation of the period-specific models, the interaction model described in Eq. (8) was used to examine whether the relationships between electricity use and its main drivers differed across organisational arrangements. The results, summarized in Table 6, are discussed below. The baseline coefficients correspond to the SRW period and indicate that occupancy and climatic variables remain statistically relevant predictors of electricity use. The interaction terms highlight statistically significant structural differences across periods. In particular, the interaction between occupancy and the NO RW period is positive and significant ($p < 0.001$), suggesting a comparatively stronger sensitivity of electricity use to occupancy in the NO RW arrangement compared with SRW. This behaviour may be associated with a more intensive use of occupant-driven loads during fully on-site operation, such as shared devices (e.g., printers) and meeting spaces, which are plausibly used more frequently when all personnel are present simultaneously. In contrast, the interaction between occupancy and RW is not statistically significant, indicating no clear difference in the occupancy-

[4] Sensitivity tests using NO RW and RW as alternative climatic references produced comparable results.

Table 4
Descriptive statistics (filtered daily dataset).

Variable	Arrangement	n	Mean	Standard deviation	Median	Interquartile range
Electricity use (kWh/day)	NO RW	244	574.80	166.87	549.76	224.35
	RW	245	411.63	175.85	362.50	204.81
	SRW	239	363.90	174.21	336.10	246.02
Occupancy (man-hours/day)	NO RW	244	1125.10	248.40	1152.80	303.75
	RW	245	797.68	301.83	800.50	476.44
	SRW	239	783.63	419.40	867.25	554.31
Outdoor air temperature (°C)	NO RW	244	19.63	6.98	18.54	12.29
	RW	245	20.21	7.15	19.93	12.82
	SRW	239	20.88	6.15	21.29	10.63

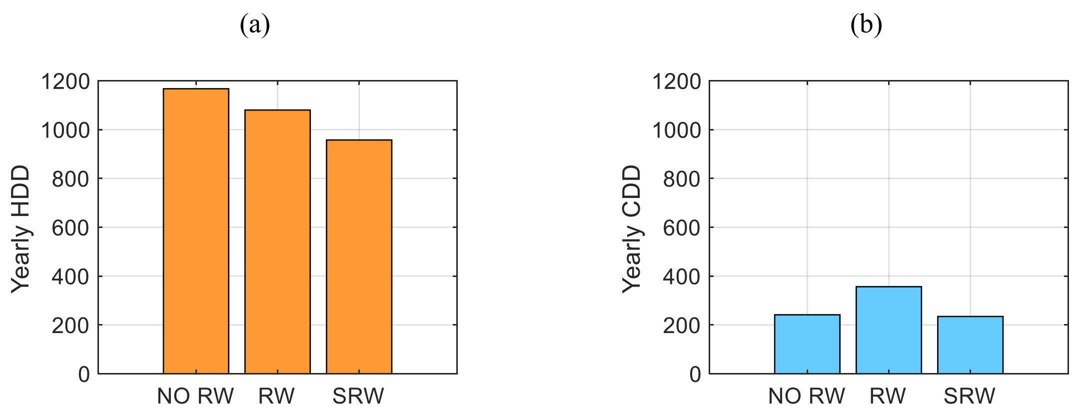

Fig. 1. Yearly Heating Degree Days (a) and Cooling Degree Days (b) across NO RW, RW, and SRW operational arrangements.

Table 5
Regression results for the three periods (arrangements).

Arrangement	Coefficient	Estimate	SE	t	p-value
NO RW (n = 244)	Intercept	63.302	27.806	2.277	0.0237
	Occupancy	0.32469	0.022594	14.371	3.32e-34
	HDD	34.352	1.4876	23.093	6.55e-63
	CDD	35.224	2.6641	13.222	2.40e-30
	R^2	0.755	–	–	–
	Adj. R^2	0.752	–	–	–
	Durbin–Watson	1.052	–	–	–
RW (n = 245)	Intercept	73.943	17.144	4.313	2.35e-05
	Occupancy	0.24885	0.018558	13.409	5.28e-31
	HDD	37.325	1.5704	23.767	4.11e-65
	CDD	27.561	2.1078	13.076	6.89e-30
	R^2	0.767	–	–	–
	Adj. R^2	0.764	–	–	–
	Durbin–Watson	1.024	–	–	–
SRW (n = 239)	Intercept	73.931	10.824	6.83	7.20e-11
	Occupancy	0.23415	0.010895	21.491	2.16e-57
	HDD	41.258	1.6032	25.734	2.60e-70
	CDD	17.923	2.2164	8.0865	3.26e-14
	R^2	0.842	–	–	–
	Adj. R^2	0.840	–	–	–
	Durbin–Watson	1.281	–	–	–

Table 6
Interaction regression results.

