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Commentary

Injury prediction as a non-linear system

Benjamin D. Stern [a, *], Eric J. Hegedus [b], Ying-Cheng Lai [c]

[a] Department of Outpatient Rehabilitation, HonorHealth, Scottsdale, AZ, USA
[b] Department of Physical Therapy, High Point University, High Point, NC, USA
[c] School of Electrical, Computer and Energy Engineering, Arizona State University, Tempe, AZ, USA

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1. Background- The injury prediction debate

The purpose of screening in sports is to examine large populations of asymptomatic individuals aiming to predict who is at greatest risk of sustaining an injury. Ideally, once at-risk athletes are identified, scientists, clinicians, and coaches would address variables associated with risk by using behavior modification, changing training regime, or improving movement strategies (mitigate risk). This approach is logical and would be of great benefit to active individuals everywhere, but sports scientists cannot agree on whether it is possible.

Some sports scientists have advocated the use of individual tests and measures that are associated with injury to stratify risk based on linear models and multiple regression methodology (Freckleton & Pizzari, 2013; Hewett, 2016). Critics of this approach have countered that no *single* test or measure nor any combination thereof has demonstrated strong enough sensitivity and specificity to predict injury and that, therefore, risk screening (high sensitivity) and injury prediction (high specificity) should be abandoned in favor of placing all players on every team on an injury prevention program (Bahr, 2016, 2016b). Still others have begun to wonder whether injury screening and prediction are too complex for the linear models that have been used in the past (van Dyk & Clarsen, 2017). It is also possible that a recursive model employing ongoing, frequent monitoring of athletes may address some of these shortcomings.

In 2016, Bittencourt et al. (Bittencourt et al., 2016) advanced thinking in this area by recommending more frequent screening as well as proposing that injury might be predicted by "a complex interaction of a web of determinants". Germaine to this concept is that resistance to injury is nonlinear, dynamic, and composed of interdependent factors. We are struck at the similarity between prediction of injury and predicting wildly complex events such as the path of hurricanes (Lorenz, 1963; Wang, Lai, & Grebogi, 2016). Although marked improvements have occurred in recent years, the prediction of the path of a hurricane is an imperfect science, but useful enough to guide critical decisions and give estimates.

The purpose of this viewpoint is to propose and explain the hypothesis that an athlete's resistance to injury is a nonlinear, dynamic system. As such, individual resistance to injury should not be viewed as a steady state, an inherent assumption in any pre-season testing model. We propose that, as with the tracking of a volatile weather pattern like a hurricane, frequent sampling of variables through athlete testing is a prerequisite to understanding the behavior of the human system and to detecting when there is a change in the resistance of the system to injury. Moreover, better detection of a change in the system could lead to a better understanding of which athlete is at a greater risk for injury-paramount in order to efficiently target preventative interventions.

2. Athletes, like hurricanes are nonlinear, dynamic systems

Hurricanes and athletes are both nonlinear dynamic systems. The web of determinants for a hurricane includes wind speed, wind direction, humidity, and sea surface temperature, among others (Brennan & Majumdar, 2011). Because of the continuous-time

* Corresponding author.
E-mail address: Benjamin.Stern@HonorHealth.com (B.D. Stern).

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nature of the system, it is necessary to collect data as frequently as possible. In fact, existing data-based methods to analyze nonlinear dynamical systems all require continuously sampled time series data to enable the intrinsic properties of the system to be determined with confidence. Hurricane strength and path changes over time based on changes to the web of determinants and the factors acting on the system. The difference between the actual position of a hurricane and one predicted 48 hours in advance has improved from 450 nautical miles in the 1970's to less than 100 nautical miles today (Lewis, 2014). Early forecasts relied on patterns found in older data. Over time, in addition to improving technology (computing power, data from satellites and hurricane hunter aircraft, etc.), meteorologists have incorporated new, dynamic models which rely on increasingly accurate measurements of current conditions (Brennan & Majumdar, 2011).

Using dynamic models, powerful computers process the over 40 million observations (determinants) which are collected multiple times daily to update parameters and generate deterministic and ensemble 10- and 15-day forecasts respectively (Magnusson, Bidlot, Bonavita, & etal, 2018). The ensemble includes 50 forecasts generated by slightly varying the measured conditions and parameters obtained from the initial observations. Compare this process and technology with the current state of the art of athlete injury prediction where, for example, a single leg squat is performed preseason and we expect the results to tell us who will be injured during the season. This common model used in athletics frequently and globally is far less than dynamic.

