Proposal	Contact PI's Surname	Initials	Application Number	Panel
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MARSDEN FUND FULL RESEARCH PROPOSAL

Standard Application Form

1A. TITLE OF RESEARCH PROPOSAL

A new generation of statistical models for spatial point process data

1B. IDENTIFICATION

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1D. SUMMARY

A dataset comprising the spatial locations of events or items of interest is called a spatial point pattern. Such data arise in myriad areas, as diverse as epidemiology, ecology, and archaeology. Typically, models for the distribution of such data incorporate two fundamental components, one relating to persistent spatial (fixed) effects and the other reflecting (stochastic) interactions between points, such as a tendency to cluster together. For example, for a pattern of disease cases the first component would relate to the variation in underlying population density while the latter could represent infectious transmission.

A fundamental task, with critical practical consequences, is to separate these components in the analysis of any given pattern. This is notoriously difficult because of a lack of identifiability: in most current models the two competing representations of spatial variation yield identical predictions, and therefore cannot be distinguished even with unlimited data. However, leveraging recent developments on some specific examples, allied to progress in related areas of statistics, we will develop a new, comprehensive suite of flexible 'hybrid' models incorporating both components in an identifiable manner, overcoming a decades-long stalemate on progress. This will allow us to attack important research questions that have previously remained elusive.

2A. BACKGROUND

A *spatial point pattern* is a dataset recording the observed locations of events or items of interest. Figure 1 shows the pattern of human campylobacter infections in the Manawatu region of New Zealand recorded in two different years [55, 38]: spatial maps of disease cases are important for surveillance of public health risk [41, 31, 44, 23, 73, 38]. In other examples, the disposition of artefacts in an ancient cemetery could reflect social strata [67], and the spatial pattern of alarm calls of capuchins in a jungle may reflect social organisation [22].

Figure 1: Campylobacter cases in Manawatu.

Statistical methodology for spatial point patterns can extract this information efficiently and rigorously [9, 30, 40, 53]. The observed pattern is treated as the outcome of a random spatial *point process* [20]. Statistical methodology for point processes has become a highly active research topic, leveraging recent advances in statistical theory, algorithms and computing [9, 53, 54].

This project addresses unsolved, fundamental challenges in this methodology, with important practical consequences. The foremost problem is *unidentifiability.* An apparent cluster of disease cases, for example, could be attributable either to a common systemic cause (such as a common source of infection) or to stochastic dependence between the points (such as contagion between infected cases) [44, 43, 29, 55]. Distinguishing between these competing explanations is vital for understanding the disease aetiology and public health risk [31, 39]. Yet, for half a century, this has been thought to be fundamentally impossible. The standard statistical approach is to formulate a maximal model that includes all potential sources of variability, then use formal statistical procedures to decide which components of the model are needed to explain the data. But, by a famous result of Bartlett [16], point process models that include both deterministic heterogeneity and stochastic dependence may be technically "unidentifiable" or "confounded", in that the model parameters cannot be determined from observation. The two competing explanations yield identical predictions, and therefore cannot be distinguished, even with infinite amounts of data.

In elementary statistics, unidentifiability is a defect of the model used, and can often be avoided simply by altering the model or the experiment. For spatial point processes, however, it has proved extremely difficult to construct models that simultaneously incorporate both deterministic heterogeneity and stochastic dependence, are identifiable and tractable for statistical inference, and are realistic descriptions of the data. Progress has been achieved only in specific application fields, for example in seismology, after decades of research [56, 57].

Faced with this apparent impasse, research on statistical methodology for spatial point patterns has essentially evolved as two separate streams, one focussed on deterministic trend, and the other on dependence between points. Recent progress in smoothing techniques, such as kernel and spline methods (a key research area of PI Davies and AI Hazelton), now permits estimation of the deterministic trend in a highly flexible and computationally efficient manner [28, 34, 70, 71, 18, 21, 23, 22, 26], but this work typically assumes independence between points. Progress in spatial point process modelling and statistical methodology now permits a rich variety of representations of inter-point dependence (a specialty of AI Baddeley) [19, 6, 52, 53, 14, 9], but typically assumes the deterministic trend is known or is rigidly parametrised. The fundamental weakness remains that deterministic trend and stochastic inter-point dependence cannot both be subjected to a high level of scrutiny in the same analysis. Statistical tools for spatial point patterns are therefore currently unsatisfactory for many important and relevant research questions.

Recent findings offer a glimmer of hope. In time series analysis (where unidentifiability is also a long-standing problem) researchers have been able to disentangle global trend from autocorrelation by constraining the model [37, 59, 45, 36]. For spatial point patterns, the task is more complex, but a similar strategy has been successful in some very specific applications [31, 46, 51, 24]. These results are limited, but they reveal the potential scope, power and utility of this general approach.

2B. OVERALL AIM OF THE RESEARCH

We aim to develop a new generation of statistical methods for the analysis of spatial point patterns, that can simultaneously support detailed inference about deterministic and stochastic sources of variation. These methods will combine the best modern techniques for modelling deterministic trend *and* stochastic dependence, in a 'hybridised' statistical modelling framework. The resulting methods will enable a much more searching analysis of important scientific questions about spatial point pattern data, for example in spatial epidemiology.

Objective 1: Development of identifiable spatial point process models. A model is unidentifiable when its statistical properties *at all spatial scales* can be explained equally well by deterministic or stochastic effects [16]. This suggests that identifiability could be recovered by constraining the model so that the deterministic effects operate at (say) a larger scale than the stochastic effects. This strategy has been used successfully (albeit in very specific fashions) in time series analysis [37, 59, 45, 36] and in spatial point pattern analysis [31, 46, 51, 24].

Our objective is to develop flexible model classes for spatial point processes in which deterministic and stochastic effects are combined and yet are identifiable. This requires theoretical, computational and practical developments. Tools for constructing 'hybrid' point process models [15, 31] will ensure that the models are well-defined and tractable. Model assumptions about the spatial scale of the deterministic and stochastic effects may either be stated explicitly (such as constraints on the derivative of the point process intensity) or incorporated implicitly (through the choice of model-fitting criteria such as spatial penalized likelihood [63, 71, 50, 32] and local composite likelihood [3, 12, 35]) or encoded as prior information in a Bayesian analysis [69, 68].

Objective 2: Implement and assess practical methods of inference. We will develop a novel library of tools necessary to permit researchers to analyse real-world data. There will be a strong focus on methods for model fitting. We will investigate the theoretical properties of our estimators within the new modelling frameworks; for example, examining how the properties of kernel estimators of intensity are impacted by assumptions on ranges of effect. We will work on computationally efficient algorithms to ensure prompt calculation of estimates at a high level of spatial resolution. Finally, we will investigate diagnostic methods to assess adequacy of model fit, building on the seminal work of the AIs [14] in spatial statistics.

Objective 3: Extend developments to point patterns on non-standard domains. There is an increasing literature dealing with points observed on special domains which require unique treatment. Good examples are given by patterns observed on linear networks [17, 58] or on the surface of a sphere [33, 42], including recent work involving PI Davies and AI Baddeley [48, 61]. Little is known about how one should combine deterministic and stochastic effects in these instances, and how model fitting is affected. In response, we will assess the unique modelling requirements such data presents, and examine the feasibility of extending the work on the first two objectives to these situations.

Throughout the project, particularly Objectives 2 and 3, computational implementations will be necessary to test and appraise the developed methodology. Thus, a goal parallel to our entire body of work will be to produce corresponding software for general consumption by the research community, ensuring accessibility of our new, flexible statistical techniques. Ideal vehicles are already available, by way of AI Baddeley's prominent R [60] package `spatstat` [13, 9], as well as the `sparr` package by PI Davies and AI Hazelton [25, 27].

2C. PROPOSED RESEARCH

Suppose we observe a point pattern $\boldsymbol{x} = \{x_1, \ldots, x_n\}$, taken to be a realisation of the point process $\boldsymbol{X}$ defined within some spatial domain $W \subset \mathbb{R}^2$. Our proposed research is centred on models capable of combining deterministic and stochastic effects to describe the data at hand.