Coefficient	Estimate	SE	t	p-value
Intercept	73.543	12.289	5.985	3.43E-09
Occupancy	0.23495	0.01237	18.995	1.83E-65
HDD	41.148	1.82	22.607	8.02E-86
CDD	17.87	2.516	7.102	2.97E-12
Period RW	3.165	20.027	0.158	0.874
Period NO RW	−10.629	29.488	−0.360	0.719
Occupancy × RW	0.01003	0.02112	0.475	0.635
Occupancy × NO RW	0.09026	0.02505	3.604	0.00034
HDD × RW	−3.655	2.326	−1.571	0.117
HDD × NO RW	−6.809	2.317	−2.939	0.0034
CDD × RW	9.746	3.18	3.065	0.00226
CDD × NO RW	17.301	3.596	4.812	1.83E-06

energy relationship between RW and SRW.

Regarding climatic drivers, the heating response is significantly lower in the NO RW arrangement relative to SRW (HDD × NO RW, $p =$ 0.003), while the difference between RW and SRW is not statistically significant. This pattern may be related to higher internal heat gains during the NO RW period, generated by occupants, lighting, and office equipment, which can partially offset heating demand under colder conditions. For cooling demand, both RW and NO RW exhibit significantly stronger sensitivities compared with SRW (CDD × RW and CDD × NO RW, $p < 0.01$). This behaviour is consistent with the previous interpretation, as higher occupancy levels, and more extensive use of equipment during these arrangements are likely to increase internal heat gains, thereby contributing to higher cooling demand during warm conditions.

Overall, the interaction model suggests that the relationship between electricity use and its main drivers varied across organisational arrangements, supporting the choice of estimating separate regression models for each period.

Following the approach of Ding et al. [29], building energy signatures as a function of the two climatic variables are reported in Fig. 2 to visualise differences in the weather-related electricity response across organisational arrangements. The signatures were derived at a common reference occupancy, defined as the median daily occupancy across all

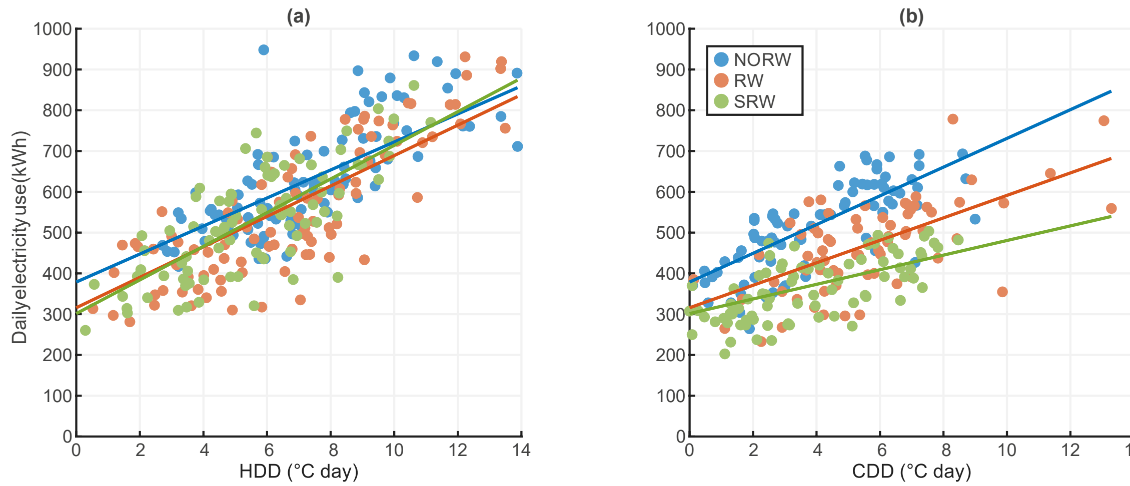

Fig. 2. Building energy signatures across NO RW, RW, and SRW operational arrangements, derived at a common reference occupancy.

periods. Under heating conditions (Fig. 2a), the three signatures are relatively close, and SRW does not exhibit a lower HDD-related sensitivity. By contrast, under cooling conditions (Fig. 2b), SRW shows a clearly lower CDD-related sensitivity. These results are consistent with the regression results and their interpretation previously reported.