With regard to athletes and injury, we would suggest that the complex physiological and psychosocial human system has distinctly separate coexisting states: (1) a healthy state and (2) an injured state. Factors that push an athlete toward either of the two states are represented by an interdependent web of determinants (independent variables in the linear model) which change continuously affecting the system as a whole as well as the relationships between the determinants themselves. The dynamics are nonlinear and small differences in the initial measurements of determinants can evolve exponentially over time. For example, an athlete quality of life self-report outcome may show little difference between players in the pre-season but show vast differences 2 months later based on life events (positive or negative) and athlete ability to cope with negative events. Each athlete's determinants are exposed to two competing forces: stress (destabilizing) input (ex: death in the family) and accommodative (stabilizing) input (ex; grief counseling). The web of determinants flows between these two paths continuously as the athlete balances stress and accommodation, nudging the athlete toward or away from injury much like a hurricane waffles on its path through the ocean. We would suggest that the determinants in this system are variable (exceptions might be BMI in a mature athlete) and that the system itself is so dynamic and irregular that hoping to capture the athlete's risk of injury by some pre-season test is folly.

A simple example involving a recreational student athlete may better elucidate these thoughts as we can demonstrate great change in a system of low resilience (Fig. 1). In our example, the student, who is in fair physical condition, decides to train for a first marathon. Fig. 1a represents the student at baseline (the large sphere represents the athlete and the smaller spheres represent just a small sample from a vast web of determinants which may include, for example, genetics, hormonal factors, personality type, load and biomechanics. Not knowing how to train, he runs every day the first week for a total of 40 miles so load increases too quickly. A few weeks later, the student is training through medial tibial pain, has increased his mileage, and has entered finals week so sleep is less, stress is more, coping skills are challenged, and quality of life decreases (Fig. 1b). As an aside, at this point, depending on the sensitivity of the test or tests, some might conclude the athlete is at risk for injury while others might still conclude this athlete is at low or no risk for injury. Keep in mind, the athlete is still in the healthy state (depending on the definition of injury), has pain, but is still in the transitional zone between health and injury. Our student is now vulnerable, running in pain, prone to more stress input (concurrently the student fails two