To model "clustering" or positive association one may use a *Cox point process* model [19, 53] in which, conditional on the realisation $\psi(x)$ of an external stochastic process $\boldsymbol{\Psi}(x)$, the point process $\boldsymbol{X}$ is a Poisson process [9, 30] with intensity function of the form

$$\lambda_{\boldsymbol{X}|\boldsymbol{\Psi}}(x) = \nu(x)\psi(x), \qquad x \in W, \tag{1}$$

where ν is a deterministic "trend" function that would be modelled using advanced smoothing techniques. This modelling scheme has been used in several application-specific examples e.g. [31, 51]. For identifiability we require $\mathbb{E}[\boldsymbol{\Psi}(x)] \equiv 1$ so that the marginal intensity of $\boldsymbol{X}$ is $\lambda_{\boldsymbol{X}}(x) = \nu(x)$. The stochastic component $\boldsymbol{\Psi}$ plays the role of a random effect [9, p. 450], and gives rise to positive spatial correlation; it is governed by a vector of correlation parameters θ. It is technically challenging to construct new models for $\mathbf{\Psi}$ which have desired properties such as a specified spatial correlation structure. Consequently the model for $\mathbf{\Psi}$ is usually selected from a menu of formulations which have been theoretically analysed: reasonable choices for $\mathbf{\Psi}$ include log-Gaussian random fields, shot-noise fields and random mosaic models.

Figure 2 shows a synthetic example in $W = [0, 1]^2$. The left panel was generated from a purely deterministic intensity function $\lambda_{\boldsymbol{X}}(x) = \nu(x)$; this is contrasted with a dataset generated using the multiplicative construction of (1) using the same deterministic function $\nu(x)$. There we see smaller-scale sporadic clustering in tandem with the overall heterogeneity—in practice, this would be the nature of the data we observe (cf. Figure 1). As the volume of data increases we can hope to obtain an ever more accurate estimate of the marginal intensity $\lambda_{\boldsymbol{X}|\mathbf{\Psi}}(x)$, but that will generally not provide any means of separating the relative contributions of ν and ψ.

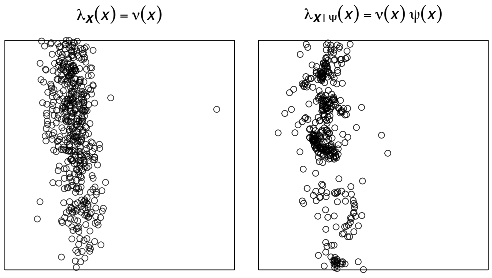

Figure 2: Artificially generated data used to illustrate a deterministic intensity (left) and a random intensity combining deterministic and stochastic effects (right).

Complicated forms of dependence between points can also be described using Gibbs point process models [62, 6, 47] which can best be formulated and fitted using their (Papangelou) conditional intensity $\lambda_{\boldsymbol{X}}(u \mid \boldsymbol{x})$, $u \in W$. By the Möbius inversion formula, this can be factorised as

$$\lambda_{\boldsymbol{X}}(u \mid \boldsymbol{x}) = \beta(u)G(u \mid x), \qquad u \in W, \tag{2}$$

where $\beta(u)$ is the deterministic trend and $G(u \mid \boldsymbol{x})$ contains only interaction terms. This can be treated analogously to (1) by modelling β using advanced smoothing techniques, while G can only take certain forms which are known (from previous research) to satisfy the technical requirements. An important difference is that the trend β and intensity $\lambda_{\boldsymbol{X}}$ are no longer equal, but are approximately related by a functional equation [7].

Historically it has been important that the terms which induce stochastic dependence, $\mathbf{\Psi}(x)$ in (1) and $G(u \mid \boldsymbol{x})$ in (2), cannot be chosen willy-nilly because they must satisfy technical constraints. They have usually been selected from a short menu of models that have previously been constructed and checked for validity in the literature. In both cases, *products* of terms chosen from the menu are also valid, so that $\mathbf{\Psi}(x)$ could be replaced by $\mathbf{\Psi}_1(x) \dots \mathbf{\Psi}_m(x)$ where $\mathbf{\Psi}_j(x), j = 1, \dots, m$ are processes known to satisfy the technical conditions, and similarly $G(u \mid \boldsymbol{x})$ may be validly replaced by a product of such terms [15]. This increases the scope of modelling considerably.

Application-specific examples in the literature reveal the extraordinary flexibility made possible by hybrid deterministic-stochastic modelling frameworks such as (1); the intuition behind which is supported by the real-world context of the data at hand [14, 31, 46, 51]. This in turn shines a light on the potential for significant advances in spatial point process statistics. The fundamental challenge, however, is to be able to separately capture and hence reliably model *both* $\nu(x)$ and the properties of the stochastic driving mechanism $\mathbf{\Psi}(x)$ given an observed dataset. Work to date on this difficult problem has remained ad-hoc and severely limited in a more general sense.

Our proposed research thus seeks to develop a new generation of statistical methods that circumvent the inherent unidentifiability by placing informed, readily estimable constraints on the component processes. This will overcome a decades-long stalemate on progress and allow us novel, highly flexible means to address complex research questions arising in a variety of disciplines.

Objective 1: Development of identifiable spatial point process models. Strategies for proceeding are best posed by first considering a particular model design, followed by specification of the nature of the component processes. For the sake of exposition, let us remain with the formulation laid out by (1). Diggle et al. [31] used a spatiotemporal version of this design for the analysis of gastrointestinal infections in a region of the UK. They addressed the issue of identifiability between the deterministic and stochastic elements by effectively making assumptions about the smoothness of ν. In more detail, they estimated ν by (spatially adaptive) kernel smoothing with a subjectively chosen global bandwidth h, and then accounted for the residual variation in the intensity using a *log-Gaussian Cox process* [52] as the stochastic driving mechanism $\mathbf{\Psi}$. In this sense, ψ arises as a realisation of $\mathbf{\Psi}$ where

$$\mathbf{\Psi}(x;\theta) = \exp\{Y(x;\theta)\}; \qquad x \in W \subset \mathbb{R}^2, \tag{3}$$

where Y is taken to be a stationary, isotropic Gaussian random field with parameter $\theta = \{\mu, \sigma^2, \phi\}$ in which we define a mean μ, variance σ^2, and correlation scale parameter ϕ. With the kernel estimate of the deterministic trend treated as known, the parameters necessary for (3) were subsequently estimated using minimum contrast methods [53, 30]. An approach of this sort is pragmatic and can be effective, but it raises some theoretical difficulties. If the bandwidth follows the usual asymptotic regimen for consistency of the kernel estimator, then we may expect $\hat{\nu} \to \lambda_{\boldsymbol{X}|\mathbf{\Psi}}$ as $n \to \infty$ [70], technically obviating the need for ψ. On the other hand, if we place some lower bound on the bandwidth h, then $\hat{\nu}$ will not be a consistent estimator in general.

As part of our proposed work we will pursue the idea that stochastic variation may be distinguished from deterministic trend by consideration of scale. One approach is to operate under formal assumptions on the curvature of ν. We anticipate this will lead to theoretical identifiability for some classes of stochastic models $\mathbf{\Psi}$, if suitable constraints are placed on the range of spatial correlation. Equivalently we may look at contributions of ν and $\mathbf{\Psi}$ in the frequency domain, explaining the high frequency variations through the stochastic element. The idea is rather general, and could for instance be used to resolve the identifiability problem studied by Bartlett [16].

There is some precedent in the literature for the above strategy. In kernel density estimation, guidelines to optimal bandwidth selection can be linked to the estimated smoothness of the target function via its second derivative [64, 66]. An adaptation of such an approach in the presence of spatial dependence, by studying these properties of a kernel estimate of ν, is one avenue of pursuit.

Moving away from kernel smoothing, note that model identifiability will also typically be assured if the deterministic trend is specified parametrically. In principle this means we can represent that term using some kind of bivariate spline with a fixed number of knots [71]. We will address two questions that naturally arise. First, what can be said about identifiability under an asymptotic regimen in which the number of knots increases with the n, but at a (much) slower rate? Second, how much flexibility can we hope to achieve in practice from a spline estimate of trend while permitting reasonable estimates of model parameters?

A different approach is to circumvent problems of identifiability through use of local likelihood methods, recently pioneered by AI Baddeley [3]. This involves creation of a pastiche of local models built up from a pre-specified "template" model which itself does not exhibit spatial inhomogeneity. Each localised model is fitted using likelihood functions weighted to the data in the neighbourhood of the estimation point in question. Issues of scale therefore remain, and are bound up with calibration of the instrumental kernel weights. We will seek to further develop this approach.

Objective 2: Implement and assess practical methods of inference. The work under this objective follows naturally from theoretical developments under the first objective. In essence, we seek to ensure that theoretical knowledge is effectively translated to practical methodologies for model fitting and diagnosis.