3.3. Effect of organisational arrangements on daily occupancy

The boxplots in Fig. 3 display the distribution of on-site daily occupancy ($O_{t,P}$) from Monday to Friday for the three organisational arrangements. Each panel refers to one arrangement (period) and reports the median value for each weekday. Under NO RW, the distribution was relatively homogeneous across the week, with median daily man-hours peaking on Tuesday and Thursday, consistent with the afternoon shifts. Friday occupancy was lower compared with mid-week values but remained close to 1000 man-hours. Overall, the pattern is indicative of a compact and stable on-site presence distributed evenly from Monday to Friday.

With the introduction of RW, a clear structural reduction in on-site personnel was observed. Median values decreased across all weekdays, particularly on Monday and Friday, which may be related to their proximity to the weekend.

In the SRW arrangement, as expected, on-site presence declined sharply on Friday, with the median reaching 58 man-hours (the value is not null because of the staff responsible for site-security and essential services). To compensate for the sharp decline on Friday, on-site presence tended to increase on other weekdays.

The statistical results, detailed in Table 7, indicate significant differences in occupancy between arrangements. Weekly aggregated comparisons confirm a strong reduction of occupancy during remote work, further decreased under the synchronised schedule. Daily comparisons show that the transition from NO RW to RW was significant for every weekday, while the shift from RW to SRW was statistically significant on all days except Thursday, when on-site presence remained comparable to RW.

3.4. Effect of organisational arrangements on electricity use and energy savings

The distribution of normalised daily electricity use ($E_{norm,t,P}$) from Monday to Friday across the three organisational arrangements is shown in Fig. 4. Under NO RW, electricity demand remained relatively stable

