Supplementary materials for this article are available at https://doi.org/10.1007/s13253-024-00669-z.

Incorporating Phenology to Estimate Species' Population Trends from Snapshot Citizen-Science Data

Emily B. DENNIS, Byron J. T. MORGAN, Colin A. HARROWER, Nigel A.D. BOURN, and Richard FOX

Citizen-science data are increasingly used to contribute to our understanding of biodiversity change, but analysing such data requires suitable statistical methods, often to deal with forms of bias. We develop a new approach for modelling data from a snapshot, mass-participation citizen-science scheme for UK butterflies, the Big Butterfly Count (BBC). Butterfly abundance varies throughout the year as one or more generations of each species emerge and die off, and the timing (phenology) of emergences varies annually due to weather and climate. Thus, counts from the short 3-week BBC sampling period are susceptible to bias due to this inter-annual variation in phenology. We adapt the Generalised Abundance Index, drawing upon phenology estimates from standardised monitoring scheme data, to account for phenological bias in the estimation of species' abundance trends from BBC data. The method is demonstrated via application to empirical and simulated data, revealing that not accounting for phenology leads to biased trend estimates, particularly for summer-flying single-generation species. Drawing upon phenology information, the new approach allows for the reporting of abundance trends from a snapshot citizen-science scheme, creating the potential to maximise available data sources to increase our understanding of changes in butterfly populations, particularly in urban environments.

Key Words: Big Butterfly Count; Concentrated likelihood; Generalised Abundance Index; Mass participation; Phenology adjustment; UK Butterfly Monitoring Scheme.

1. INTRODUCTION

Expanded, reliable monitoring of species' populations is vital to understand the severity of the global biodiversity crisis. In many existing monitoring schemes, the underlying data

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E. B. Dennis · N. A. D. Bourn · R. Fox, Butterfly Conservation, Manor Yard, East Lulworth, Wareham, Dorset, UK.

E. B. Dennis · B. J. T. Morgan (✉), School of Mathematics, Statistics and Actuarial Science, University of Kent, Canterbury, UK (E-mail: *B.J.T.Morgan@kent.ac.uk*).

C. A. Harrower, UK Centre for Ecology & Hydrology, Crowmarsh Gifford, Wallingford, Oxfordshire, UK.

Journal of Agricultural, Biological, and Environmental Statistics
https://doi.org/10.1007/s13253-024-00669-z

Published online: 30 November 2024

are often collected by volunteer observers, and such biodiversity citizen science (CS; also called community or participatory science), involving the participation of members of the public in gathering scientific data, has increased rapidly in recent years (Pocock et al. 2017). There is a long history of ecological monitoring of various taxa through designed surveys with standardised protocols undertaken by experienced and committed volunteers, but recent growth in CS is mostly attributed to schemes based upon opportunistic or mass-participation sampling with less strict protocols (Pocock et al. 2017). These schemes have fewer barriers to participation and thus attract larger numbers of observers, many with little or no prior experience of biodiversity monitoring. There is evidence for the benefits of CS to the participants, for example, through increases in knowledge and benefits to well-being and nature connectedness (Peter et al. 2021; Butler et al. 2024), but from a statistical perspective there are outstanding challenges for analysing CS data for biodiversity monitoring, some of which involve dealing with various forms of bias (Johnston et al. 2023).

The Big Butterfly Count (BBC; https://bigbutterflycount.org) launched in the UK in 2010 as an annual survey of widespread butterfly species, which encourages broad participation particularly from members of the general public who are not already involved in biodiversity monitoring. The scheme involves a minimal sampling protocol: participants simply note the abundance of selected common species for 15 min during bright weather at any UK location.

This contrasts with the UK Butterfly Monitoring Scheme (UKBMS), which began in 1976 and is considered the "gold standard" for butterfly population monitoring. It predominantly consists of a national network of >2000 transects on which counts of butterflies are made weekly, under standardised favourable weather conditions, from 1st April to 29th September (Pollard and Yates 1993). UKBMS data are used to estimate population trends for 58 of the 59 UK resident and regular breeding butterfly species (UKBMS 2023), to help monitor population status (Fox et al. 2023), and contribute to Red List assessments (Fox et al. 2022) and official biodiversity indicators (JNCC 2022). The scheme requires a high level of identification skills and commitment; thus, UKBMS participants are typically experienced butterfly observers, whereas the BBC encourages and attracts broader participation (almost 95,000 participants in 2023). UKBMS sites are typically in semi-natural habitats, whereas BBC sampling is mostly undertaken in gardens and urban areas (Dennis et al. 2017a).

Using data from four years (2011–2014), Dennis et al. (2017a) showed that estimates of abundance change of common butterfly species could be obtained from the BBC that were comparable to those estimated from UKBMS data. However, the study also showed that the short, three-week sampling season "rendered BBC counts susceptible to bias caused by inter-annual phenological variation in the timing of species' flight periods" and that BBC count totals were related to butterfly phenology and sampling effort. The abundance of adult butterflies of each species varies throughout the year according to the emergence (and death) of one or more generations, and phenological sampling bias has been identified as one of the key challenges for drawing robust inference about insect populations. Didham et al. (2020) refer to the "groundhog effect"—where a decline in population size may be falsely indicated by a progressive phenological shift in insect activity in response to changing climate or other factors. The UKBMS captures this seasonality by weekly sampling, and statistical methods have been developed to account for missing data (Dennis et al. 2013, 2016). In contrast, the short BBC sampling period captures just a small proportion of species' flight periods, and this will vary annually (Dennis et al. 2017a) as the timing of emergence changes each year in response to weather and climate (Roy and Sparks 2000; Hodgson et al. 2011).

We present a new approach which accounts for the inter-annual variation in sampled species' phenology and can therefore be used to produce robust abundance indices and trends from snapshot CS data. The approach draws upon phenology estimates from standardised monitoring (UKBMS) data and is demonstrated via application to BBC and simulated data.

2. THE BIG BUTTERFLY COUNT

The BBC began in 2010 and takes places for 23–24 days from mid-July to early August, to reflect the peak total abundance period for UK butterflies (Table S1 details the sampling dates for each year and summarises the spatial coverage of the scheme). If counting from a fixed position, the maximum number of each species seen at any time is recorded to reduce the risk of double counting. No training is provided and minimal data verification is undertaken. The BBC is restricted to counts of selected widespread butterfly (and some day-flying moth) species, to minimise misidentifications.