If identifiability is enabled through placing restrictions on the curvature of ν, then a natural approach is to estimate this component of the intensity through a kernel estimate with a corresponding kind of constraint. However, we face theoretical challenges because the curvature of the kernel estimate $\hat{\nu}$ will be an amalgam of the true curvature of ν with additional high frequency 'wiggles' corresponding to noise in the dataset at hand. It follows that applying a theoretical bound on the curvature of ν to the estimator $\hat{\nu}$ will not necessarily guarantee consistent estimation. Some insight into this problem exists for univariate smoothing [65]; extending these results to the bivariate setting will permit design of a consistent kernel estimator of ν under curvature constraints. We will then seek to develop data-driven bandwidth selectors for use in this constrained setting. Finally, we will also explore the extension of these results from fixed bandwidth kernel estimation to spatially adaptive estimation (e.g. based on the methods of [1]); shown to be well-suited to point pattern data [23, 22]. In principle the utilisation of these constrained kernel estimators will allow us to estimate consistently the parameters θ of the residual stochastic process $\mathbf{\Psi}$. We will conduct numerical experiments to assess the practicability of this approach for single instances of point patterns (see relevant commentary on the difficulties faced in general e.g. [49]).

Turning to spline methods, we note that while knot selection (including both the number and position of knots) is often relatively unimportant for univariate splines, this choice is likely to be far more important in the 2D setting [63, 71]. The curse of dimensionality means that a dense grid of knots locations will not be practicable, and even with smaller numbers of knots, optimal choice between knot arrangements will be challenging. We will examine these issues in the presence of various driver processes $\boldsymbol{\Psi}$, taking account of estimation accuracy and computational expense.

Local likelihood methods have the powerful advantage that they are easily deployed in applications: they do not require the construction and theoretical analysis of bespoke models. Existing theory, methodology and computational techniques relevant to the template model require only minor modification. The main disadvantage is that the final result is not fully specified in the familiar sense of a “fitted model” [3]. Appropriate bandwidth selection for the kernel weights requires attention, and we will seek to further develop such methods in line with theoretical advancements.

Diagnostic methods are important for the assessment of any statistical model. In the setting of spatial point processes, the work of the AIs [14, 4, 10] was seminal. However, for the hybrid models at hand we will need to develop new tools, including analogues of residuals, leverage and influence, that are capable of indicating the extent to which deterministic and stochastic elements of the model are uniquely determined by the data at hand.

Objective 3: Extend developments to point patterns on non-standard domains. Spatial point patterns are most commonly assumed to arise in continuous 2D space. However, emerging research is highlighting the substantial challenges that arise when the pattern arises on another domain, such as the surface of a sphere [33, 42] or a linear network [17, 58]. The left panel of Figure 3 shows the spatial pattern of street crimes reported in an urban area of Chicago, USA [2]. Here the crime locations are constrained to lie on the street network. Similar examples include road traffic accidents [61] and microscopic features on the dendrite network of a neuron [5].

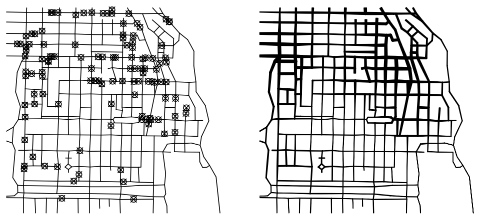

Figure 3: Street crimes observed in an area of Chicago (left) and corresponding nonparametric intensity estimate (right; line thickness proportional to intensity) using state-of-the-art methodology.

The major challenge here is that the network is not homogeneous, so there are no non-trivial homogeneous random processes on a network, and most of the standard recipes for model-building are not successful [8]. A linear network is the simplest example of a “substrate” on which the data are constrained to lie. This constraint affects the entire approach to data analysis and completely invalidates many classical techniques which assume homogeneity. Even the simple task of non-parametric estimation of intensity is challenging on a linear network. Existing methods for 2D point patterns cannot be transferred directly to a network; attempting to do so has led to fallacious results [72] which were subsequently pointed out [48]. In recent work involving PI Davies and AI Baddeley [48, 61] it is demonstrated that a 2D kernel intensity estimate of the points, renormalised by a convolution of the 2D kernel with arc-length measure on the network, leads to a statistically consistent estimator of intensity on the network. On the right of Figure 3 is such an estimate for the Chicago data.

Research on relevant statistical methods is still in its infancy for such problems, and no general parametric modelling solutions presently exist, much less any hybridised deterministic-stochastic frameworks. However, the concept of combining the two sources of variation in modelling such a pattern remains sound with similar scale-specific intuition. In the Chicago crimes example the fixed heterogeneity in the population in that urban area could be explained via a deterministic trend, with the stochastic component used to capture any more sporadic, localised crime tendencies.

In our final task of the proposed research we aim to make a substantial contribution to this emerging area of study. We will use hybridisation and localisation strategies to construct point process models on a linear network which are amenable to analysis while being sufficiently flexible to model real data. The modelling and estimation tools developed in Objectives 1 and 2 will be enlisted and tested in this challenging context.

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[67] Smith BA, **Davies TM**, Higham CFW (2015) Spatial and social variables in the Bronze Age phase 4 cemetery of Ban Non Wat, Northeast Thailand, *Journal of Archaeological Science: Reports* **4** 362-370.

[68] Taylor BM, **Davies TM**, Rowlingson BS, Diggle PJ (2015) Bayesian inference and data augmentation schemes for spatial, spatiotemporal and multivariate log-Gaussian Cox processes in R, *Journal of Statistical Software* **63** 1-48.

[69] Taylor BM, Diggle PJ (2014) INLA or MCMC? A tutorial and comparative evaluation for spatial prediction in log-Gaussian Cox processes, *Journal of Statistical Computation and Simulation* **84** 2266-2284.

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[73] Zhang ZJ, **Davies TM**, Gao J, Wang Z, Jiang QW (2013) Identification of high-risk regions for schistosomiasis in the Guichi region of China: an adaptive kernel density estimation-based approach, *Parasitology* **140** 868-875.

2F. TIMETABLE

Number of Years (maximum of 3): **3**

Year 1: 2020

- Investigation of spatial identifiability for models of point process data.
  - Derive general properties of models under specific constraints on deterministic and stochastic components.
  - Conduct 'proof-of-concept' empirical tests/simulations for the different formulations investigated above to assess 'practical identifiability' i.e. what we might hope to learn from individual datasets.
- Develop formal model designs for the most promising identifiable frameworks.
- PI Davies and AI Hazelton visited by AI Baddeley at the University of Otago. Plan and draft 2 manuscripts dealing with the different aspects of the theory and and practical consequences of constraining individual model components. Recruit PhD student.

Year 2: 2021

- A concentration on practical methods of model fitting and inference for newly developed hybrid spatial point process models.
  - Develop data-driven ways to secure constraints on the deterministic and stochastic components as required.
  - Develop estimation methods for deterministic components in the presence of spatial dependence and vice-versa.
  - Empirically investigate estimation techniques.
- Develop diagnostic tools for newly developed models, to assess their fit to data. Assess estimation methods, plots, and ease of interpretation.
- Further visit between the three named members of the research team (venue TBD). Plan and draft 2-3 manuscripts on practical fitting methods, diagnostic investigation, and applications. Recruit 2-year postdoctoral fellow.

Year 3: 2022

- Development of hybridised modelling techniques for point patterns on linear networks.
  - Define stochastic processes on networks; assess properties.
  - Building on recent work for smoothing network data, design possible modelling frameworks for linear network data combining deterministic and stochastic effects.
  - Test models using empirical and real-world data.
- Consider potential for similar models for alternative domains, such as point patterns observed on the surface of a sphere.
- Further visit between the three named members of the research team (venue TBD). Plan 1-2 manuscripts with particular focus on modelling point pattern data observed on linear networks.

In tandem with the above, we will implement methodological advancements in the open-source software package R, extending the functionality of existing R libraries developed by the research team. We recognise, and are particularly motivated by, the need for accessibility of cutting-edge statistical methods for inference to the wider research community. We expect this to serve as an excellent avenue for the drafting of additional 'tutorial-style' manuscripts and software vignettes for applied researchers and other users, thereby raising the profile of New Zealand's expertise in these areas. Furthermore, progress will be reported on regularly at both local and international statistics conferences.

2G. ROLES AND RESOURCES

The proposed programme of research seeks to bridge the critical gap that currently exists between flexible smoothing methods for estimation of fixed components of trend on the one hand, and stochastic models to describe point-to-point interaction on the other. This is perfectly reflected in the composition of the research team, which brings together two of Australasia's top statistical researchers in spatial point processes (AI Baddeley) and kernel smoothing (AI Hazelton), along with a 2-year postdoctoral fellow and a 3-year Ph.D. student, under the leadership of emerging research heavyweight PI Davies. This trans-Tasman group has the experience and dynamism to conduct world leading research, firmly positioning New Zealand at the frontier of spatial statistics.