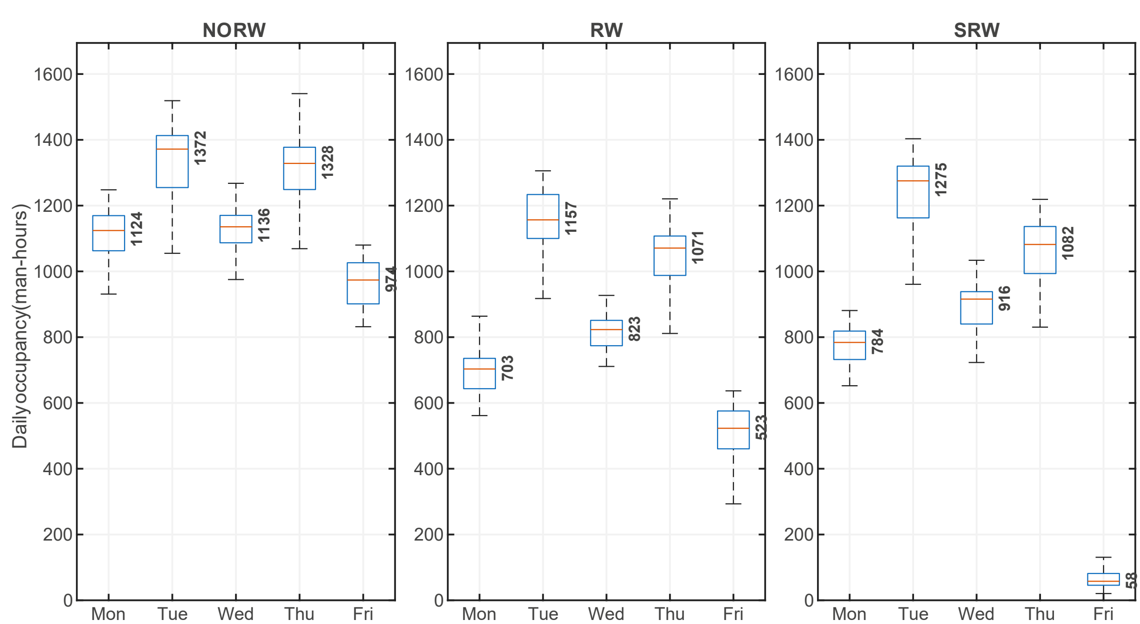

Fig. 3. Weekday distribution of on-site daily occupancy ($O_{t,P}$) across NO RW, RW, and SRW operational arrangements.

Table 7
Statistical tests on daily man-hours.

Test	Method	Comparison	p-value	Interpretation
Pairwise comparisons (weekly aggregate)	Mann–Whitney *U* test α = 0.05	RW vs NO RW	1.442e-12	Significant difference
		SRW vs RW	0.007929	Significant difference
Pairwise comparisons (daily)	Mann–Whitney *U* test α = 0.05	*Monday*		
		RW vs NO RW	6.132e-12	Significant difference
		SRW vs RW	4.594e-06	Significant difference
		Tuesday		
		RW vs NO RW	6.04e-09	Significant difference
		SRW vs RW	9.835e-05	Significant difference
		Wednesday		
		RW vs NO RW	4.514e-13	Significant difference
		SRW vs RW	1.364e-06	Significant difference
		Thursday		
		RW vs NO RW	1.576e-11	Significant difference
		SRW vs RW	0.4022	No significant difference
		Friday		
		RW vs NO RW	6.84e-15	Significant difference
		SRW vs RW	3.028e-10	Significant difference

throughout the week, reflecting a consistent on-site operational regime, with a weekly average of daily median values around 530 kWh. Introducing RW was associated with a clear downward shift across all weekdays, reducing the weekly average of daily medians to approximately 355 kWh. This pattern suggests that reduced on-site presence coincided with lower electricity demand. The SRW arrangement was characterised by a further reduction in electricity use, with a weekly average of daily medians of roughly 330 kWh. This additional reduction was primarily concentrated on Fridays, while differences on the other weekdays were more limited.

Overall, on a yearly basis, remote work was associated with an average 29% (CI95% 25.3 – 32.6) reduction in normalised electricity use and the SRW scheme was associated with an additional aggregate reduction of 5.6% (CI95% 0.7 – 12.0).

Mean daily Energy Savings (ES) for each weekday are summarized in Fig. 5. Comparing RW with NO RW (left panel), reductions ranged from 21.8% to 37.6%, with the largest decrease observed on Friday. Confidence intervals suggest that these savings were consistently positive throughout the week. Under the SRW scheme (right panel), additional reductions relative to RW were primarily observed on Friday, reaching a mean reduction of 37.3% (CI95% 24.4 – 49.6), whereas savings on the remaining weekdays were smaller and statistically inconclusive, as confidence intervals overlap zero.

Statistical analysis (Table 8) is consistent with these patterns. Pairwise tests suggest statistically significant differences both between NO RW vs RW and between SRW vs RW, although the effect size for the latter is smaller. Day-level comparisons show that RW vs NO RW differences were significant on all weekdays, while SRW vs RW was statistically significant only on Friday, suggesting that any additional energy savings associated with synchronised remote work were primarily concentrated during this day of the week.

To better illustrate the intra-day implications of the SRW scheme, mean hourly normalised electricity use is shown in Fig. 6 for Wednesday (selected as a representative mid-week working day) and Friday.

The Wednesday profiles (Fig. 6a) show that RW and SRW exhibited very similar intra-day patterns and remained substantially below NO RW throughout most of the operating period. This suggests that, on an ordinary mid-week working day, the transition from NO RW to remote-work arrangements substantially reshaped the daily profile, whereas the transition from RW to SRW had a negligible effect.

In contrast, on Friday (Fig. 6b), both transitions resulted in clear changes in the daily profile, with SRW yielding consistently lower electricity use than RW, particularly during core working hours.