We consider BBC data for 2011–2022 and restrict our analyses to the 17 widespread butterfly species which have featured in the count throughout this time period. Table S2 provides species information, including scientific names, and summarises the quantity of BBC data per species. We omit data sampled in 2010 when the sampling period was only nine days. Technically, participants may submit counts undertaken throughout July and August, but we restrict the analysis to counts undertaken only within the official sampling period each year. Counts of more than 1000 individuals are large for the BBC and so are also excluded to minimise potential errors. The data set analysed consists of almost 786,000 counts (including counts where no butterflies were seen) comprising almost 9.5 million individuals counted. Figure S1 summarises the spatial distribution of BBC counts each year.

To produce robust abundance indices and trends for BBC data, a method that accounts for varying species' phenology with respect to the short sampling period is needed. We will adapt the Generalised Abundance Index (GAI, Dennis et al. 2016) for this purpose.

3. GENERALISED ABUNDANCE INDEX

The GAI is routinely used for estimating seasonal variation and accounting for missing counts in UKBMS data, to produce annual indices of abundance. Counts made throughout the UKBMS season vary according to the emergence of one or more generations of adult butterflies and roughly 30% of potential counts in the 26-week season are missed (Dennis et al. 2013), for example, due to unsuitable weather conditions or recorder unavailability.

In outline, suppose that counts are made at S sites, each visited on at most V occasions, for a given species and year. Each count, $y_{s,v}$, for site s and visit v is regarded as the realisation of a random variable, such as Poisson, with expectation $\lambda_{s,v} = N_s a_{s,v}$, where the likelihood takes the form

$$L(\boldsymbol{\theta}; \mathbf{y}) \propto \prod_{s=1}^{S} \prod_{v=1}^{V} \exp(-N_s a_{s,v})(N_s a_{s,v})^{y_{s,v}}. \tag{1}$$

Here N_s reflects a site parameter describing how abundant the species is at site s, and $a_{s,v}$ denotes a function modelled by parameters, $\boldsymbol{\theta}$, describing seasonal variation, for example, a spline, mixture of normal densities, or stopover model (Dennis et al. 2016, 2022). The product over visits in Equation (1) includes terms corresponding only to when visits were actually made.

A concentrated likelihood substantially reduces the number of parameters to estimate via maximum likelihood (Dennis et al. 2016). In brief, the site parameters are estimated by

$$N_s = \frac{y_{s,.}}{a_{s,.}}, \tag{2}$$

where we use the dot notation to indicate summation over visits made. The total observed count for each site is rescaled to account for incomplete sampling within the season such that N_s represents the expected total count for site s had the entire season been sampled. If a site is sampled completely for that season, then $N_s = y_{s,.}$, since in this case $a_{s,.} = 1$. Substitution of (2) into (1) results in a Poisson likelihood which can be maximised with respect to only the parameters, $\boldsymbol{\theta}$, associated with $\mathbf{a}$.

Following the fitting of the GAI to estimate site-level abundances for each year, an overall relative abundance (collated) index can be obtained by fitting a Poisson generalised linear model (GLM) to $\mathbf{N}$, with site and year effects, and a weighting for the proportion of the flight period sampled (Brereton et al. 2018). In doing so, annual turnover of sites is accounted for. The estimated year effects are used to form an index of abundance over time, which is typically presented on the $\log_{10}$ scale with a mean of 2.

3.1. UKBMS Analysis

We apply the GAI to UKBMS data to inform upon the phenological bias in BBC using flight periods estimated by UKBMS data (Sect. 3.2) and later to produce UKBMS abundance indices and trends for comparison with BBC outputs (Sect. 6.1).

To estimate flight periods for the 17 species sampled by the BBC, we applied the GAI to UKBMS data for each species in each year 2011–2022. The flexible spline formulation for $\mathbf{a}$ was used, implemented using generalised additive models (Wood 2017), to estimate species' flight period values, $\{a_v\}$, which are fixed across sites, and scaled to sum to unity, for each year. UKBMS data consist of weekly transect visits, and so the GAI is often fitted at the weekly scale. To explore flight periods with respect to the short BBC sampling period, we instead treated visits, v, as the day of the year. Estimated annual flight period curves for each species are shown in Figure S2. Error associated with the flight period curves was estimated via nonparametric bootstrapping, based on 1000 replicates, which are used in Sect. 6.

A relative abundance index was obtained for each species by fitting a Poisson GLM (see Sect. 3). Abundance trends for 2011–2022 were estimated by applying linear regression to

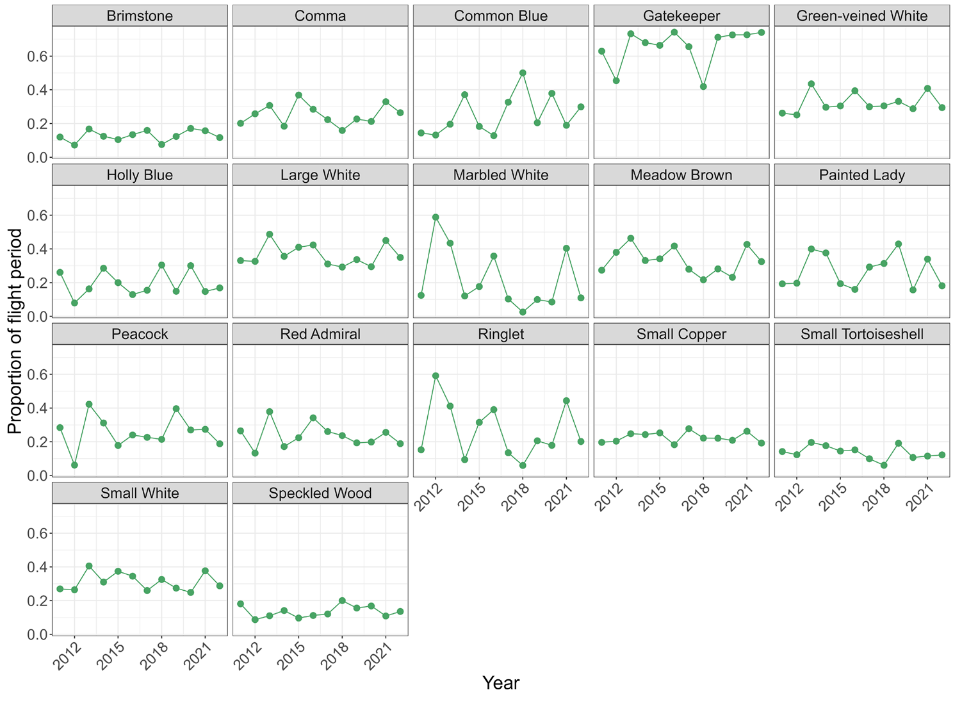

Figure 1. Proportion of each species' annual flight period covered by the BBC sampling period each year (2011–2022).

the abundance indices. 95% confidence intervals for indices and trends were produced from nonparametric bootstrapping to account for variance propagation.