PI Davies has established himself as one of New Zealand's leading young statisticians, with over two dozen papers in high-impact statistics and applications journals (e.g. *Stat. Med.*, *Ann. Appl. Stat.*, *Stat. Comp.*) and two early career research awards. He has expertise in both spatial statistics and smoothing methods, including methodological development, computational implementation and application. With **0.25 FTE**, he will lead the project, contribute to all areas of research, and be the primary supervisor of the postdoctoral and doctoral researchers. His unifying role will serve to strengthen the intersection of knowledge shared by the two experienced AIs.

AI Baddeley is a Distinguished Professor and recognised international researcher in the field of spatial point process statistics, with scores of publications in top statistics journals (e.g. *Ann. Stat.*, *JRSS B*) and numerous scientific prizes and affiliations. Building on this vast expertise, AI Baddeley will contribute in particular to theoretical developments related to estimation of interaction effects and associated software development, with a proposed **0.1 FTE**. Of note is his lead authorship of the `spatstat` software, which provides a superb dissemination vehicle for novel developments of the project: The accompanying 2005 paper by Baddeley and Turner (ref. [13] in Section 2E) has now been cited well over 1,000 times.

AI Hazelton is a prolific international researcher in kernel density estimation and related smoothing problems. He has considerable knowledge of spatial statistics and associated applications in spatial and spatio-temporal epidemiology. With a string of publications in leading statistics journals (e.g. *JRSS B*, *Ann. Appl. Stat.*), he has received the premier research prize of the New Zealand Statistical Association. Contributing **0.05 FTE**, AI Hazelton will focus in particular on methodological developments related to flexible nonparameteric trend estimation in the presence of complex models for inter-point interaction.

Collaboration between the PI and AIs will be further strengthened through the 'glue' provided by the **postdoctoral fellow** and **doctoral student**, each at **1.0 FTE**. Their specific roles will depend in part on their own strengths and interests. Suitable candidates would have strong theoretical and computational abilities, and an interest in spatial applications. While based predominately with PI Davies at the University of Otago, both will also take opportunities to spend significant amounts of time in Western Australia working with Distinguished Professor Baddeley and his research team. Their active support of the named investigators will lend particular strength to the growth of New Zealand's capacity for research into cutting-edge point process methodology.

The PI and AIs have a record of highly successful collaboration. Each pair has already published together in leading journals on various aspects of spatial statistics—Davies and Baddeley (*Stat. Comp.*, *Int. Stat. Rev.*); Davies and Hazelton (*Stat. Med.*, *Comput. Stat. Data Anal.*); Baddeley and Hazelton (*JRSS B*, discussion paper)—though never as a group of three. Coming together on this project therefore represents both a natural progression to their individual work and an opportunity to forge an outstanding new tripartite research collaboration.

The physical resources of the proposed research project are minimal, aside from the requested FTEs. The only other major requested resource will be funding for travel. At their respective institutions the investigators possess sufficient computational resources for the planned pursuits. Digital video conversations over the Internet will be scheduled regularly.

2H. ETHICAL OR REGULATORY OBLIGATIONS

N/A

5. CURRICULUM VITAE AND PUBLICATIONS

PART 1

1a. Personal details				
Full name	*Title* Dr	*First name* Tilman	*Second name(s)* Marcus	*Family name* Davies
Present position	Senior Lecturer in Statistics			
Organisation/Employer	University of Otago			
Contact address	Department of Mathematics & Statistics			
	PO Box 56			
	Dunedin, New Zealand		Post code	9054
Work telephone	03-479 7772	Mobile	021-165 2690	
Email	tdavies@maths.otago.ac.nz			
Personal website	http://www.stats.otago.ac.nz/?people=tilman_davies			

1b. Academic qualifications

2012: PhD Statistics; Massey University.
2007: Bachelor of Science Honours (BScHons) in Statistics (First class); Massey University.
2006: Bachelor of Computer and Mathematical Sciences (BCM) in Applied Statistics/German; University of Western Australia.

1c. Professional positions held

2018-present: Adjunct Research Fellow, Dept. of Mathematics and Statistics, Curtin University, Australia.
2017-present: Senior Lecturer in Statistics, University of Otago.
2012-2016: Lecturer in Statistics, University of Otago.
2009-2011: Graduate Assistant and Doctoral Student, Massey University.
2008: Statistician, The EMMES Corporation (Rockville MD, USA).

1d. Present research/professional speciality

- Analysis of planar point patterns and spatial statistics
- Kernel smoothing and density-ratios
- Computational statistics, R programming
- Biostatistical applications in geographical epidemiology and physiology

1e. Total years research experience:	10 years (incl. PhD)

1f. Professional distinctions and memberships (including honours, prizes, scholarships, boards or governance roles, etc)

Grants/Funding
2015: Awarded Marsden Fast-start Grant 15-UOO-092: ‘Smoothing and inference for point process data with applications to epidemiology’ as PI.
2014: University of Otago Research Grant (UORG): “Spatial Methods for Intensity Estimation and their Performance in Epidemiology” as PI.

Awards/Scholarships
2017: University of Otago Early Career Award for Distinction in Research.
2014: Worsley Early Career Research Award (NZ Statistical Association).
2009: Top Achiever’s Doctoral Scholarship (Bright Future Scheme; TEC, NZ).

Postgraduate/Honours Supervision
2019: Morshadur Rahman, PhD (primary supervisor; expected start date: October).

2019-present: Anna Redmond, Honours (primary supervisor).
2018-present: Megan Drysdale, Masters (co-supervisor).
2018-present: Marilette Lötter, Honours (primary supervisor).
2017-2018: Qing Ruan, Postgraduate Diploma (primary supervisor).
2016-2018: Baylee Smith, Masters (co-supervisor).
2015: Patrick Brown, Postgraduate Diploma (primary supervisor).
2014: Baylee Smith, Honours (primary supervisor).
2013: Claire Flynn, Honours (primary supervisor).

Conference/Workshop Attendance

2018: Australian Statistical Conference, Melbourne (ISCB/ASC 2018). Contributed talk.
2017: Conference Board of Mathematical Statistics 2017 Regional Workshop: Bayesian Modeling for Spatial and Spatio-Temporal Data (CBMS 2017), Santa Cruz CA, USA.
2016: Royal Statistical Society Conference (RSS 2016), Manchester, UK. Poster.
2016: Institute of Mathematical Statistics Asia-Pacific Rim Meeting (IMS/APRM 2016), Chinese University of Hong Kong, Hong Kong. Invited speaker.
2015: Otago International Health Research Network Conference (OIHRN 2015), Dunedin, NZ. Contributed talk.
2015: Joint Statistical Meetings (JSM 2015), Seattle WA, USA. Contributed talk.
2012-2016, 2018: Annual New Zealand Statistical Association Conference (NZSA/ORSNZ), main university centers around NZ. Contributed talks and poster presentations.
2012: Australian and New Zealand Association of Clinical Anatomisits Conference (ANZACA 2012), Sydney, Australia.

Invited Collaboration and Seminars

2018: Invited research visitor, Dept. of Biostatistics, UCLA, USA.
2016-2018: Invited research visitor, Dept. of Mathematics and Statistics, Curtin University, Perth, Australia.
2016, 2017: Invited research collaborator, Centre for Health Informatics Computing and Statistics (CHICAS), Lancaster University, UK.
2011-2018: Local departmental statistics seminars, Dept. of Mathematics and Statistics, University of Otago, Dunedin, NZ.
2011: Invited research visitor, Dept. of Mathematical Sciences, Aalborg University, Denmark.
2011: Invited seminar, Dept. of Mathematics and Statistics, Lancaster University, UK.
2011: Invited seminar, Dept. of Mathematics and Statistics, University of Jyväskylä, Finland.

Memberships

2016-present: Accredited Statistician (AStat)—Statistical Society of Australia Inc. (SSAI).
2012-present: Overseas member—Statistical Society of Australia Inc. (SSAI).
2009-present: Regular member—New Zealand Statistical Association (NZSA).

Professional/Outreach Roles

2019: Chair, New Zealand Statistical Association Conference (NZSA2019).
2018: Co-presenter with A. Baddeley and R. Turner for the ARC Centre for Excellence in Mathematics and Statistics 3-day workshop on spatial statistics, University of Melbourne.
2014-present: Director of Studies (100-level statistics: Dept. of Mathematics & Statistics, Otago).
2013-present: Sole author/presenter of the annual 3-day University of Otago "Introduction to R" programming workshop (SWoPS 1: Statistics Workshops for Postgraduates and Staff).
2013-present: Schools Liaison Officer, Dept. of Mathematics & Statistics, Otago.