Aside from the daily analysis, it was also informative to assess whether the energy impacts of RW and SRW exhibited seasonality. Fig. 7 presents a combined view of the average daily monthly occupancy (a) and the corresponding normalised electricity use (b) across the three arrangements. When moving from NO RW to RW, reductions in occupancy were consistently accompanied by lower normalised electricity use. In the transition from RW to SRW, however, this relationship was not systematically observed in all months (e.g., January). Nevertheless, in most months, despite higher occupancy, normalised electricity use remained lower, suggesting a partial decoupling between presence and

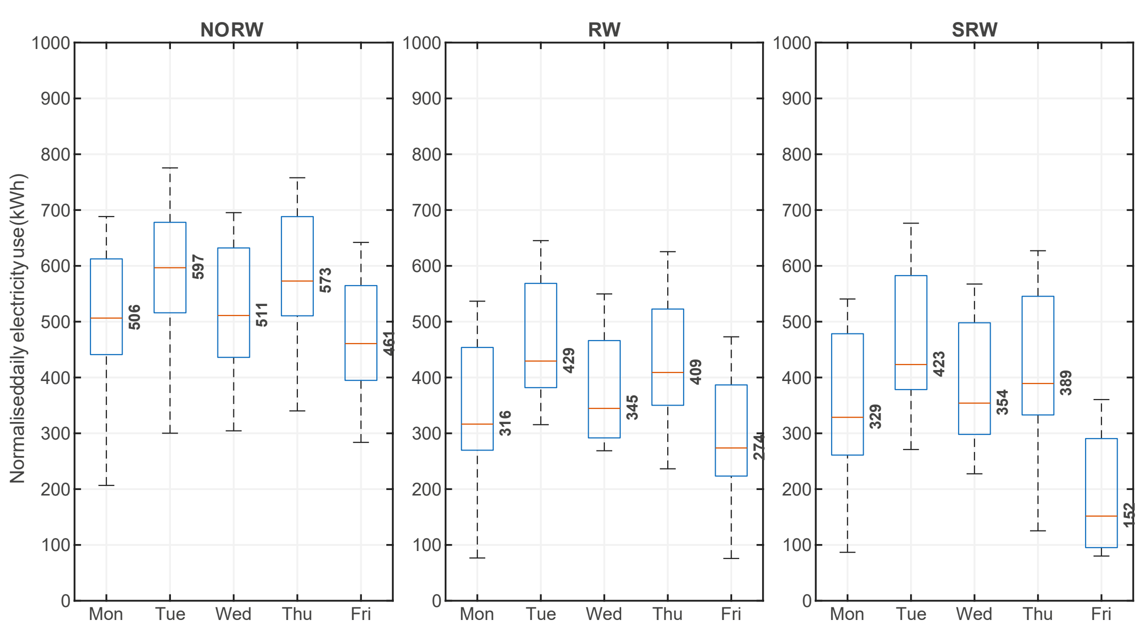

Fig. 4. Weekday distribution of normalised daily electricity use ($E_{norm,t,P}$) across NO RW, RW, and SRW operational arrangements.