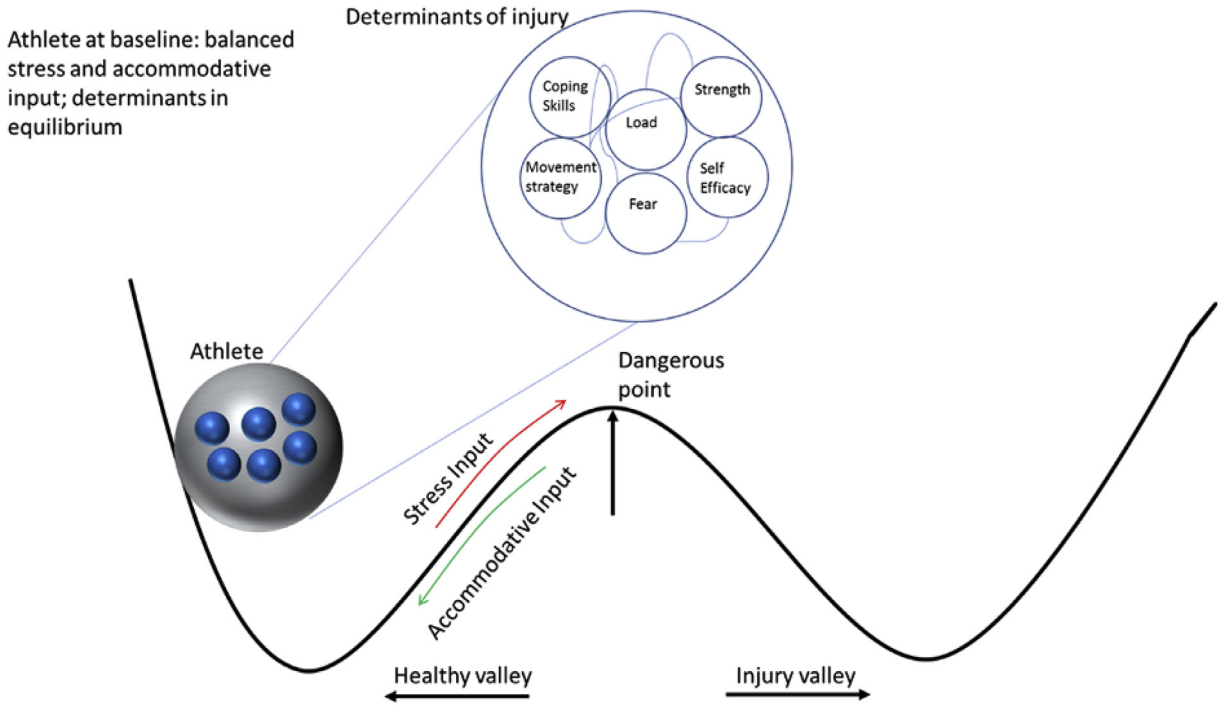

Fig. 1a. Determinants of injury in athlete at steady-state or baseline.

academic examinations) and once he passes the tipping point, change is unavoidable (Fig. 1c). Perhaps, he can be saved by more accommodative input (student decides that the marathon is not for him or the 8 weeks of hip strengthening he has been doing improves his ground reaction force or movement pattern) (Fig. 1d). Throughout this scenario, the system changes but so do the relationships among the variables or determinants within the system. This model allows the athlete to be observed and examined as a fluid, dynamic system.

3. Is there any evidence resistance to injury is a dynamic system?

There is some support for viewing the athlete's resistance to injury as a dynamic system. Strength, power, and markers of muscle damage can vary dramatically throughout a season (Kraemer, Looney, Martin, & etal, 2013; McMaster, Gill, Cronin, & McGuigan, 2013). Physiological components of human performance can vary over the course of a single day (Ammar, Chtourou, & Souissi, 2017; Atkinson & Reilly, 1996; Kafkas, Taskiran, Sahin Kafkas, & etal, 2016). There is inherent uncertainty of the athlete's condition in the time period adjacent to and during exposure to physical activity. By monitoring intensity and duration within 30 minutes of each training session and match, Gabbett and colleagues identified a relationship between spikes in training load and injury (Gabbett, 2004). Thus, some factors associated with injury behave deterministically or predictably over short periods of time. In response to usual daily experiences (training, sleep, stress, illness, etc.), an individual's physiological and psychosocial states are in constant flux (Ammar et al., 2017; Elkington, Cassar, Nelson, & Levinger, 2017; Finger et al., 2015; Kraemer et al., 2013). The way that most injury prediction studies are conducted is, unfortunately, not valuable in a dynamic system because these studies don't tell us enough about how the system behaves over time.

4. Suggested changes in injury risk assessment

Studies examining the predictive value of various tests and measures on injury risk generally collect data from the screen just prior to the start of the sports season and injury data is then collated and analyzed at some point after the season (Hegedus, McDonough, & Bleakley, 2016; van Dyk, Bahr, Whiteley, & etal, 2016; Warren, Smith, & Chimera, 2015). Upon analyzing the data, positive or negative associations between injuries and the screening results are assumed. However, the time interval between initial measurements and the actual injury often leaves a period of weeks to months during which the factors contributing to injury may change or evolve for any number of reasons. Recency of data matters (Chen et al., 2016, 2017; Leutbecher & Palmer, 2008; Palmer, 1993). If the athlete is a fluid, dynamic system then the analogy of the hurricane is appropriate and collecting data more frequently as in hurricane path prediction is critical. Just as hurricane tracking has improved with advances in technology, we may construct new dynamic models to predict injury in athletes using increasingly accurate, continuous measurement of current conditions (Fig. 2). Wearable technology like heart rate monitors, inertial sensors and global positioning systems (GPS) are making real-time, continuous data more accessible. However, for some, cost is a limitation. In those cases where lower technology assessment tools are the only option, not only would we recommend sampling more frequently but also we would advocate for a more complete sampling model that captures more of the possible web of determinants. Some of these determinants cannot be changed by interventions but are still valuable like genetic predisposition, age, past injury, and gender. Many other determinants can be assessed and altered and we would recommend the following as examples:

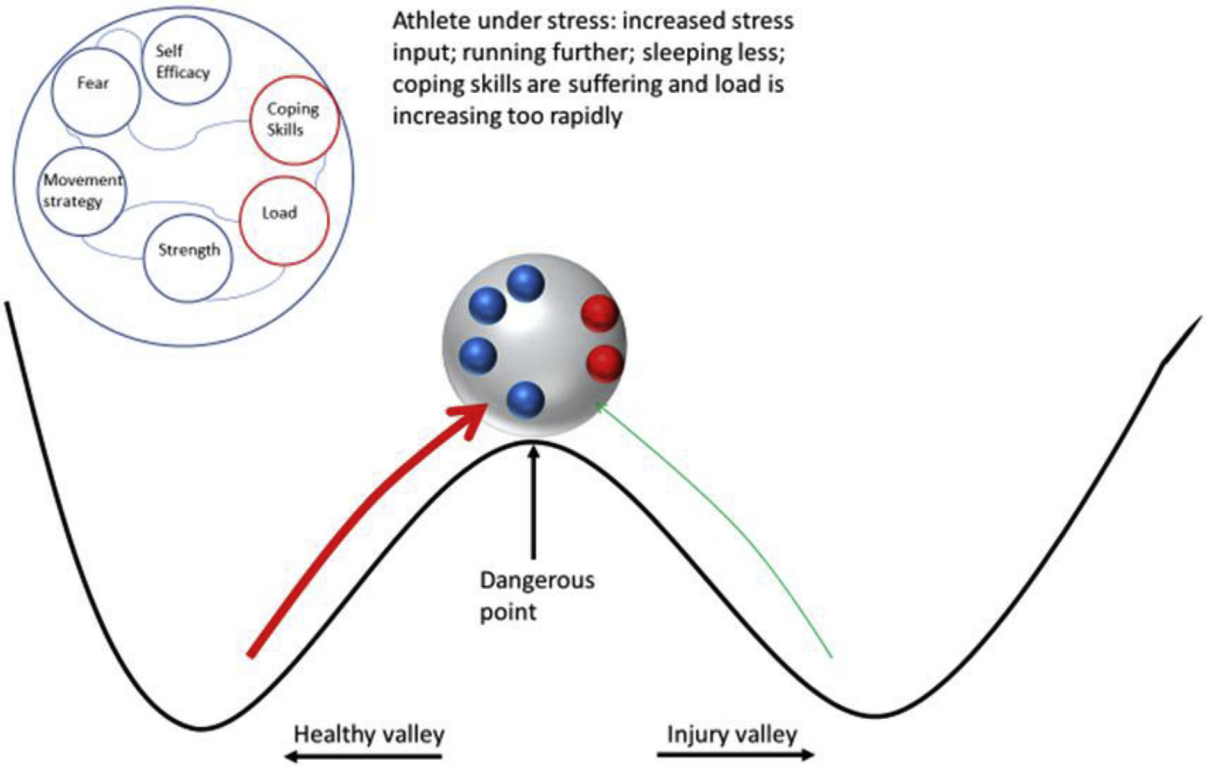

Fig. 1b. Determinants of injury in an athlete under stress and near the tipping point.