1g. Total number of *peer reviewed* publications and patents	Journal articles	Books	Book chapters, books edited	Conference proceedings	Patents
	25	1	0	1	0

PART 2

2a. Research publications and dissemination

Peer reviewed journal articles

1. **Davies TM**, Lawson AB **(2019)** An evaluation of likelihood-based bandwidth selectors for spatial and spatiotemporal kernel estimates, *Journal of Statistical Computation and Simulation* **89**(7) 1131-1152.
2. **Davies TM**, Schofield MR, Cornwall J, Sheard PW **(2019)** Modelling multilevel spatial behaviour in binary-mark muscle fibre configurations, *Annals of Applied Statistics* [to appear] (doi: To be assigned).
3. Rakshit S, **Davies TM**, Moradi MM, McSwiggan G, Nair G, Mateu J, Baddeley A **(2019)** Fast kernel smoothing of point patterns on a large network using 2D convolution, *International Statistical Review* [to appear] (doi: 10.1111/insr.12327).
4. **Davies TM**, Baddeley A **(2018)** Fast computation of spatially adaptive kernel estimates, *Statistics and Computing* **28**(4) 937-956.
5. **Davies TM**, Flynn CR, Hazelton ML **(2018)** On the utility of asymptotic bandwidth selectors for spatially adaptive kernel density estimation, *Statistics & Probability Letters* **138** 75-81.
6. **Davies TM**, Marshall JC, Hazelton ML **(2018)** Tutorial on kernel estimation of continuous spatial and spatiotemporal relative risk, *Statistics in Medicine* **37**(7) 1191-1221.
7. **Davies TM**, Jones K, Hazelton ML **(2016)** Symmetric adaptive smoothing regimens for estimation of the spatial relative risk function, *Computational Statistics & Data Analysis* **101** 12-28.
8. **Davies TM**, Sheard PW, Cornwall J **(2016)** Letter to the Editor: Comment on Makino et al. and observations on spatial modeling, *Anatomical Science International* **91**(4) 423-424.
9. Farrell S, **Davies TM**, Cornwall J **(2015)** Use of clinical anatomy resources by musculoskeletal outpatient physiotherapists in Australian public hospitals: A cross-sectional study, *Physiotherapy Canada* **67**(3) 273-279.
10. Fletcher JGR, Stringer MD, Briggs CA, **Davies TM**, Woodley SJ **(2015)** CT morphometry of adult thoracic intervertebral discs, *European Spine Journal* **24**(10) 2321-2329.
11. Smith BA, **Davies TM**, Higham CFW **(2015)** Spatial and social variables in the Bronze Age phase 4 cemetery of Ban Non Wat, Northeast Thailand, *Journal of Archaeological Science: Reports* **4**(34) 362-370.
12. Taylor BM, **Davies TM**, Rowlingson BS, Diggle PJ **(2015)** Bayesian inference and data augmentation schemes for spatial, spatiotemporal and multivariate log-Gaussian Cox processes in R, *Journal of Statistical Software* **63**(7) 1-48.
13. Cornwall J, **Davies TM**, Lees D (2013) Student injuries in the dissecting room, *Anatomical Sciences Education* **6**(6) 404-409.
14. **Davies TM** (2013) Jointly optimal bandwidth selection for the planar kernel-smoothed density-ratio, *Spatial and Spatio-temporal Epidemiology* **5**(1) 51-65.

15. **Davies TM** (2013) Scaling oversmoothing factors for kernel estimation of spatial relative risk, *Epidemiological Methods* **2**(1) 67-83.
16. **Davies TM**, Bryant DJ (2013) On circulant embedding for Gaussian random fields in R, *Journal of Statistical Software* **55**(9) 1-21.
17. **Davies TM**, Cornwall J, Sheard PW (2013) Modelling dichotomously marked muscle fibre configurations, *Statistics in Medicine* **32**(24) 4240-4258.
18. **Davies TM**, Hazelton ML (2013) Assessing minimum contrast parameter estimation for spatial and spatiotemporal log-Gaussian Cox processes, *Statistica Neerlandica* **67**(4) 355-389.
19. Taylor BM, **Davies TM**, Rowlingson BS, Diggle PJ (2013) `lgcp` - An R package for inference with spatial and spatiotemporal log-Gaussian Cox processes, *Journal of Statistical Software* **52**(4) 1-40.
20. Zhang ZJ, **Davies TM**, Gao J, Wang Z, Jiang QW (2013) Identification of high-risk regions for schistosomiasis in the Guichi region of China: an adaptive kernel density estimation-based approach, *Parasitology* **140**(7) 868-875.
21. Zhang ZJ, Chen DM, Chen Y, **Davies TM**, Vaillancourt JP, Liu WB (2012) Risk signals of an influenza pandemic caused by highly pathogenic avian influenza subtype H5N1: Spatio-temporal perspectives, *Veterinary Journal* **192**(3) 417-421.
22. **Davies TM**, Hazelton ML, Marshall JC (2011) `sparr`: Analyzing spatial relative risk using fixed and adaptive kernel density estimation in R, *Journal of Statistical Software* **39**(1) 1-14.
23. Sanson RL, Harvey N, Garner MG, Stevenson MA, **Davies TM**, Hazelton ML, O'Connor J, Dubé C, Forde-Folle KN, Owen K (2011) Foot-and-mouth disease model verification and 'relative validation' through a formal model comparison, *OIE Scientific and Technical Review* **30**(2) 527-540.
24. **Davies TM**, Hazelton ML (2010) Adaptive kernel estimation of spatial relative risk, *Statistics in Medicine* **29**(23) 2423-2437.
25. Hazelton ML, **Davies TM** (2009) Inference based on kernel estimates of the relative risk function in geographical epidemiology, *Biometrical Journal* **51**(1) 98-109.

Peer reviewed books

- **Davies TM (2016)** *The Book of R: A First Course in Programming and Statistics*, No Starch Press, San Francisco, USA; 832pp.

Refereed conference proceedings

- **Davies TM**, Sheard PW, Cornwall J **(2013)** Development of a novel statistical method to test spatial distributions of skeletal muscle fiber types, *In proceedings of the 2012 Meeting of the Australian and New Zealand Association of Clinical Anatomists (ANZACA)*; *Clinical Anatomy* 26, 641-660.

5. CURRICULUM VITAE AND PUBLICATIONS

PART 1

1a. Personal details				
Full name	*Title* Prof.	*First name* Martin	*Second name(s)* Luke	*Family name* Hazelton
Present position	Professor of Statistics			
Organisation/Employer	Massey University			
Contact address	Tennent Drive			
	Private Bag 11222			
	Palmerston North		Post code	4442
Work telephone	06-356 9099	Mobile	021-863 438	
Email	m.hazelton@massey.ac.nz			
Personal website (if applicable)	http://www.massey.ac.nz/~mhazelto/			

1b. Academic qualifications

1993, D.Phil in Statistics, University of Oxford
1989, BA Hons in Mathematics (First Class), University of Oxford

1c. Professional positions held

From September 2019, Professor of Statistics, University of Otago
2017-Sept. 2019, Head of the Institute/School of Fundamental Sciences, Massey University
2006-Sept. 2019, Chair of Statistics, Massey University
1997-2006, Lecturer–Associate Professor in Statistics, University of Western Australia
1994-1997, Lecturer in Statistical Science, University College London
1993-1994, Research Officer in Transport Studies, University of Oxford
1992-1993, Stipendiary Lecturer in Mathematics, Jesus College, University of Oxford

1d. Present research/professional speciality

Network tomography
Kernel smoothing
Spatial statistics
Statistical modelling and inference for transport networks
Biostatistics and statistical methods in epidemiology

1e. Total years research experience:	28 years

1f. Professional distinctions and memberships (including honours, prizes, scholarships, boards or governance roles, etc)

2017, Awarded Marsden grant 17-MAU-037, 'Lattice polytope samplers: theory, methods and applications', as sole PI

2016, Invited speaker at 4th IMS-APRM conference, The Chinese University of Hong Kong

2015, AI on Marsden grant 15-UOO-092, 'Smoothing and inference for point process data with applications to epidemiology'

2014, Awarded Littlejohn Research Award, the premier research award of the New Zealand Statistical Association

2014, Awarded Marsden grant 14-MAU-017, 'Modelling, inference and prediction for dynamic traffic networks', as sole PI

2014-2016, president of the New Zealand Statistical Association

2014, Invited International Lecturer, Croucher Foundation Advanced Study Institute, Hong Kong University of Science and Technology

2013, Keynote speaker at 2013 New Zealand Statistical Association/ Operations Research Society of New Zealand conference, Hamilton

2013, Invited speaker at HKUST Workshop on Day-to-Day Dynamical System Approach for Modeling Transportation Systems, Hong Kong

2013-2016, Associate Investigator on Australian Research Council Discovery Grant 'Statistical methodology for events on a network, with application to road safety'

2013-present, Associate Editor, Transportmetrica B: Transport Dynamics

2012-present, Principal Investigator in the Infectious Disease Research Centre (`www.idrec.ac.nz`)

2011-present, Theory and Methods Editor, Australian and New Zealand Journal of Statistics

2011, plenary speaker at Statistical Concepts and Methods for the Modern World Conference, Colombo, Sri Lanka

2011, External academic on Graduating Year Review panel for Bachelor of Mathematical Sciences at Auckland University of Technology

2010-2014, Awards Committee Convenor, New Zealand Statistical Association

2010-2011, Associate Editor, Australian and New Zealand Journal of Statistics

2009, invited speaker at DADDY: Workshop on Day-to-day Dynamics for Transportation Networks, Salerno, Italy

2008-2016, Associate Editor, Journal of the Korean Statistical Association

2008-2011, Awarded Marsden grant MAU0807, 'New tools for statistical inference for network-based transportation models', as sole PI

2007-present, member of the Editorial Advisory Board, Transportation Research Part B

2007, Grant assessor for Hong Kong City University

2006, Invited speaker at joint Australian/New Zealand Statistics Conference, Auckland

2006-present, Member of the New Zealand Statistical Association

2006, Grant assessor for the Israel Science Foundation

2005-2008, Grant assessor for Australian National Health & Medical Research Council

2005, Author of read paper at Royal Statistical Society Research Meeting, See [28] in publication list.