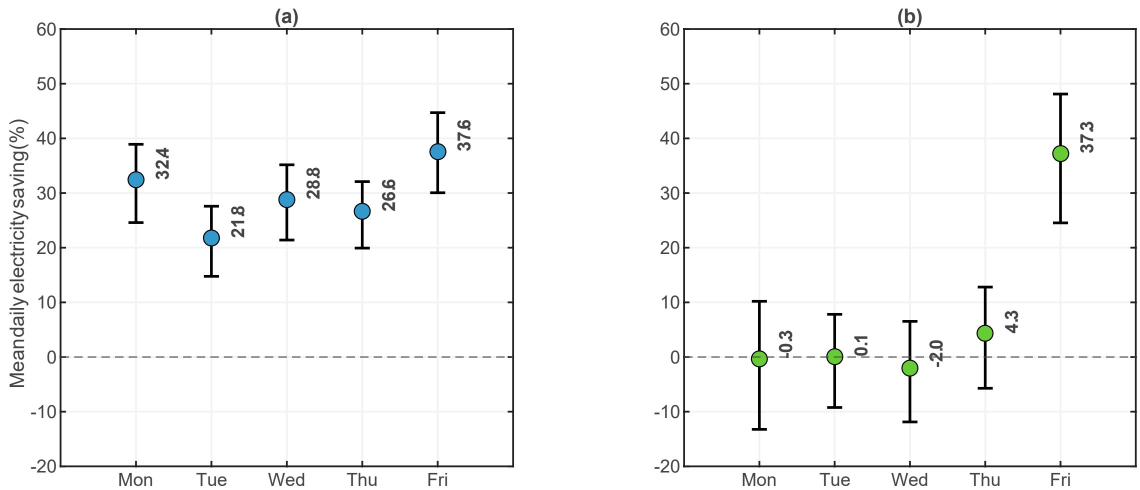

Fig. 5. Mean daily electricity saving per weekday for RW vs NO RW and SRW vs RW, with 95% confidence intervals.

Table 8
Statistical tests on normalised daily electricity use.

Test	Method	Comparison	p-value	Interpretation
Pairwise comparisons (weekly aggregate)	Mann–Whitney *U* test α = 0.05	RW vs NO RW	1.443e-08	Significant difference
		SRW vs RW	0.04271	Significant difference
Pairwise comparisons (daily)	Mann–Whitney *U* test α = 0.05	*Monday*		
		RW vs NO RW	7.693e-10	Significant difference
		SRW vs RW	0.9217	No significant difference
		Tuesday		
		RW vs NO RW	4.657e-07	Significant difference
		SRW vs RW	0.9971	No significant difference
		Wednesday		
		RW vs NO RW	2.889e-09	Significant difference
		SRW vs RW	0.6051	No significant difference
		Thursday		
		RW vs NO RW	3.02e-09	Significant difference
		SRW vs RW	0.4023	No significant difference
		Friday		
		RW vs NO RW	4.09e-11	Significant difference
		SRW vs RW	1.322e-06	Significant difference

electricity use under synchronised scheduling. Despite the measure, the month of December saw a considerable increase in occupancy, which was reflected in the electricity use. The monthly analysis further suggests that the additional effect of SRW was more evident during summer months. This is consistent with the regression results, where the CDD coefficient decreases substantially from NO RW to RW and further to SRW, while the HDD coefficient does not show a comparable decrease.

Fig. 8 shows the estimated mean daily electricity saving per month. The left subplot (RW vs NO RW) suggests that remote work (RW) was associated with substantial reductions in monthly electricity use, particularly during intermediate and warm seasons. The right subplot (SRW vs RW) indicates that additional reductions associated with SRW tended to be more pronounced during warmer months and were negligible during colder periods. This pattern is broadly consistent with the previously described results, which showed a stronger sensitivity to CDDs in the transition from RW to SRW, while no comparable effect was observed for HDDs. Accordingly, concentrating remote work on Fridays appeared to be associated with a reduced sensitivity of electricity use to high outdoor temperatures, potentially contributing to lower additional demand during hot periods. This seasonal interpretation should be considered with caution, because the daily regression framework does not explicitly capture thermal inertia, solar gains, humidity, or short-term weather dynamics.

4. Conclusions

This study provides an empirical assessment of how different organisational remote work arrangements relate to office-level energy use. Based on a three-year field, quasi-experimental study comparing a baseline no remote work configuration, a conventional unsynchronised remote work scheme, and a synchronised remote work arrangement, the analysis contributes to addressing two gaps in the literature: the scarcity of long-term empirical evidence and the limited number of studies evaluating synchronised remote work models.

The analysis was conducted through regression, and the results were complemented by statistical tests. Occupancy patterns varied substantially across arrangements: unsynchronised remote work was associated with a distributed reduction in on site presence throughout the week, whereas synchronisation was characterised by a pronounced drop on Fridays accompanied by a redistribution of occupancy across Monday to Thursday.

Introducing remote work was associated with a 29% reduction in climate-normalised electricity use (CI95% 25.3–32.6) compared with no remote work, with daily reductions between 22% and 38% and monthly reductions exceeding 30% in several months. Synchronisation was associated with an additional 5.6% reduction (CI95% 0.7–12.0%) compared with the unsynchronised case, driven almost entirely by Fridays, where average savings reached 37.3% (CI95% 24.4–49.6). Seasonal analysis suggested that the synchronisation effect was strongest during warmer months, when reduced internal heat gains may have contributed to attenuating the impact of high outdoor temperatures on electricity demand.