3.2. PHENOLOGICAL BIAS IN BBC

To visualise the potential phenological bias in BBC, the daily flight period estimates obtained for each species from applying the GAI to UKBMS data were totalled for the BBC sampling period for each year to determine the proportion of each species' flight period captured by the BBC annually—see Fig. 1. The proportion of the flight period sampled shows variation among years for all species, but summer-flying univoltine (single generation) species, such as Marbled White and Ringlet, show particularly high inter-annual variability. Figure S3 shows how the BBC sampling period captures different proportions of the Marbled White flight period for four example years, with the proportion varying from 0.12 (in 2011 and 2014) to 0.59 in 2012. In contrast, species with two or more generations during the year, such as Speckled Wood and Small Tortoiseshell, will usually have a longer total annual flight period than univoltine species. The BBC sampling period captures a smaller proportion of their total flight period; therefore, the phenological bias shows less variation from year to year.

4. PHENOLOGY ADJUSTMENT

The GAI was developed for standardised monitoring data, typically collected along transects, where sites are clearly defined and revisited repeatedly within and across years. CS data such as from the BBC do not have such a structure; it consists of many locations, which are often only sampled once. To adapt the GAI to produce abundance indices and trends for BBC data, we define the discrete spatial scale of a BBC "site" to be a 1 km x 1 km square and pool BBC counts within each year to this spatial scale. In doing so, in part due to the large amount of participation, BBC sites obtain some replication across multiple days within the BBC sampling period. Since BBC data consist of "checklists" of species seen, zero counts are also formed. Exploration of alternative site sizes suggests broadly similar results, with 1 km found to be the most appropriate choice (Section S1 of the supplementary material).

The GAI typically assumes a single count, $y_{s,v}$ for site s and visit v (in a given year), whereas by pooling BBC data for defined (1 km square) sites, there is the potential for multiple "entries" (i.e. BBC 15-minute counts) for a given site and visit (day). To accommodate these multiple entries, the likelihood now takes the form

$$L \propto \prod_{m=1}^{M} \prod_{v=1}^{V} \exp(-N_m a_{m,v} \kappa_{m,v})(N_m a_{m,v})^{y_{m,v,\cdot}}, \tag{3}$$

where $\kappa_{m,v}$ is the number of entries for site m and visit v and $y_{m,v,\cdot} = \sum_{\kappa} y_{m,v,\kappa}$ is the sum of the counts over those entries.

The number of sites, M, in a mass-participation CS data set such as BBC, is high; therefore, a concentrated likelihood approach is valuable for reducing the number of parameters to estimate. Here, omitting an additive constant,

$$\ell = \log(L) = \sum_{m=1}^{M} N_m \sum_{v=1}^{V} a_{m,v} \kappa_{m,v} + \sum_{m=1}^{M} \sum_{v=1}^{V} y_{m,v,\cdot} \log(N_m a_{m,v}),$$

leading to

$$\frac{\partial \ell}{\partial N_m} = -\sum_{v=1}^{V} a_{m,v} \kappa_{m,v} + \frac{y_{m,\cdot,\cdot}}{N_m},$$

and equating to zero we obtain

$$N_m = \frac{y_{m,\cdot,\cdot}}{\sum_{v=1}^{V} a_{m,v} \kappa_{m,v}} \tag{4}$$

As in the original GAI, substitution of (4) into (3) results in a Poisson likelihood which can be maximised with respect to only the parameters, $\boldsymbol{\theta}$, associated with seasonal variation, $\mathbf{a}$.

However, since the BBC sampling period only represents a snapshot of most species' flight periods, accurate flight period estimation from applying the GAI to BBC data is not possible for all species. Furthermore, species' phenology can already be estimated reliably from UKBMS data (Sect. 3.1). Thus, for each species and year, we produce estimates of N_m for each BBC site (1 km square) from Equation (4) using daily estimates of $\{a_v\}$ from the GAI applied to UKBMS data (Sect. 3.1). There is a risk of BBC counts being submitted that fall outside a species' flight period (for example due to misidentification), which would result in very large estimates of N_m; therefore, estimates of N_m based on $\sum_v a_v < 0.001$, for sampled v, were omitted from analyses.

Since many BBC sites are not sampled in multiple years (see Table S5), estimating an abundance index from BBC data using a GLM (as for UKBMS data) would result in a proportion of the data not contributing to estimation of the index. Thus, following Dennis et al. (2016), an overall measure of BBC abundance per year for a given species can be measured by

$$G = \frac{1}{M} \sum_{m=1}^{M} \hat{N}_m. \tag{5}$$

There is substantial turnover in BBC sites (1 km squares) each year, but the total number of sites counted per year is high; therefore, G is unlikely to be biased by such turnover. In Sect. 5, we describe a simulation study, where the suitability of the phenology adjustment approach for varying numbers of sites is assessed.

We compare phenology adjustment outputs to results which are unadjusted for phenology, where the average BBC count per species and year is calculated by scaling the total count (for the BBC sampling period) by the sampling effort (number of 15-minute counts made).

5. SIMULATION STUDY

We now assess the performance of the phenology adjustment approach via simulation. Count data were simulated to resemble snapshot CS data based upon the BBC, and we assess the phenology adjustment approach for trend estimation over a 12-year period.

We simulated counts from a Poisson distribution with expectation $\lambda_{m,v,k} = N_{m,k} a_{v,k}$, where k denotes the year, and $\{a_{v,k}\}$ are daily flight period estimates from UKBMS data for each year (Sect. 3.1), for three species selected to have varying phenology patterns with respect to the BBC sampling period (Marbled White, Gatekeeper and Holly Blue). In year $k = 1$, $\{N_{m,1}\}$ were sampled from all estimates of $\mathbf{N}$ from the actual BBC data (for all species and years, see Sect. 6) for a given total number of sites M. Values of $\{N_{m,k}\}$ for years $k = 2, \ldots, 12$ were then generated based upon two trend scenarios: (i) 0% change over 12 years (thus fixing values of N across years for each site), (ii) a decline of 25% over 12 years. This was an idealised linear decline without variability added.