2003-present, paper on plug-in bandwidth matrices for density estimation is most highly cited ever in *Journal of Nonparametric Statistics* (Web of Science). See [39] in publication list

2002, Invited speaker at 16th Australian Statistics Conference, Canberra, Australia

2002-2004, President, West Australian Branch of the Statistical Society of Australia

1998, Author of read paper at Royal Statistical Society General Meeting. See [48] in publication list.

1997-present, Supervised 13 PhD students, 9 as primary supervisor. Of the 10 to have completed to date, 7 secured academic posts

1987-1989, Exhibitioner in mathematics, St Anne's College, University of Oxford

1g. Total number of *peer reviewed* publications and patents	Journal articles	Books	Book chapters, books edited	Conference proceedings	Patents
	82	0	9	5	0

PART 2

2a. Research publications and dissemination

Peer reviewed journal articles (selected)

1. Liao, S. J., Marshall, J., **Hazelton, M. L.**, & French, N. P. **(2019)**. Extending statistical models for source attribution of zoonotic diseases: a study of campylobacteriosis. *Journal of the Royal Society Interface*, **16(150)**, 20180534.
2. Davies, T.M., Marshall, J.C. and **Hazelton, M.L. (2018)**. Tutorial on kernel estimation of continuous spatial and spatiotemporal relative risk with accompanying instruction in R. *Statistics in Medicine*, **37**, 1191-1221.
3. Davies, T.M., Flynn, C. and **Hazelton, M.L. (2018)**. On the utility of asymptotic bandwidth selectors for spatially adaptive kernel density estimation. *Statistics and Probability Letters*, **138**, 75-81.
4. Watling, D.P. and **Hazelton, M.L. (2018)**. Asymptotic approximations of transient behaviour for day-to-day traffic models. *Transportation Research Part B*, **118**, 90-105.
5. **Hazelton, M.L. (2017)**. Testing for changes in spatial relative risk. *Statistics in Medicine*, **36**, 2735-2749.
6. **Hazelton, M.L.** and Bilton, T.P. **(2017)**. Polytope samplers for network tomography. *Australian and New Zealand Journal of Statistics*, **59(4)**, 495-511.
7. **Hazelton, M.L.** and Cox, M.P. **(2016)**. Bandwidth selection for kernel log-density estimation. *Computational Statistics and Data Analysis*, **103**, 56-67.
8. **Hazelton, M.L.** and Parry, K. **(2016)**. Statistical methods for comparison of day-to-day traffic models. *Transportation Research Part B*, **92(A)**, 22-34.
9. Davies, T.M., Jones, K. and **Hazelton, M.L. (2016)**. Symmetric adaptive smoothing regimens for estimation of the spatial relative risk function. *Computational Statistics and Data Analysis*, **101**, 12-18.
10. Pirikahu, S., Jones. G., **Hazelton, M.L.** and Heuer, C. **(2016)**. Bayesian methods of confidence interval construction for the population attributable risk from cross-sectional studies. *Statistics in Medicine*, **35** 3117-3130.
11. **Hazelton, M.L. (2015)**. Network tomography for integer-valued traffic. *Annals of Applied Statistics*, **9(1)**, 474-506.
12. Fernando, W.T.P.S, Ganesalingam, S. and **Hazelton, M.L. (2014)**. A comparison of estimators of the geographical relative risk function. *Journal of Statistical Computation and Simulation*, **84(7)**, 1471-1485.
13. Davies, T.M and **Hazelton, M.L.** (2013). Assessing minimum contrast parameter estimation for spatial and spatiotemporal log-Gaussian Cox processes. *Statistica Neerlandica*, **67(4)**, 355-389.
14. Parry, K. and **Hazelton, M.L.** (2013). Bayesian inference for day-to-day dynamic traffic models. *Transportation Research Part B*, **50**, 104-115.
15. Parry, K. and **Hazelton, M.L.** (2012). Estimation of origin-destination matrices from link counts and sporadic routing data. *Transportation Research Part B*, **46**, 175-188.
16. **Hazelton, M.L.** and Turlach, B.A. (2011). Semiparametric regression with shape constrained penalized splines. *Computational Statistics and Data Analysis*, **55**, 2871-2879.

17. Davies, T.M., **Hazelton, M.L.** and Marshall, J.C. (2011). sparr: Analyzing spatial relative risk using fixed and adaptive kernel density estimation in R. *Journal of Statistical Software*, **39**, 1-14.
18. **Hazelton, M.L.** (2011). Assessing log-concavity of multivariate densities. *Statistics and Probability Letters*, **81**, 121-125.
19. Davies, T.M. and **Hazelton, M.L.** (2010). Adaptive kernel estimation of spatial relative risk. *Statistics in Medicine*, **29**, 2423-2437.
20. **Hazelton, M.L.** (2010). Bayesian inference for network-based modes with a linear inverse structure. *Transportation Research Part B*, **44**, 674-685.
21. **Hazelton, M.L.** (2010). Statistical inference for transit system origin-destination matrices. *Technometrics*, **52**, 221-230.
22. Marshall, J.C. and **Hazelton, M.L.** (2010). Boundary kernels for adaptive density estimators on regions with irregular boundaries. *Journal of Multivariate Analysis* **101**, 949-963.
23. **Hazelton, M.L.** and Turlach, B.A. (2010). Semiparametric density deconvolution. *Scandinavian Journal of Statistics* **37**, 91-108.
24. **Hazelton, M.L.** and Turlach, B.A. (2009). Nonparametric density deconvolution by weighted kernel estimators. *Statistics and Computing*, **19**, 217-228.
25. **Hazelton, M.L.** and Marshall, J.C. (2009). Linear boundary kernels for bivariate density estimation. *Statistics and Probability Letters*, **79**, 999-1003.
26. **Hazelton, M.L.** and Davies, T.M. (2009). Inference based on kernel estimates of the relative risk function in geographical epidemiology. *Biometrical Journal*, **51**, 98-109.
27. **Hazelton, M.L.** (2008). Statistical inference for time varying origin-destination matrices. *Transportation Research Part B*, **42**, 442–452.
28. **Hazelton, M.L.** (2007). Bias reduction in kernel binary regression. *Computational Statistics and Data Analysis*, **51**, 4393-4402.
29. **Hazelton, M.L.** and Turlach, B.A. (2007). Reweighted kernel density estimation. *Computational Statistics and Data Analysis*, **51**, 3057-3069.
30. Baddeley, A., Turner, R., Moller, J. and **Hazelton, M.** (2005). Residual analysis for spatial point processes (with discussion). *Journal of the Royal Statistical Society Series B*, **67**, 617-666. Read before the Royal Statistical Society on Wednesday 22nd June 2005.
31. Duong, T and **Hazelton, M.L.** (2005). Cross-validation bandwidth matrices for multivariate kernel density estimation. *Scandinavian Journal of Statistics*, **32**, 485-506.
32. Duong, T. and **Hazelton, M.L.** (2005). Convergence rates for unconstrained bandwidth matrix selectors in multivariate kernel density estimation. *Journal of Multivariate Analysis*, **93**, 417-433.
33. Gurrin, L.C., Scurrah, K. and **Hazelton, M.L.** (2005). Tutorial in biostatistics: Spline smoothing with linear mixed models. *Statistics in Medicine*, **24**, 3361-3381.
34. **Hazelton, M.L.** and Watling, D.P. (2004). Computation of equilibrium distributions of Markov traffic assignment models. *Transportation Science*, **38**, 331-342.