A key implication of these findings is that the energy-saving value of remote work depends not only on the amount of remote work adopted, but also on how it is temporally coordinated across employees. In the analysed case, the additional benefit of the synchronised arrangement arose mainly from the creation of a predictable low-occupancy Friday, on which non-essential HVAC, lighting and auxiliary services in large portions of the building were reduced or kept inactive. Therefore, the transferability of the observed savings is likely to be greatest in office buildings where services can be spatially or temporally modulated in

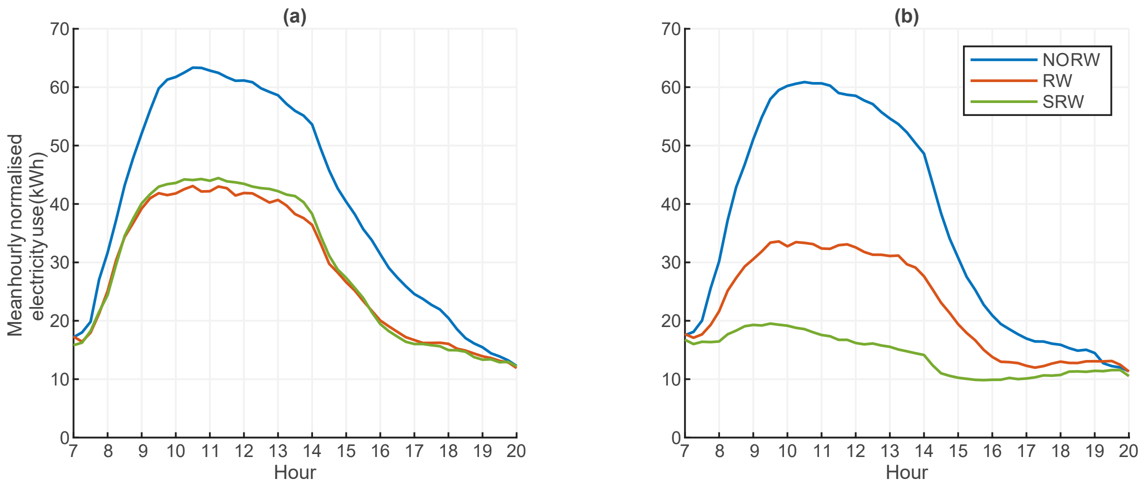

Fig. 6. Mean hourly normalised electricity use for Wednesday (a) and Friday (b).