Simulations were performed for $M = 1000, 2500, 5000, 10000, 50000$, where M is the total number of sites (across all years), but sites are then sampled to account for the fact that most are not revisited in multiple years (based upon BBC data, defining a site by a 1 km square). For each site and year combination, a number of visits (days with a count made) were then simulated, as well as the number of 15-minute counts made on each day, based upon sampling frequencies in BBC data. Full details are given in Section S2 of the

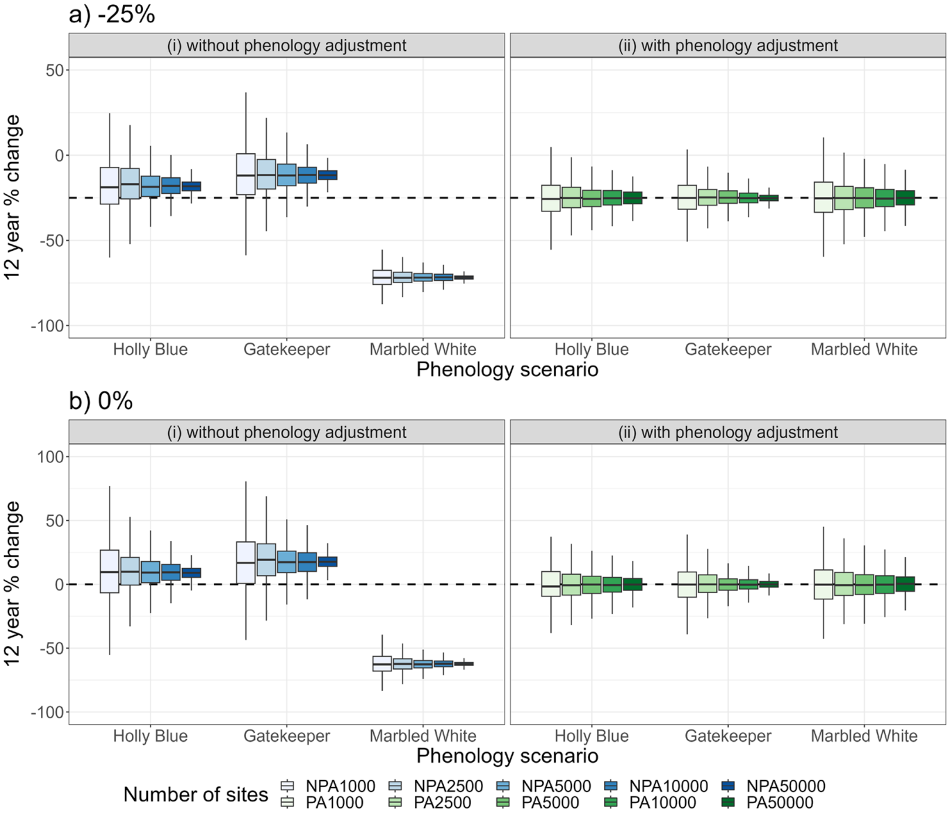

Figure 2. Boxplots summarising trends estimates from 1000 simulations per scenario applied (i) without (NPA) and (ii) with (PA) phenology adjustment. Horizontal dashed lines indicated the true percentage change over 12 years of (a) -25% or (b) 0%. Outliers have been omitted: across all 60 scenarios, which each summarise 1000 simulation replications, on average 2.9% of the replications were omitted .

supplementary material, including summaries of the number of sites sampled per year across simulations.

Having simulated the counts, abundance indices and trends were calculated either with or without applying phenology adjustment. 1000 simulations were undertaken for each scenario (0% or -25% trend over 12 years, three species' phenologies, five values of M). To account for uncertainty in phenology estimation, bootstrapped estimates of the flight periods (from UKBMS data) were used, such that they vary among iterations. We consider the statistical power of detecting a trend for various scenarios, based on the significance (at the 5% level) of the linear regression through the simulated indices.

5.1. Simulation Results

Trends estimated from simulated data without phenology adjustment show considerable bias (Fig. 2(i)), particularly for the scenarios based on the phenology of Marbled White, a species for which the proportion of the flight period captured by the BBC sampling period varies greatly year to year (Fig. 1). For both trend scenarios (-25% and 0% change over

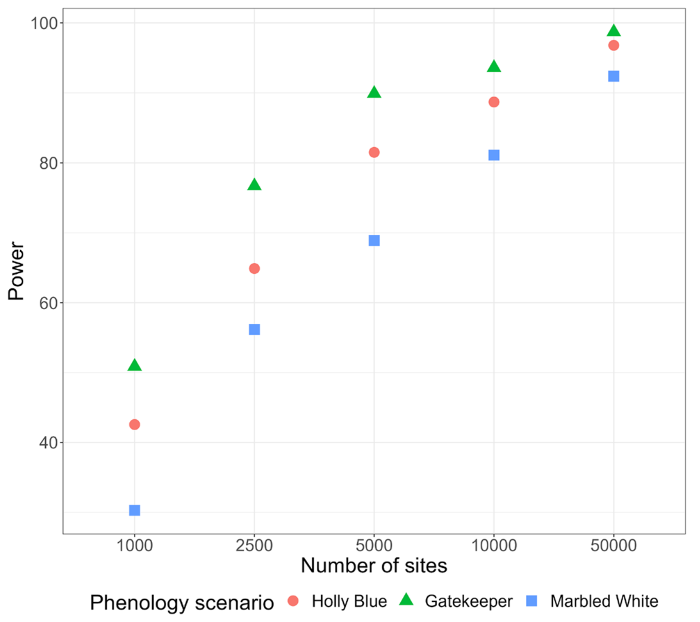

Figure 3. Power (percentage of simulated trends significant at the 5% level) to detect a decline of 25% over 12 years for three species' phenology scenarios and total numbers of sites, M, when phenology adjustment has been applied.

12 years), estimated trends without phenology adjustment for Holly Blue and Gatekeeper were consistently more positive, whereas for Marbled White they were more negative than the true trend. When phenology was not accounted for, the fluctuations in the simulated abundance indices resembled the underlying annual proportions of the species' flight period covered by the snapshot sampling period (comparing Figs. 1 and S4(i)). Power to detect trends is low (less than 3%) for all scenarios when phenology adjustment is not applied (Table S3).