35. **Hazelton, M.L.** (2004). Density estimation from aggregate data. *Computational Statistics*, **19**, 407-423.
36. Sircombe, K.N. and **Hazelton, M.L.** (2004). Comparison of detrital zircon age distributions by kernel functional estimation. *Sedimentary Geology*, **171**, 91-111
37. **Hazelton, M.L.** (2004). Density estimation from aggregate data. *Computational Statistics*, **19**, 407-423.
38. **Hazelton, M.L.** (2003). A graphical tool for assessing normality. *The American Statistician*, **57**, 285-288.
39. **Hazelton, M.L.** (2003). Variable kernel density estimation. *Australian and New Zealand Journal of Statistics*, **45**, 271-284.
40. Duong, T and **Hazelton, M.L.** (2003). Plug-in bandwidth selectors for bivariate kernel density estimation. *Journal of Nonparametric Statistics*, **15**, 17-30.
41. **Hazelton, M.L.** (2003). Some comments on origin-destination matrix estimation. *Transportation Research Part A*, **37**, 811-822.
42. **Hazelton, M.L.** (2003). Total travel cost in stochastic assignment models. *Networks and Spatial Economics*, **3**, 457-466.
43. **Hazelton, M.L.** (2002). Day-to-day variation in Markovian traffic assignment models. *Transportation Research Part B*, **36**, 637-648.
44. **Hazelton, M.L.** (2001). Estimation of origin-destination trip rates in Leicester. *Journal of the Royal Statistical Society, Series C (Applied Statistics)*, **50**, 423-433.
45. **Hazelton, M.L.** (2001). Inference for origin-destination matrices: estimation, reconstruction and prediction. *Transportation Research Part B*, **35**, 667-676.
46. **Hazelton, M.L.** (2000). Marginal density estimation from incomplete bivariate data. *Statistics and Probability Letters*, **47**, 75-84.
47. **Hazelton, M.L.** (2000). Estimation of origin-destination matrices from link flows on uncongested networks. *Transportation Research Part B*, **34**, 549-566.
48. Broughton, J., **Hazelton, M.L.** and Stone, M. (1999). Influence of light-level on the incidence of road casualties and the associated effect of summertime clock changes. *Journal of the Royal Statistical Society, Series A*, **162**, 137-175. Read before the Royal Statistical Society on 14 October 1998.
49. **Hazelton, M.L.** (1998). Bias annihilating bandwidths for kernel density estimation at a point. *Statistics and Probability Letters*, **38**, 305-309.
50. **Hazelton, M.L.** (1998). Some remarks on Stochastic User Equilibrium. *Transportation Research Part B*, **32**, 101-108.
51. **Hazelton, M.L.** (1996). Bandwidth selection for local density estimators. *Scandinavian Journal of Statistics*, **23**, 221-232.
52. **Hazelton, M.L.** (1996). Optimal rates for local bandwidth selection. *Journal of Nonparametric Statistics*, **7**, 57-66.
53. **Hazelton, M.L.** (1995). Improved Monte Carlo inference for models with additive error. *Statistics and Computing*, **5**, 343-350.

5. CURRICULUM VITAE AND PUBLICATIONS

PART 1

1a. Personal details				
Full name	*Title* Professor	*First name* Adrian	*Second name(s)* John	*Family name* Baddeley
Present position	Professor of Computational Statistics			
Organisation/Employer	Curtin University			
Contact address	School of Mathematics & Statistics			
	GPO Box U1987			
	Perth, Western Australia		Post code	6845
Work telephone	+61 410 447 821	Mobile	+61 410 447 821	
Email	Adrian.Baddeley@curtin.edu.au			
Personal website (if applicable)	www.spatstat.org			

1b. Academic qualifications

1980, PhD, Mathematical Statistics, Cambridge University
1976, BA(Hons), Pure Mathematics and Statistics, Australian National University.

1c. Professional positions held

2015–present, Professor of Computational Statistics, Curtin University.
2013–2014, Research Professor, Centre for Exploration Targeting, University of Western Australia.
2010–2012, Research Scientist, CSIRO Mathematics Informatics & Statistics, Perth, Australia.
1994-2010, Full Professor of Statistics, University of Western Australia.
1988–1994, Research group leader, CWI (Centre for Mathematics and Computer Science), Amsterdam, Netherlands.
1985-1988, Research scientist, CSIRO Division of Mathematics & Statistics, Sydney, Australia.
1982–1985, Lecturer in Statistics, University of Bath, UK.
1979–1982, Research Fellow of Trinity College, Cambridge, UK.

1d. Present research/professional speciality

Statistical methodology for spatial data. Statistical computing and statistical software.

1e. Total years research experience:	42 years

1f. Professional distinctions and memberships (including honours, prizes, scholarships, boards or governance roles, etc)

2017, John Curtin Distinguished Professorship, Curtin University.
2015, Honorary DSc, Aalborg University.
2013, Australian Research Council, Discovery Outstanding Researcher Award
2008, Matheron Lecturer, International Association for Mathematical Geology.
2004, Pitman Medal, Statistical Society of Australia.
2001, Centenary Medal, Australian Government.
2001, Hannan Medal, Australian Academy of Science.
2000, elected Fellow of the Australian Academy of Science.

1995, Medal of the Australian Mathematical Society.
1991, Adjunct Professor, University of Leiden, Netherlands.
1979, Prize Research Fellowship, Trinity College Cambridge.
1979, Smith-Knight Prize (1st Class), University of Cambridge.
1977, External Research Studentship, Trinity College Cambridge.
1977, Commonwealth Postgraduate Research Scholarship.
1976, University Medal, Australian National University.

1g. Total number of *peer reviewed* publications and patents	Journal articles	Books	Book chapters, books edited	Conference proceedings	Patents
	87	2	11	18	0

PART 2

2a. Research publications and dissemination

Peer reviewed journal articles (selected)

1. S. Rakshit, T.M. Davies, M.M. Moradi, G. McSwiggan, G. Nair, J. Mateu, and A. **Baddeley**. Fast kernel smoothing of point patterns on a large network using 2D convolution. *International Statistical Review*, **2019**. In press. `DOI: 10.1111/insr.12327`.
2. S. Rakshit, A. **Baddeley**, and G. Nair. Efficient code for second-order analysis of events on a linear network. *Journal of Statistical Software*, **2019**. In press.
3. K. Hingee, A. **Baddeley**, P. Caccetta and G. Nair. Computation of lacunarity from covariance of spatial binary maps. *Journal of Agricultural, Biological and Environmental Statistics* 24: 264-288. **2019.**
4. M. Moradi, O. Cronie, E. Rubak, R. Lachieze-Rey, J. Mateu and A. **Baddeley**. Resample-smoothing of Voronoi intensity estimators. *Statistics and Computing* **2019**, In press. Published online 22 january 2019.
5. A. **Baddeley**, E. Rubak and R. Turner. Leverage and influence diagnostics for Gibbs spatial point processes. *Spatial Statistics* 29: 15–48, **2019.**
6. T.M. **Davies** and A. **Baddeley**. Fast computation of spatially adaptive kernel estimates. *Statistics and Computing* 28: 937-956, **2018.**
7. A. **Baddeley**. Local composite likelihood for spatial point processes. *Spatial Statistics*, 22:261–295, **2017.**
8. A. **Baddeley**, A. Hardegen, T. Lawrence, R.K. Milne, G. Nair, and S. Rakshit. On two-stage Monte Carlo tests of composite hypotheses. *Computational Statistics and Data Analysis*, 114:75–87, **2017.**
9. A. **Baddeley** and G. Nair. Poisson-saddlepoint approximation for Gibbs point processes with infinite-order interaction: in memory of Peter Hall. *Journal of Applied Probability*, 54(4):1008–1026, December **2017.**
10. S. Rakshit, G. Nair, and A. **Baddeley**. Second-order analysis of point patterns on a network using any distance metric. *Spatial Statistics*, 22(1):129–154, **2017.**
11. A. **Baddeley**, G. Nair, S. Rakshit, and G. McSwiggan. 'Stationary' point processes are uncommon on linear networks. *STAT*, 6(1):68–78, **2017.**
12. A. **Baddeley**, R. Turner, and E. Rubak. Adjusted composite likelihood ratio test for spatial Gibbs point processes. *Journal of Statistical Computation and Simulation*, 86(5):922–941, **2016.**
13. T. Lawrence, A. **Baddeley**, R.K. Milne, and G. Nair. Point pattern analysis on a region of a sphere. *Stat*, 5(1):144–157, **2016.**
14. G. McSwiggan, A. **Baddeley**, and G. Nair. Kernel density estimation on a linear network. *Scandinavian Journal of Statistics*, 44(2):324–345, **2016.**
15. I.W. Renner, J. Elith, A. **Baddeley**, W. Fithian, T. Hastie, S.J. Phillips, G. Popovic, and D.I. Warton. Point process models for presence-only analysis. *Methods in Ecology and Evolution*, 6(4):366–379, **2015.**
16. A. **Baddeley**, J.-F. Coeurjolly, E. Rubak, and R. Waagepetersen. Logistic regression for spatial Gibbs point processes. *Biometrika*, 101(2):377–392, **2014.**
17. A. **Baddeley**, P.J. Diggle, A. Hardegen, T. Lawrence, R.K. Milne, and G. Nair. On tests of spatial pattern based on simulation envelopes. *Ecological Monographs*, 84(3):477–489, **2014.**
18. A. **Baddeley**, A. Jammalamadaka, and G. Nair. Multitype point process analysis of spines on the dendrite network of a neuron. *Applied Statistics (Journal of the Royal Statistical Society, Series C)*, 63(5):673–694, **2014.**

