I have several scientific contributions [Doyon et al., 2008, Gautier et al., 2010, Hocking et al., 2011, Hocking, 2012, Hocking et al., 2013a,b, Rigaill et al., 2013, Hocking et al., 2014, Suguro et al., 2014, Venuto et al., 2014, Hocking et al., 2015, Hocking, 2015, Chicard et al., 2016, Shimada et al., 2016, Hocking and Ekstrøm, 2016, Hocking et al., 2017, Maidstone et al., 2017, Drouin et al., 2017, Hocking and Killick, 2017, Alirezaie et al., 2018, Depuydt et al., 2018a,b, Hocking, 2019, Jewell et al., 2019, Sievert et al., 2019, Hocking et al., 2020, Fotoohinasab et al., 2020a,b, Hocking and Bourque, 2020, Abraham et al., 2021, Fotoohinasab et al., 2021, Hocking, 2021, Liehrmann et al., 2021, Kolla et al., 2021, Barnwal et al., 2022, Chaves et al., 2022, Hocking et al., 2022b, Mihaljevic et al., 2022, Vargovich and Hocking, 2022, Hocking, 2022, Barr et al., 2022a,b, Hocking et al., 2022a, Harshe et al., 2023, Hillman and Hocking, 2023, Hocking and Srivastava, 2023, Runge et al., 2023, Tao et al., 2023, Sweeney et al., 2023, Hocking, 2023, Rust and Hocking, 2023, Bodine et al., 2024a, Gurney et al., 2024, Kaufman et al., 2024, Tao et al., 2024, Fowler and Hocking, 2024, Sutherland et al., 2024, Hocking, 2024a,b,c,d, Bodine et al., 2024b, Nguyen and Hocking, 2024, Thibault et al., 2024, Truong and Hocking, 2024, Agyapong et al., 2025, Nguyen and Hocking, 2025].

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