In comparison, applying the phenology adjustment results in generally unbiased abundance indices (Figure S4(ii)) and trend estimates across a range of scenarios (Fig. 2(ii)). Scenarios with fewer sites show some loss of accuracy and greater variation in trend estimation. More simulation summaries are provided in Table S3. Power to detect a decline of 25% over 12 years is greater than 80% across phenology scenarios when data were simulated from 10,000 or more sites (Fig. 3). Sampling levels for actual BBC data exceed that of the $M = 10,000$ scenarios (see Tables S4 and S8).

6. APPLICATION

Phenology adjustment (Sect. 4) was applied to BBC data for 17 species, using flight period estimates from UKBMS data (Sect. 3.1). For each species, the annual average abundance estimates, G, from BBC data were converted to an index on the $\log_{10}$ scale with a mean of 2, for comparison with UKBMS abundance indices. Phenology-adjusted BBC abundance trend estimates for 2011–2022 were produced by applying linear regression to the indices.

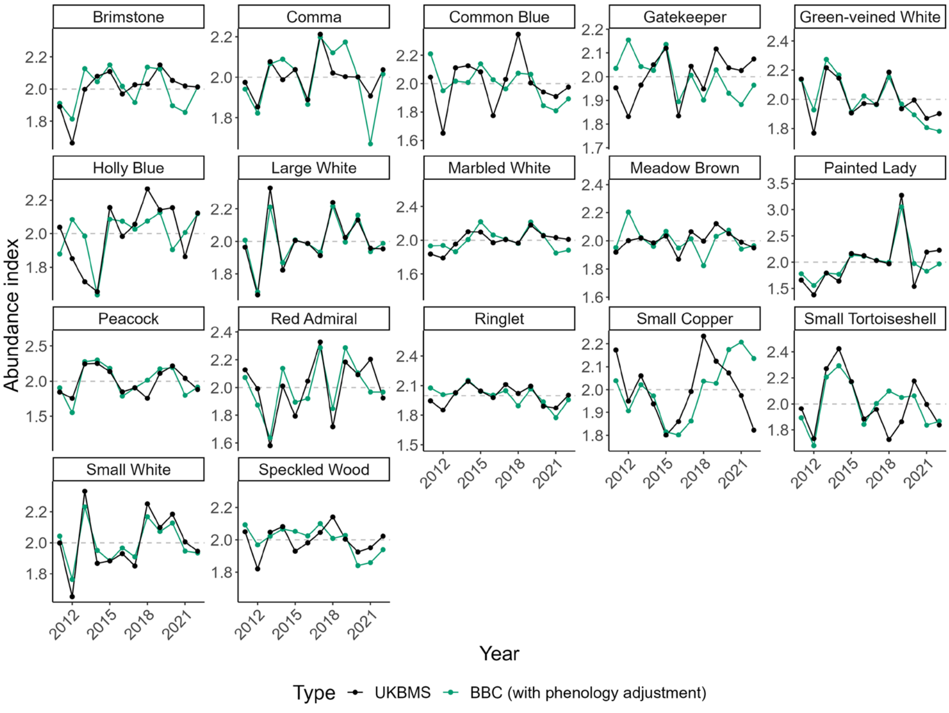

Figure 4. Relative abundance indices produced from BBC data using phenology adjustment (green) and from UKBMS data (black). Indices are on the $\log_{10}$ scale with a mean value of 2 (indicated by the horizontal dashed lines).

Estimates of uncertainty in the BBC indices and trends were calculated using a bootstrap with 1000 replicates. The bootstrapped daily flight period estimates (Sect. 3.1) were used in combination with resampling of the BBC counts at the site (1 km square) level; thus, estimates of N_m (Eq. 4) were produced for each bootstrap replicate and combined to produce 1000 estimates of the index G for each year (Eq. 5), from which confidence intervals were produced by taking quantiles. Confidence intervals for the difference between BBC and UKBMS abundance trends were similarly calculated using bootstrapping.

Unadjusted species results were also calculated from BBC data for each year for comparison with phenology-adjusted outputs. The indices without phenology adjustment were similarly rescaled to the $\log_{10}$ scale for comparison with UKBMS indices.

Results presented here are based upon using UKBMS data from the full sampling period (April-September), but in practice, annual reporting of BBC data, which typically occurs in late August, precedes the completion of the UKBMS sampling season. Thus, timely reporting of BBC results may require phenology adjustment based on only partial UKBMS data for the current year. Section S3 tests this scenario by applying phenology adjustment to BBC data based on UKBMS data up to mid-August only for the most recent year (2022).

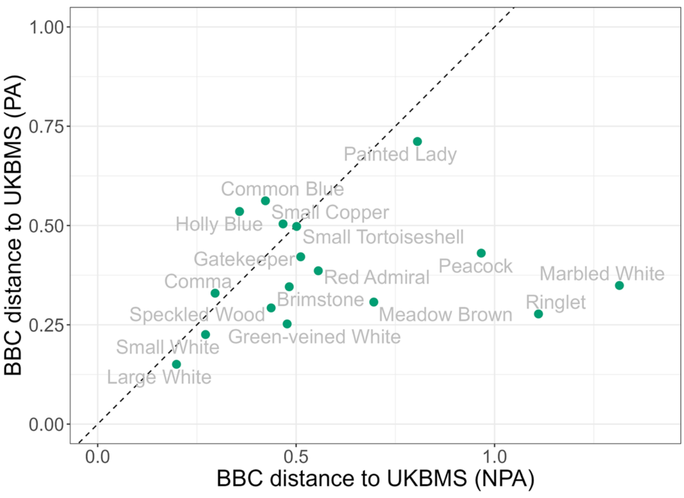

Figure 5. Comparison of Euclidean distances between BBC and UKBMS abundance indices without (NPA) and with (PA) phenology adjustment. Dashed line indicates 1–1 line.