19. A. **Baddeley** and R. Turner. Bias correction for parameter estimates of spatial point process models. *Journal of Statistical Computation and Simulation*, 84:1621–1643, **2014**.
20. R.S. Anderssen, A. **Baddeley**, F.R. DeHoog, and G.M. Nair. Solution of an integral equation arising in spatial point process theory. *Journal of Integral Equations and Applications*, 26(4):437–453, **2014**.
21. A. **Baddeley**, Y.-M. Chang, Y. Song, and R. Turner. Residual diagnostics for covariate effects in spatial point process models. *Journal of Computational and Graphical Statistics*, 22:886–905, 2013.
22. A. **Baddeley**, Y.M. Chang, and Y. Song. Leverage and influence diagnostics for spatial point processes. *Scandinavian Journal of Statistics*, 40:86–104, 2013.
23. A. **Baddeley** and D. Dereudre. Variational estimators for the parameters of Gibbs point process models. *Bernoulli*, 19:905–930, 2013.
24. A. **Baddeley**, R. Turner, J. Mateu, and A. Bevan. Hybrids of Gibbs point process models and their implementation. *Journal of Statistical Software*, 55(11):1–43, 2013.
25. A. **Baddeley**, Y.M. Chang, Y. Song, and R. Turner. Nonparametric estimation of the dependence of a spatial point process on a spatial covariate. *Statistics and its Interface*, 5:221–236, 2012.
26. Q.W. Ang, A. **Baddeley**, and G. Nair. Geometrically corrected second order analysis of events on a linear network, with applications to ecology and criminology. *Scandinavian Journal of Statistics*, 39:591–617, 2012.
27. A. **Baddeley** and G. Nair. Fast approximation of the intensity of Gibbs point processes. *Electronic Journal of Statistics*, 6:1155–1169, 2012.
28. A. **Baddeley** and G. Nair. Approximating the moments of a spatial point process. *Stat*, 1(1):18–30, 2012.
29. A. **Baddeley**, E. Rubak, and J. Møller. Score, pseudo-score and residual diagnostics for spatial point process models. *Statistical Science*, 26:613–646, 2011.
30. A. **Baddeley**, M. Berman, N.I. Fisher, A. Hardegen, R.K. Milne, D. Schuhmacher, and R. Turner. Spatial logistic regression and change-of-support for Poisson point processes. *Electronic Journal of Statistics*, 4:1151–1201, 2010.
31. S.S. Singh, B. Vo, A. **Baddeley**, and S. Zuyev. Filters for spatial point processes. *SIAM Journal on Control and Optimization*, 48(4):2275–2295, 2009.
32. A. **Baddeley**, J. Møller, and A.G. Pakes. Properties of residuals for spatial point processes. *Annals of the Institute of Statistical Mathematics*, 60:627–649, 2008.
33. J.F. Wallace, M. Canci, X. Wu, and A. **Baddeley**. Monitoring native vegetation on an urban groundwater supply mound using airborne digital imagery. *Journal of Spatial Science*, 53:63–73, 2008. ISSN 1449-8596.
34. A. **Baddeley**, R. Turner, J. Møller, and M. **Hazelton**. Residual analysis for spatial point processes (with discussion). *Journal of the Royal Statistical Society, Series B*, 67(5):617–666, 2005.
35. R. Foxall and A. **Baddeley**. Nonparametric measures of association between a spatial point process and a random set, with geological applications. *Applied Statistics*, 51(2):165–182, 2002.
36. A. **Baddeley**, J. Møller, and R. Waagepetersen. Non- and semiparametric estimation of interaction in inhomogeneous point patterns. *Statistica Neerlandica*, 54(3):329–350, 2000.

37. A. **Baddeley** and R. Turner. Practical maximum pseudolikelihood for spatial point patterns (with discussion). *Australian and New Zealand Journal of Statistics*, 42(3):283–322, 2000.
38. Y.C. Chin and A.J. **Baddeley**. Markov interacting component processes. *Advances in Applied Probability*, 32:597–619, 2000.
39. K. Schladitz and A.J. **Baddeley**. A third order point process characteristic. *Scandinavian Journal of Statistics*, 27:657–671, 2000.
40. Y.C. Chin and A.J. **Baddeley**. On connected component Markov point processes. *Advances in Applied Probability*, 31:279–282, 1999.
41. W.S. Kendall, M.N.M. van Lieshout, and A.J. **Baddeley**. Quermass-interaction processes: conditions for stability. *Advances in Applied Probability*, 31:315–342, 1999.
42. M.N.M. van Lieshout and A.J. **Baddeley**. Indices of dependence between types in multivariate point patterns. *Scandinavian Journal of Statistics*, 26:511–532, 1999.
43. A.J. **Baddeley** and R.D. Gill. Kaplan-Meier estimators of interpoint distance distributions for spatial point processes. *Annals of Statistics*, 25:263–292, 1997.
44. A.J. **Baddeley**, M.N.M. van Lieshout, and J. Møller. Markov properties of cluster processes. *Advances in Applied Probability*, 28:346–355, 1996.
45. A.J. **Baddeley** and M.N.M. van Lieshout. Area-interaction point processes. *Annals of the Institute of Statistical Mathematics*, 47:601–619, 1995.
46. M.N.M. van Lieshout and A.J. **Baddeley**. A nonparametric measure of spatial interaction in point patterns. *Statistica Neerlandica*, 50:344–361, 1996.
47. A.J. **Baddeley**, R.A. Moyeed, C.V. Howard, and A. Boyde. Analysis of a three-dimensional point pattern with replication. *Applied Statistics*, 42(4):641–668, 1993.
48. R.A. Moyeed and A.J. **Baddeley**. Stochastic approximation of the MLE for a spatial point pattern. *Scandinavian Journal of Statistics*, 18:39–50, 1991.
49. A.J. **Baddeley** and J. Møller. Nearest-neighbour Markov point processes and random sets. *International Statistical Review*, 57:89–121, 1989.
50. A.J. **Baddeley** and B.W. Silverman. A cautionary example on the use of second-order methods for analyzing point patterns. *Biometrics*, 40:1089–1094, 1984.

Peer reviewed books

1. A. **Baddeley**, E. Rubak, and R. Turner. *Spatial Point Patterns: Methodology and Applications with R*. Chapman and Hall/CRC, London, **2015**.
2. A. **Baddeley** and E.B. Vedel Jensen. *Stereology for Statisticians*. Chapman and Hall/CRC, London, **2005**.

Peer reviewed book chapters, books edited (selected)

1. A. **Baddeley**. Modelling strategies. In A.E. Gelfand, P.J. Diggle, M. Fuentes, and P. Guttorp, editors, *Handbook of Spatial Statistics*, chapter 20, pages 339–369. CRC Press, Boca Raton, 2010.
2. A. **Baddeley**. Multivariate and marked point processes. In A.E. Gelfand, P.J. Diggle, M. Fuentes, and P. Guttorp, editors, *Handbook of Spatial Statistics*, chapter 21, pages 371–402. CRC Press, Boca Raton, 2010.
3. A. **Baddeley**. Spatial point processes and their applications. In A. **Baddeley**, I. Bárány, R. Schneider, and W. Weil, editors, *Stochastic Geometry: Lectures given at the C.I.M.E. Summer School held in Martina Franca, Italy, September 13–18, 2004*, Lecture Notes in Mathematics 1892 (subseries: Fondazione C.I.M.E., Firenze), pages 1–75. Springer-Verlag, 2006.
4. M.N.M. van Lieshout and A.J. **Baddeley**. Extrapolating and interpolating spatial patterns. In A.B. Lawson and D.G.T. Denison, editors, *Spatial cluster modelling*, chapter 4, pages 61–86. Chapman and Hall/CRC Press, Boca Raton, 2002.