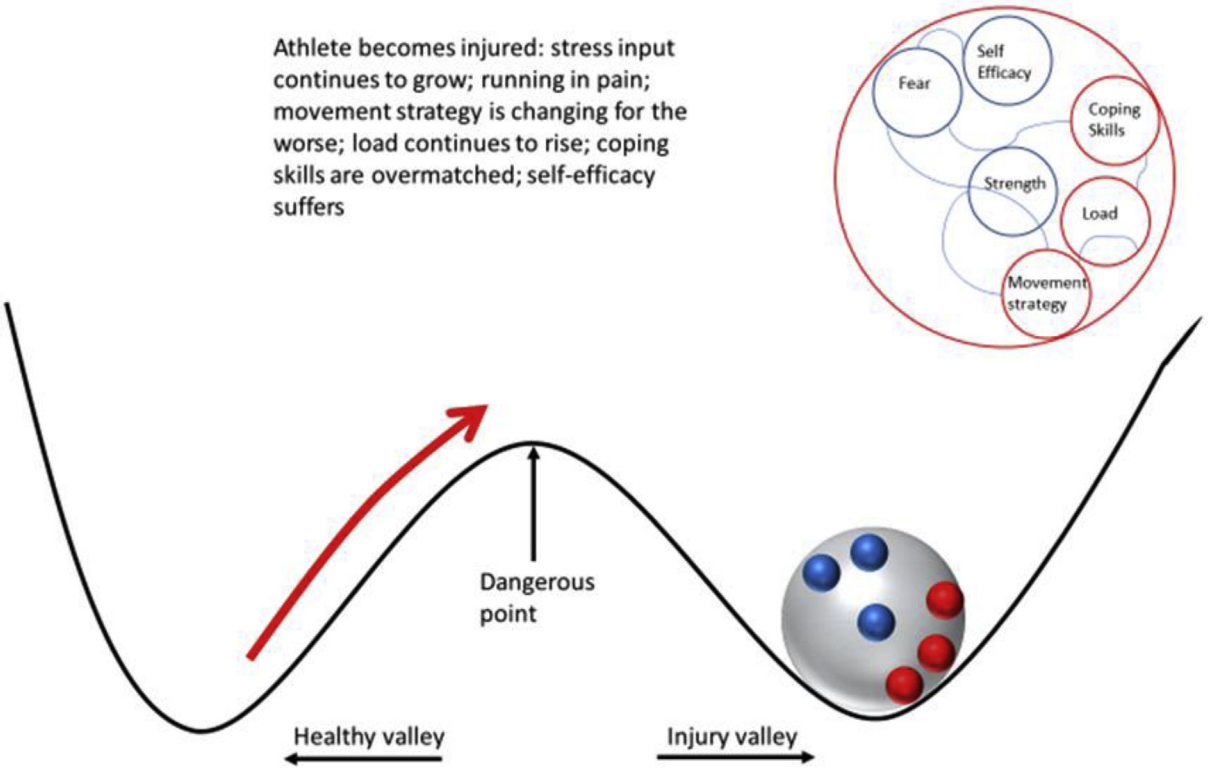

Fig. 1c. Determinants of injury in an athlete who has crossed the boundary and transitioned from a healthy state to an injured state.

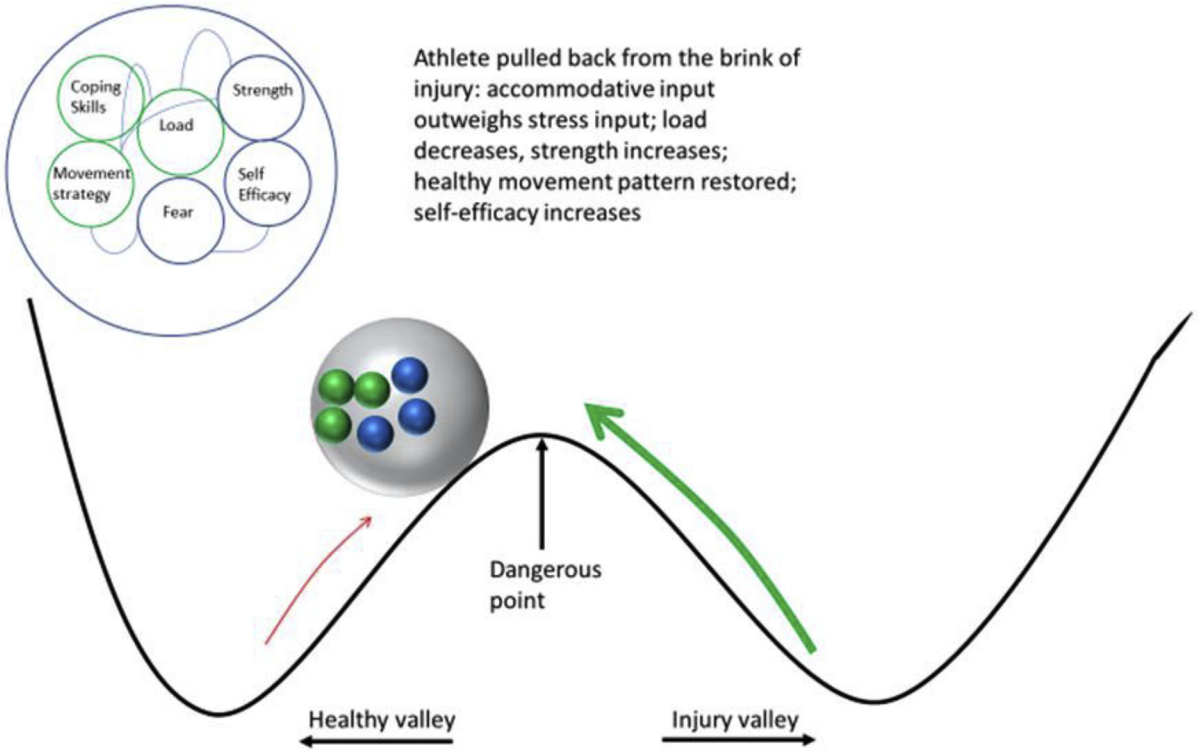

Fig. 1d. Determinants of injury in athlete pulled back from the brink of injury.