6.1. RESULTS

Figure 4 compares phenology-adjusted abundance indices from BBC data to abundance indices produced from UKBMS data. In general, the BBC indices show a similar pattern to UKBMS indices, reflecting the inter-annual variability in butterfly populations. In terms of euclidean distance, phenology-adjusted BBC indices were closer to UKBMS indices than BBC indices produced without phenology adjustment for 13 out of 17 species (Fig. 5). Similarly, Pearson correlations with UKBMS indices were larger (when phenology adjustment had been applied) for 12 out of 17 species (Figure S5). Improvements from phenology adjustment are greatest for species with higher variation in the proportion of the flight period sampled by BBC each year, rather than whether a small or large proportion of the flight period is typically captured (Figure S6). Thus, summer-flying univoltine species, such as Marbled White and Ringlet, benefited most from phenology adjustment, which is also evident from comparing with the indices without phenology adjustment (Figure S7). Applying phenology adjustment based on UKBMS data up to mid-August only for the most recent year was also effective, but additional scaling of flight period estimates is recommended for later-flying species (see Section S3 of the supplementary material).

Abundance trends for 2011–2022 estimated from BBC data (with phenology adjustment) were lower than trends from UKBMS data for 14 out of 17 species (Fig. 6a). The 95% confidence intervals for the difference in trends (BBC-UKBMS, Fig. 6b) only overlapped zero for three species, suggesting significantly lower BBC trends for 12 species and significantly more positive BBC trends for two species (Small Copper and Small Tortoiseshell). Trend estimates for Painted Lady, a migrant species, were positive and large in magnitude from both BBC and UKBMS and are shown in Figure S8. Overall the BBC trends varied in direction across species; trends were significantly (based on 95% CI) negative for 6 species and significantly positive for 6 species. In comparison, UKBMS trends for 2011–2022 were

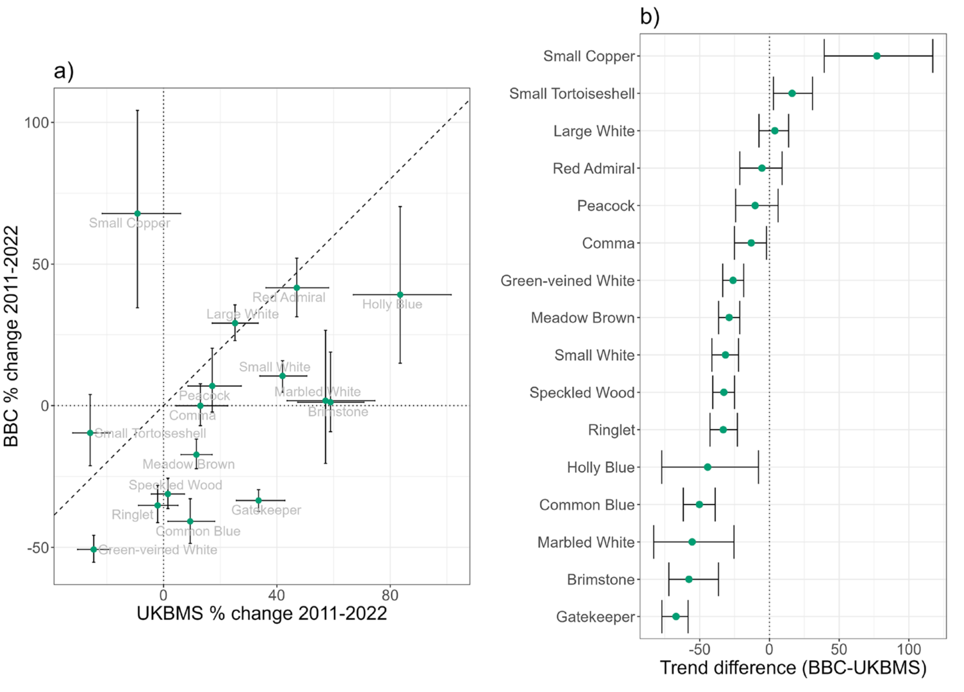

Figure 6. Comparison of (a) and difference between (b) abundance trend estimates for 2011–2022 from UKBMS (using the GAI approach) and BBC (with phenology adjustment approach). Error bars represent 95% confidence intervals produced using nonparametric bootstrapping. The dashed line represents the 1–1 line and dotted lines represent zero. Painted Lady was excluded (see Figure S8 for same figure with Painted Lady included).

significantly positive for 12 out of 17 species, with significant declines for this time period for two species (Green-veined White and Small Tortoiseshell).

Confidence interval widths were generally similar for UKBMS and BBC trends, although BBC trend estimates were typically more precise for the species with greater levels of sampling, for example, Gatekeeper, and correspondingly, species sampled less by BBC had reduced precision, such as Small Copper.

7. DISCUSSION

We have proposed an approach to adjust for the phenological bias that a snapshot CS scheme, such as the BBC, may be susceptible to. In doing so robust abundance indices and trends may be obtained. The simulation study demonstrated that not accounting for varying phenology led to biased trend estimates, particularly for summer-flying univoltine species where the proportion of the flight period captured by the BBC was particularly variable.

7.1. Limitations

The new approach relies upon phenology estimation from a secondary source, in this case from UKBMS data. Future work could explore alternatives, which would be necessary where standardised monitoring data are not available, which is typically the case. For example, phenology may be estimable from opportunistic data sources (Bishop et al. 2013; Clarke and Dennis 2020), and/or modelled directly through climate information, or other known drivers of phenological variation. Here a bootstrap was used to account for uncertainty in phenology estimates from UKBMS data, but consideration may be needed where this is not possible and uncertainty of the phenology information is not available.

Species' flight periods were assumed to be the same across sites, but in practice these could vary, for example, with respect to climate region or growing degree days (Hodgson et al. 2011; Schmucki et al. 2016). This could be particularly important for a species such as Common Blue, which exhibits spatial variation in voltinism (number of generations) within the UK (see Dennis et al. 2022), and was one of the few species for which phenology adjustment did not seem to improve the BBC abundance index.

Minimal validation of BBC data is undertaken, and misidentifications and/or errors could potentially bias results. Sufficient sample sizes would be expected to overcome this issue, but it could be explored in future. Future work could also consider producing finer scale BBC outputs, for example, at country level within the UK—as for UKBMS trend reporting (UKBMS 2023; Fox et al. 2023). The simulation results may be used to inform upon a minimal sampling level needed to produce reliable trend estimates at smaller spatial scales.