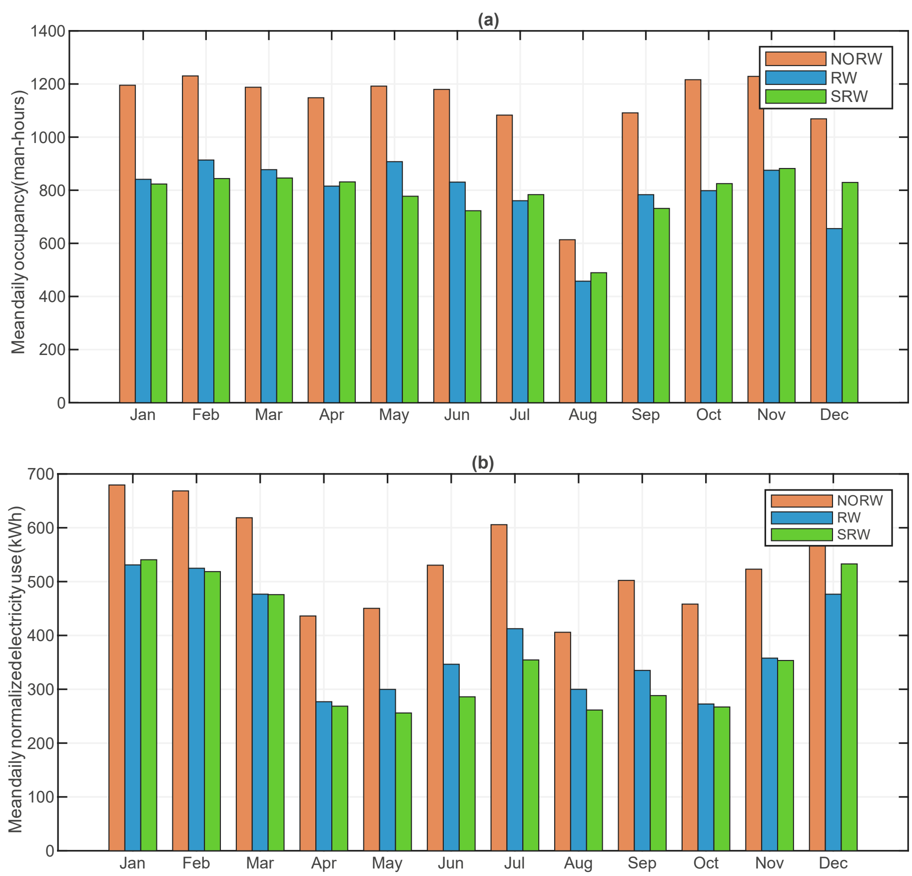

Fig. 7. Mean daily occupancy (a) and mean daily normalised electricity use (b) per month across NO RW, RW, and SRW operational arrangements.

response to coordinated occupancy reductions. While the results of this study are most directly transferable to office buildings with comparable technical, climatic and organisational boundary conditions, they nonetheless suggest that synchronised remote work may represent a relevant organisational energy-management measure.

In line with the study methodological limitations, the findings should be interpreted as empirical associations observed under real operating conditions. At the same time, these findings concern office-level electricity use only and should not be interpreted as net whole-system energy or emissions savings, which also depend on other system-level factors.

Further work should strengthen causal inference through multi-building analyses and, where feasible, concurrent control groups, matched comparison buildings, or randomised crossover designs. End-use sub-metering would help quantify the contribution of individual energy end uses, while broader assessments could include household energy use, transport, and non-energy outcomes such as wellbeing, collaboration, productivity, and organisational acceptance.

CRediT authorship contribution statement

Luca Migliari: Writing – review & editing, Writing – original draft,

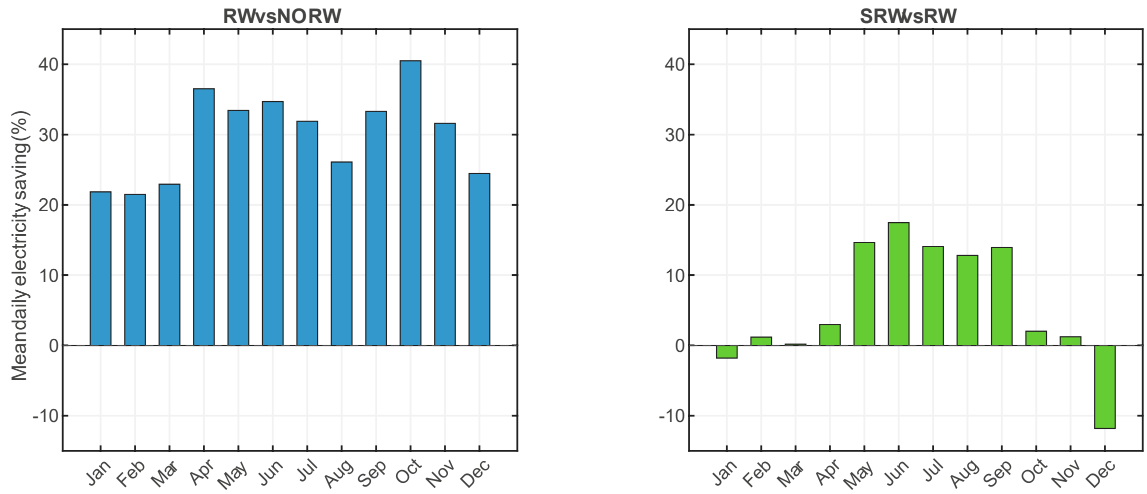

Fig. 8. Mean daily electricity saving per month (%) for RW vs NO RW and SRW vs RW.

Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Francesco Mola:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Microsoft Copilot to revise the English language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The data used in this study are available in Mendeley Data under a CC BY 4.0 license.

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