1. Self-report measures that examine life stress, anxiety, and coping skills
2. Sleep quality assessment
3. Nutrition log
4. Beighton hypermobility testing
5. Physical Performance tests of stability, power and motor control

This list is not meant to be exhaustive but instead, to serve as an

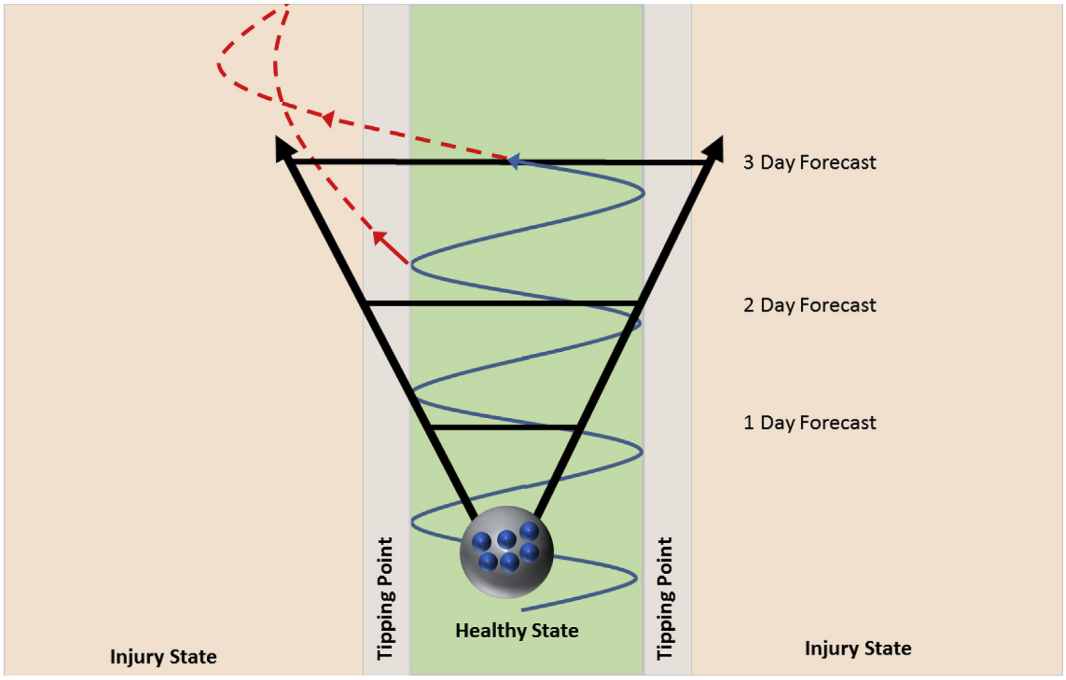

Fig. 2. The system underlying the occurrences of non-contact injuries evolves continuously and frequent collection of data allows us to monitor the evolution or changes in the system over time. The further into the future we attempt to forecast the less confidence we have in our forecast.

example of affordable sampling from multiple domains that would still be time efficient.

In sum, screening can improve allocation of resources, stratification of patients by risk and inform decision making. Results assist with prediction about the athlete's current state, but system properties limit forecasting far in the future with any degree of accuracy. Minor changes may result in profound differences over time which influence the ensemble of possible scenarios (Ruelle & Takens, 1971). Like improving prediction of a wildly uncertain hurricane path, we may improve injury prediction by viewing athletes and their resistance to injury as dynamic systems. Viewing athletes and injury risk through this lens will lead to improved sampling techniques and a better understanding of the relationship of injury variables to each other and hopefully, to keeping more athletes from the tipping point.

5. Key points

- Athletes and resistance to injury, like hurricanes, represent a dynamic system.
- Prediction of injury methodology must improve if we are to capture meaningful relationships among variables and between variables and injury in a non-linear system, that evolves continuously over time.
- More frequent and a broader sampling of the athlete's web of injury determinants is required if we are to predict and modify injury risk.

Author contributions

Conceptualization B.D.S., E.J.H., Y.C.L; Manuscript review and editing B.D.S., E.J.H., Y.C.L; Writing original draft B.D.S.

Declaration of competing interests

The authors declare no competing or financial interests.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ptsp.2019.10.010.

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