7.2. Habitats

Phenology-adjusted BBC trends were predominantly lower than corresponding trends from UKBMS data. This contrasts with previous findings (Dennis et al. 2017a), but in that case trends covered a short time period (2011–2014) and were based on UKBMS data from only the BBC sampling period. Here the UKBMS trends were estimated from data across the entire flight season; therefore, differences compared to BBC trends could arise for multivoltine species if the generation(s) not captured by the BBC sampling period have different population growth trajectories from the generation sampled by the BBC. However, our results do not indicate the difference in trends to be greater for multivoltine species. A more likely explanation is that the two schemes sample different habitats in which species' populations may be responding differently.

UKBMS transect locations are typically self-selected and biased towards sites that are managed for nature conservation (Brereton et al. 2011). The BBC samples more urban habitat than the UKBMS (Dennis et al. 2017a); thus, the lower BBC trends found here could support findings that UK butterfly population declines are stronger in urban areas than rural areas (Dennis et al. 2017b). Furthermore, an assumption of the phenology adjustment approach is therefore that species' flight periods are the same in rural and urban habitats, which could warrant further investigation, for example, see Dennis et al. (2017b).

Dennis et al. (2017a) also reported that 65% of BBC counts are undertaken in gardens. Plummer et al. (2024) produced abundance trends for butterflies in UK gardens which were comparable or even more positive than trends for the wider landscape. However, the gardens sampled were predominantly located in suburban and rural areas, rather than in heavily urbanised areas which are typically detrimental to butterfly and other insect biodiversity (Piano et al. 2020). Further research could assess the spatial coverage in BBC sampling locations to better understand why differences between BBC and UKBMS trends were found, and thus explore how population changes may be varying across the landscape.

7.3. Time Periods

It is also important to note that the trends estimated here were based on a relatively short period of 12 years (2011–2022). Long-term monitoring is important for insects such as butterflies due to high inter-annual variability in populations which can mask underlying population trends if data are not analysed over a sufficiently long time frame (White 2019; Didham et al. 2020). Fox et al. (2019) demonstrated the sensitivity of 10-year population trends to the start year for butterflies and macro-moths. Despite this, our simulation study suggested that sampling at the current high levels achieved by BBC is sufficient to detect a decrease of 25% in abundance over 12 years, and the power to detect changes would be expected to increase with more years of data. The BBC therefore has the potential to reveal greater insights into butterfly population changes as longer-term trends become possible.

Due to the extended sampling period (April–September), as well as detailed data collation, verification processes and analysis, there is a lag in reporting of UKBMS results until spring the following year; hence, rapid reporting of BBC results has the potential to provide an early signal of how butterfly populations are faring in a given year. Phenology adjustment was still effective when using UKBMS data from an incomplete sampling season in the most recent year, meaning that adjusted BBC results could be produced at the end of the summer.

Despite this, snapshot mass-participation sampling such as BBC should be seen as a complement rather than replacement of standardised monitoring such as the UKBMS. Standardised monitoring schemes are vital for validation and testing of statistical methods for other citizen-science data sets (Johnston et al. 2023). Moreover, by sampling semi-natural habitats, the UKBMS provides data on the UK's, often threatened, habitat-specialist butterfly species, whereas BBC only produces trends for common species.

However, trends of common, widespread species are still of importance. The decline of formerly abundant species may underlie the global insect decline phenomenon (van Klink et al. 2024), and such species play important rôles in ecosystem functioning and in delivering ecosystem services (Winfree et al. 2015). UK populations of widespread butterfly species have declined by 17% on average since 1976 (Fox et al. 2023), and decreases have been reported elsewhere (Van Dyck et al. 2009; Wepprich et al. 2019). The drivers of declines in common species are generally not well understood, making effective conservation action difficult. Sampling a wider variety of habitats, such as garden and urban areas from BBC data, has the potential to provide further insights on population changes of the UK's common butterflies. This may be realised by combining data sources such as BBC and UKBMS in an integrated analysis (Besbeas et al. 2002; Schaub and Kéry 2021), for example, building upon the recently developed extended GAI (Dennis et al. 2024), to achieve more representative trends (Boyd et al. 2023).

7.4. Wider Potential

The approach presented here may be relevant to other scenarios liable to the "groundhog effect" (Didham et al. 2020), in particular other snapshot schemes such as the RSPB Big Garden Birdwatch or the Fourth of July Butterfly Count in North America. Various taxa are likely to be susceptible to variable and/or shifting phenology and associated sampling biases, such as birds (Cooper 2014; Massimino et al. 2021), plants (Chen et al. 2013), and many invertebrates (Møller 2019; Gardiner and Didham 2020), which may then lead to biased population trend estimates without suitable modelling. Phenology adjustment may also be useful for butterflies beyond the UK: for example, 15-minute timed butterfly counts have been introduced across Europe (Schmucki et al. 2020). Although not restricted to such a short sampling period, the need to account for species' phenology is still relevant when only single or minimal sampling visits are made and the flight period may not be sufficiently sampled.

There is an ongoing need for the development of suitable statistical methods for analysing CS data (Johnston et al. 2023). By using external information on species' phenology, the new approach addresses the phenological bias that counts from snapshot CS sampling are susceptible to, and thus provides a basis for such data to contribute meaningfully to enhancing our understanding of biodiversity change.

Declarations

Conflict of interest The authors have no conflict of interest to declare.

[Received March 2024. Revised October 2024. Accepted November 2024.]

REFERENCES

Besbeas P, Freeman SN, Morgan BJT, Catchpole EA (2002) Integrating mark-recapture-recovery and census data to estimate animal abundance and demographic parameters. Biometrics 58(3):540–547

Bishop TR, Botham MS, Fox R, Leather SR, Chapman DS, Oliver TH (2013) The utility of distribution data in predicting phenology. Methods Ecol Evol 4(11):1024–1032

Boyd RJ, Powney GD, Pescott OL (2023) We need to talk about nonprobability samples. Trends Ecol Evol 38(6):521–531

Brereton TM, Botham MS, Middlebrook I, Randle Z, Noble D et al (2018) United Kingdom Butterfly Monitoring Scheme report for 2017. UK Centre for Ecology & Hydrology, Butterfly Conservation, British Trust for Ornithology and Joint Nature Conservation Committee

Brereton TM, Cruickshanks KL, Risely K, Noble DG, Roy DB (2011) Developing and launching a wider countryside butterfly survey across the United Kingdom. J Insect Conserv 15:279–290

Butler CW, Hamlin I, Richardson M, Lowe M, Fox R (2024) Connection for conservation: The impact of counting butterflies on nature connectedness and wellbeing in citizen scientists. Biol Cons 292:110497

Chen G, Kéry M, Plattner M, Ma K, Gardner B (2013) Imperfect detection is the rule rather than the exception in plant distribution studies. J Ecol 101(1):183–191

Clarke HE, Dennis EB (2020) A new method for calculating butterfly abundance trends for small regional areas. J Insect Conserv 24:779–790

Cooper CB (2014) Is there a weekend bias in clutch-initiation dates from citizen science? Implications for studies of avian breeding phenology. Int J Biometeorol 58:1415–1419

Dennis EB, Diana A, Matechou E, Morgan BJT (2024) Efficient statistical inference methods for assessing changes in species' populations using citizen science data. J Royal Statistical Society Series A. https://doi.org/10.1093/jrsssa/qnae105

Dennis EB, Fagard-Jenkin C, Morgan BJT (2022) rGAI: An R package for fitting the generalized abundance index to seasonal count data. Ecol Evol 12(8):e9200

Dennis EB, Freeman SN, Brereton T, Roy DB (2013) Indexing butterfly abundance whilst accounting for missing counts and variability in seasonal pattern. Methods Ecol Evol 4(7):637–645

Dennis EB, Morgan BJT, Brereton TM, Roy DB, Fox R (2017) Using citizen science butterfly counts to predict species population trends. Conserv Biol 31(6):1350–1361

Dennis EB, Morgan BJT, Freeman SN, Brereton TM, Roy DB (2016) A generalized abundance index for seasonal invertebrates. Biometrics 72(4):1305–1314

Dennis EB, Morgan BJT, Roy DB, Brereton TM (2017) Urban indicators for UK butterflies. Ecol Ind 76:184–193

Didham RK, Basset Y, Collins CM, Leather SR, Littlewood NA, Menz MH et al (2020) Interpreting insect declines: seven challenges and a way forward. Insect Conserv Div 13(2):103–114

Fox R, Dennis EB, Brown AF, Curson J (2022) A revised Red List of British butterflies. Insect Conserv Div 15(5):485–495

Fox R, Dennis EB, Purdy KM, Middlebrook I, Roy DB, Noble DG et al (2023) The State of the UK's Butterflies 2022. Butterfly Conservation, Wareham, UK

Fox R, Harrower CA, Bell JR, Shortall CR, Middlebrook I, Wilson RJ (2019) Insect population trends and the IUCN Red List process. J Insect Conserv 23(2):269–278

Gardiner T, Didham RK (2020) Glowing, glowing, gone? Monitoring long-term trends in glow-worm numbers in south-east England. Insect Conserv Div 13(2):162–174

Hodgson JA, Thomas CD, Oliver TH, Anderson BJ, Brereton TM, Crone EE (2011) Predicting insect phenology across space and time. Glob Change Biol 17(3):1289–1300

JNCC (2022). UK Biodiversity Indicators 2022 - C6 Insects of the wider countryside (butterflies). Available from: https://jncc.gov.uk/our-work/ukbi-c6-insects-of-the-wider-countryside/ (accessed November 8, 2023)

Johnston A, Matechou E, Dennis EB (2023) Outstanding challenges and future directions for biodiversity monitoring using citizen science data. Methods Ecol Evol 14(1):103–116

Massimino D, Harris SJ, Gillings S (2021) Phenological mismatch between breeding birds and their surveyors and implications for estimating population trends. J Ornithol 162(1):143–154

Møller AP (2019) Parallel declines in abundance of insects and insectivorous birds in Denmark over 22 years. Ecol Evol 9(11):6581–6587

Peter M, Diekötter T, Höffler T, Kremer K (2021) Biodiversity citizen science: Outcomes for the participating citizens. People Nat 3(2):294–311

Piano E, Souffreau C, Merckx T, Baardsen LF, Backeljau T, Bonte D et al (2020) Urbanization drives cross-taxon declines in abundance and diversity at multiple spatial scales. Glob Change Biol 26(3):1196–1211

Plummer KE, Dadam D, Brereton T, Dennis EB, Massimino D, Risely K et al (2024) Trends in butterfly populations in UK gardens—New evidence from citizen science monitoring. Insect Conserv Div 17:345–357

Pocock MJO, Tweddle JC, Savage J, Robinson LD, Roy HE (2017) The diversity and evolution of ecological and environmental citizen science. PLoS ONE 12(4):e0172579

Pollard E, Yates TJ (1993) Monitoring Butterflies for Ecology and Conservation: the British Butterfly Monitoring Scheme. Chapman & Hall, London

Roy DB, Sparks TH (2000) Phenology of British butterflies and climate change. Glob Change Biol 6(4):407–416

Schaub M, Kéry M (2021) Integrated population models: theory and ecological applications with R and JAGS. Elsevier, London

Schmucki R, Pe'er G, Roy DB, Stefanescu C, Van Swaay CA, Oliver TH et al (2016) A regionally informed abundance index for supporting integrative analyses across butterfly monitoring schemes. J Appl Ecol 53:501–510

Schmucki R, Sevilleja C, Dennis EB, Harrower CA, Kazlauskis K et al (2020) Tools to support butterfly monitoring and analysis. Butterfly Conservation Europe. Available from: https://nora.nerc.ac.uk/id/eprint/529525

UKBMS (2023). UKBMS official statistics. Available from: https://ukbms.org/official-statistics (accessed December 12, 2023)

Van Dyck H, Van Strien AJ, Maes D, Van Swaay CA (2009) Declines in common, widespread butterflies in a landscape under intense human use. Conserv Biol 23(4):957–965

van Klink R, Bowler DE, Gongalsky KB, Shen M, Swengel SR, Chase JM (2024) Disproportionate declines of formerly abundant species underlie insect loss. Nature 628:359–364

Wepprich T, Adrion JR, Ries L, Wiedmann J, Haddad NM (2019) Butterfly abundance declines over 20 years of systematic monitoring in Ohio, USA. PLoS ONE 14(7):e0216270

White ER (2019) Minimum time required to detect population trends: the need for long-term monitoring programs. Bioscience 69(1):40–46

Winfree R, Fox WJ, Williams NM, Reilly JR, Cariveau DP (2015) Abundance of common species, not species richness, drives delivery of a real-world ecosystem service. Ecology Letters **18**(7), 626–635

Wood SN (2017) Generalized Additive Models: an introduction with R. CRC Press, New York